AITA

ARTIFICIAL INTELLIGENCE

THEORY and APPLICATIONS

2021
Vol :1 Num : 2

Special Issue
Full Papers

Bi-annual

ISSN : 2757-9778
ISBN : 978-605-69730-2-4

Open Access

Izmir Bakircay University

Artificial Intelligence Studies in Healthcare Research and Application Center

Izmir / TURKEY

https://aita.bakircay.edu.tr

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Artificial Intelligence Theory and Applications

An International Open Access Journal

Volume 1, Number 2, 2021 – Special Issue

Publishing office: http://aita.bakircay.edu.tr, İzmir Bakırçay University, 35665 Menemen / Seyrek, İzmir, TURKEY. [Phone: (+90) (232) 493 00 00]
Advertising information: If you are interested in advertising or other commercial opportunities please e-mail aita@bakircay.edu.tr and your enquiry will be passed to the correct person who will respond to you within 48 hours.
Publication information: Artificial Intelligence Theory and Applications (ISSN: 2757-9778 || ISBN:978-605-69730-2-4). For 2021, volume 1(2) is scheduled for publication.

Artificial Intelligence Theory and Applications

ISSN: 2757-9778
ISBN: 978-605-69730-2-4

Volume 1, Number 2, 2021

Special Issue

May 26, 2021
Izmir Bakircay University

TURKEY

Published with the contributions of the
International Association of Artificial Intelligence in Health.

Preface to the Special Issue

This Special Issue of Artificial Intelligence Theory and Application journal is published for the studies that were submitted to 2nd International Artificial Intelligence in Health Congress which was held on April 16-18, 2021. All abstracts and some of the full text versions of these studies were published as Volume 1 and Number 2 of our journal.

Although the main theme of the congress was about artificial intelligence applications in heath domain especially during Covid-19 pandemic period, other research pertaining to non-pandemic circumstances in variety of health-related domains were also carried out and presented within the scope of the congress. The special issue includes both domain-specific theoretical and background-associated academic studies and practice-oriented work which covers topics and subjects such as pandemic management, vaccine and drug studies, health service management and public health, biomedical material and device design, health data modelling and analytics and neuroscience as well as clinical and non-clinical application domains like oncology, cancer, radiology, dentistry and nursery.

As editorial members of the journal, we do hope that the outputs of the special issue will be beneficial to corresponding audiences and the results of these academic work may contribute to extend the current body of knowledge on artificial intelligence applications in health domain.

Dr. Abdulkadir HIZIROGLU
Editor-in-Chief

Full Papers List for AITA (Volume 1, Number 2, 2021 - Special Issue)

Artificial Intelligence Theory and Applications

Full Papers

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Clinical Evaluation of IST-CovNet in Detecting COVID-19

Sabri ŞİROLU[1], Rauf HAMİD[1], Toghrul MAMMADOV[1], Mehmet Can YAVUZ [2], Sara Atito Ali AHMED [2], Mehmet Umut ŞEN[2], İrem ÇUHADAR [1], Ebru ÖZBEZEN [2], Berrin YANIKOĞLU YEŞİLYURT [2]

[1] *Istanbul University-Cerrahpasa, Cerrahpasa Medical Faculty*
[2] *Sabancı University, Faculty of Engineering and Natural Sciences*

* Corresponding Author: Istanbul University-Cerrahpasa, Cerrahpasa Medical Faculty, Turkey

Publication Information

Keywords :

- COVID-19,
- Deep learning,
- Computed tomography

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

CT imaging has become routine in the diagnosis of COVID-19 due to the long time to obtain RT-PCR results in the diagnosis of COVID-19 and the high rate of false negatives. In this study, the errors of the system we developed for the detection of COVID-19 in CT images were examined and recommendations for its use in the clinical process were evaluated.

The deep learning-based system has been trained using tagged CT images. The IST-C dataset was created retrospectively from patients who applied to the Radiology Department of CTF between March-August 2020 and it consists of images from 336 COVID-19 infected patients, 245 normal lungs and 131 non-COVID-19 pneumonia, tumor, and emphysema patients. The average age of the patients is 52±17 years, 405 men and 274 women. During the testing phase, a total of 250 patients were evaluated (100 infected with COVID-19, 100 had normal lung parenchyma, and 50 non-COVID-9 pneumonia, tumor, and emphysema) and a 90.8% success was observed.

Minimal lung involvement in 5, respiratory motion artifacts in 2 patients, pleural effusion and passive atelectasis accompanying COVID-19 were detected in 2 patients, in a total of 9 misclassified COVID-19 images. Images with normal parenchyma who were classified as COVID-19 showed atelectasis, motion artifacts in two patients each and both motion artifacts and areas of atelectasis in two patients. Sequela densities due to previous tuberculosis, a nodule located close to the diaphragm and mosaic attenuation due to possible pulmonary hypertension were observed in one patient each. In non-COVID patients, a mass was detected in 2, and a non-COVID infection was detected in 3.

When the COVID-19 probability assigned by the system for each image was examined and 0.3 was selected as the adjustable warning threshold, it was observed that the false negative rate decreased to 4% and the false positive rate was at an acceptable level (20%).

1. Introduction

COVID-19, caused by the SARS-CoV-2 virus, is a highly contagious disease, which spread rapidly around the world starting early 2020. The definitive diagnosis of the infection is achieved by using reverse transcriptase polymerase chain reaction (RT-PCR) for the viral DNA [1, 2].

As the false positivity and negativity of the RT-PCR test are not negligible and due to long time to obtain the result, CT imaging has become routine in the diagnosis of COVID-19 [3]. In this study, the errors of the system we developed for the detection of COVID-19 in CT images were examined and recommendations for its use in the clinical process were evaluated.

2. Methods

The deep learning-based system has been trained using tagged CT images. The tagging took place by the consensus of 3 radiologists (SŞ, RH, TM), who have thoracic imaging experiences of 5 years, 3 years and 2 years, respectively. The dataset was named IST-C and was created retrospectively from patients who applied to Cerrahpasa Faculty of Medicine, Radiology Department between March 2020, and August 2020. It consists of images from 336 COVID-19 infected patients, 245 individuals with normal lung parenchyma and 131 patients tagged as “others”. Three common diagnoses (tumor, non-COVID pneumonia and emphysema) were tagged as “others” to train the system for the differential diagnosis. Other parenchymal findings were included under the normal group. The average age of the patients was 52±17 years, 405 men and 274 women. The system assigned each patient a score ranging from 0 to 1, with 1 as the highest probability of COVID-19 and 0 as the lowest probability of a normal parenchyma or a non-COVID pathology. 0.5 was chosen as the threshold.

For the testing phase a total of 250 patients were evaluated (100 infected with COVID-19, 100 normal, and 50 others).

3. Results

During the testing phase, a 90.8% success was achieved.

9 out of the 100 COVID-19 images were falsely classified as non-COVID. When examined, we found that 5 of them had minimal lung involvement, 2 of them had respiratory motion artifacts and 2 of them had pleural effusion and passive atelectasis accompanying COVID-19.

9 of the 100 individuals with normal parenchyma were falsely classified as COVID-19. Of these patients 2 had subsegmental atelectasis, 2 had respiratory motion artifacts, 2 had both motion artifacts and atelectasis, 1 patient had sequela densities due to previous tuberculosis, 1 had a nodule located close to the diaphragm, and 1 had mosaic attenuation pattern due to possible pulmonary hypertension.

5 of the 50 “other” patients were falsely classified as COVID-19. 2 of them had lymphangitic carcinomatosis around a tumor and 3 had a non-COVID infection with ground glass opacities.

When the COVID-19 probability assigned by the system for each image was examined and 0.3 was selected as the adjustable warning threshold, instead of 0.5, it was observed that the false negative rate decreased to 4% and the false positive rate was at an acceptable level (20%). These values underline the value of our system as a screening method for COVID-19 in the emergency department.

References

1. V. M. Corman et al., “Detection of 2019 novel coronavirus (2019-nCoV) by real-time RT-PCR,” Eurosurveillance, vol. 25, no. 3, p. 2000045, Jan. 2020, doi: 10.2807/1560-7917.ES.2020.25.3.2000045.
2. G. D. Rubin et al., “The Role of Chest Imaging in Patient Management During the COVID-19 Pandemic,” Chest, vol. 158, no. 1, pp. 106–116, Jul. 2020, doi: 10.1016/j.chest.2020.04.003.
3. Y. Xiong et al., “Clinical and High-Resolution CT Features of the COVID-19 Infection,” Invest. Radiol., vol. 55, no. 6, pp. 332–339, Jun. 2020, doi: 10.1097/RLI.0000000000000674.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

The Status of Nursıng in Turkey in Terms of Artificial Intelligence, Machıne Learning and Big Data Applications

Gunseli UZUNHASANOGLU [1], Harika SEN [2]*

[1] *University of Health Sciences, Gülhane Health Vocational School / Department of Health Care Services Ankara / Turkey*
[2] *University of Health Sciences, Gülhane Health Vocational School / Department of Management and Organization Ankara / Turkey*

** Corresponding Author: Health Sciences University, Gülhane Health Vocational School. Turkey*
Tel.: +90 312 304 9270. E-Mail: harika.sen@sbu.edu.tr

Publication Information

Keywords :

- Nursing,
- Artificial İntelligence,
- Machine Learning,
- Big Data

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

The purpose of this review is to make a comparison by reviewing the studies of nurses in our country and the world on artificial intelligence, machine learning and big data applications.

Nurses in health system; the source of machine learning and artificial intelligence applications; own data, sensors's data, clinical evaluations, imaging and laboratory studies have a large amount of data. However, in our country, nurses don't have enough equipment to evaluate existing data and to create new systems and to use technology for the benefit of patients. In this context, it should be ensured that nursing faculties include artificial intelligence, machine learning and deep learning courses in the nursing education curriculum, organize courses / trainings for nurses working in the field, and prepare and support postgraduate theses in this field.

1. Introduction

In the light of technological developments in healthcare, research and resources on artificial intelligence, big data, deep learning, and machine learning are increasing. Although the studies on developing technology are insufficient to convince nurses and other clinicians that the results will make a difference in patient care, these new technologies will inevitably change and transform healthcare organizations and healthcare delivery [1]. A learning healthcare system based on artificial intelligence does not only improve quality, but can provide a continuous feedback loop that supports the faster conversion of data to better care to improve the health of individuals, measure the effectiveness of interventions, and monitor and protect healthy life [2]. The most significant part of developing artificial intelligence applications is undoubtedly the provision and availability of large digital data sets. Algorithms created for artificial intelligence and machine learning use these data sets to perform a task [3]. In the field of health, the concept of big data has been widely used in the last decade and has been defined in four essential areas: Volume, Velocity, Variety, and Veracity [4,5]. Volume refers to large amounts of data such as millions of patient records, velocity, the proportion of data generated in real-time with sensors or smartphones, variety, heterogeneity of the data, and veracity refers to the suitability of the data for the purpose. In recent years, the field of "value" has been proposed, representing the value of knowledge and enabling new knowledge discovery [4-6].

As the complexity and diversity of available data increase, analyzing the data and extracting relevant information becomes a critical role for healthcare [6]. Nurses have a large amount of data arising from their own collected information, information collected through sensors, clinical evaluations, imaging, and laboratory studies, which are necessary for applying data science and artificial intelligence methods. The process of making big data available begins with asking questions or recognizing opportunities, while nurses are experts in asking, identifying, responding to, and evaluating critical health-related questions [7]. It is vital that nurses demonstrate their expertise in many areas of big data and data science, including transforming their own study results into data, expanding data sources, applying data mining and modeling methods, and addressing ethical, legal, and social consequences [7]. Therefore, nurses are an essential part of this evolution. When this collected information is transferred to the joint collective nursing services data pool as standard data, the speed and quality of nursing care will increase, early warning systems will be developed in terms of the occurrence of diseases and side effects, and significant gains in time and cost will be achieved [8]. While technology is altering the way nurses spend time on patient care; nurses will transition to learning new ways of thinking and processing knowledge, nursing experience, knowledge, and skills, and practice their profession as information integrator, health coach, and provider of human care supported by artificial intelligence technologies [9].

It is evident that future technological developments will have severe effects on the nursing profession. These impacts can be transformed into an opportunity by professional nurses and can take away some of the roles of nurses while providing new roles in changing the structure of health care services. In order for nurses to be involved in deciding which aspects of their roles can be transferred to technology and which roles cannot be assigned, they must monitor the development of automated technology and artificial intelligence, be aware of big data and machine learning, and contribute to the emergence of new technologies [10]. As new algorithms are integrated into patient care processes, it will be crucial for nurses to interpret multiple data results and integrate new information into nursing by gaining practice [1, 9]. Thus, nurses can take roles in accordance with technological developments to ensure that healthcare services are suitable for the needs of patients.

The rapidly developing and changing situation with health technologies has reflections on the health implementation in Turkey. However, when domestic researches are examined, studies on this subject have only been found in a few compilations in the country. The purpose of this compilation is to make a comparison by reviewing the studies of nurses in our country and around the world on artificial intelligence, machine learning, and big data applications.

2. Material-Method

Related studies were reached by scanning Medline, Cochrane, Science direct, and PubMed databases with the keywords "nursing," "artificial intelligence," "machine learning," "big data." Among these studies, "technologies developed and made available to use by nurses" were selected. Publications related to technologies used in the field of nursing but developed by other professions were not included in this study.

3. Big Data and Artificial Intelligence Studies in Nursing Around the World

In the literature, artificial intelligence studies in the field of nursing are relatively few compared to other areas of health services. However, nurses conducted various studies for big data and big data analysis studies, which are the first steps of artificial intelligence studies. These studies were initiated in 2015-2016 and still continue to develop. Multi-stakeholder groups were formed in 2013 and 2014, focusing on the Action Plan to implement and use shareable and comparable nursing big data at the University of Minnesota School of Nursing. The purpose of this action plan is to harmonize grouped and often iterative efforts to integrate nursing data into Big Data initiatives and effectively use them to transform healthcare to improve quality and patient safety [11,12].

A mental health chatbot or psychological artificial intelligence service named "Tess" developed by Joerin et al. (2019) has been used to provide psychological support to caregivers, patients, and their families. Tess's emotional support was found to reduce depression and anxiety symptoms by 13% and 18% respectively, but cost only a fraction of a single therapy session. Tess's Elizzbot version offers optional emotional support to Healthcare professionals as well as visitors on Elizz.com to reduce burnout and increase well-being [13].

Barrera et al. (2020) developed a digital follow-up program for the inpatients in psychiatric clinics. Artificial intelligence and digital support systems have been used to enable inpatients to perform observations in a clinic where nursing observations are made every hour or every 15 minutes every night to protect the personnel's safety and minimize the interruption of patients' sleep.

Yang et al. (2020) developed a natural language processing system that describes the relationship of drugs to adverse drug events. A dataset of 505 anonymous clinical notes was trained with a repetitive access neural network and performed excellently. This learning system can be used to draw relationships between drugs and adverse drug events [15].

In 2019, Minvielle et al. developed a system (NURSENET) to monitor older adults in nursing homes, combining a piezoelectric floor sensor with a neural network algorithm aimed at measuring the physical activity of older people. By recognizing the signals generated by patients, NURSENET can isolate healthcare professionals and offers a new tool to monitor elderly activities in nursing homes efficiently [16].

Lee et al. (2014) analyzed secondary data from 716 individuals extracted from the Korea National Health and Nutrition Examination Survey from 2008 to 2010 to identify factors affecting health-related quality of life. First, a tool was developed to estimate the health-related quality of life. Analytical tools, including support vector machine learning, have revealed income, chronic diseases, depression, illness, and perceived health status as key factors predicting health-related quality of life [17].

Son et al. (2010) developed a system for classifying data on drug adherence. A support vector machine (a helpful machine learning method for data classification) was applied to identify factors predicting drug compliance in patients with heart failure. This machine learning method has helped classify patients [18].

Yu et al. developed a triage system for the emergency room in 2020. An effective system for predicting adverse clinical outcomes can be created with an emergency room triage system based on machine learning and initial nursing assessment. This new system has been observed to be more effective than the previous traditional system [19].

Song et al. (2021) evaluated patient records to develop machine learning-based prediction models for pressure sores. The complete evaluation records of the patients were collected in a shared data pool by nurses working in five different hospitals. When these data were processed, it was seen that it accurately predicted the development of pressure sores. As the model continues to work, it is predicted to have an effective warning system in preventing common pressure sores.

Bai et al. used the internet of things and machine learning to create a new infusion management and control system applied to Nursing care in 2021. In the Internet of Things technology, relevant data during the infusion process is sent to the hospital's network center so that nurses can monitor the infusion status directly from the computer screen. After this application, significant differences were obtained in terms of the rate of nurses being called to bedside during the infusion and the timely completion of the treatment compared to the classical method [21].

In Niu (2021) endoscopy rooms, an intelligent tracking system has been developed using artificial intelligence to control patients' vital signs and prevent possible complications and accidents. This system was applied by creating an experimental and control group. As a result of the application, it has been shown that patients who receive care with the standardized intelligent monitoring system have more stable blood pressure, lower incidence of adverse reactions, higher nursing satisfaction, and increased quality of nursing and the safety of the patient endoscopy room [22].

When these studies are considered, it is clearly seen that the studies on artificial intelligence and machine learning have accelerated since 2019. While these developments are taking place in the world, it is regrettable for modern nursing science that there are no studies on artificial intelligence and big data in the field of nursing in Turkey. A study in which nursing students' views on artificial intelligence technologies in our country were revealed showed that students defined *artificial intelligence* as robots, machine learning, and personal assistants, learned about artificial intelligence, and accessed social media, famous inventors, science-fiction films, and scientific publications showed. Students do not receive any education on this subject at their school. In the same study, while students expressed the contributions of artificial intelligence applications to nursing under the headings of reducing workload, making things easier, reducing margins of error, facilitating transportation and positioning, and providing convenience in drug preparation; they also expressed the themes of decreasing workforce, getting out of control of robots, and replacing human beings with technology as a risk. The majority of the students stated that the world is ready for developments related to artificial intelligence, but Turkey is not [23]. According to these results, it can be said that nursing students need effective training programs on artificial intelligence and big data.

5. Conclusion

Studies show that health services are positively affected by the data evaluation studies of nurses, and therefore, nurses' potential to affect patient care is essential. Nurses will be able to positively affect the quality of patient care and healthcare services as they develop the large amount of data they have and their skills to process this data. It is predicted that new technologies will undertake some of the work done by nurses in the future. In this context, technology may change the way nurses spend their physical effort and time on patient care, but the need for nurses will surely continue. Nursing experiences and data collection skills can form the basis of new technologies to be developed in health services, and the classification and evaluation of new data to be obtained can be included in the new job descriptions of nurses. Studies on artificial intelligence applications in our country in the field of nursing have not been reached yet.

In this context, it should be put on the agenda whether nursing faculties will include artificial intelligence, machine learning, and deep learning courses in the nursing education curriculum. Although the curriculum has limited hours, artificial intelligence and machine learning must be introduced to nursing students to keep up with this new paradigm affecting both society and research. In addition, courses/training should be organized for nurses who attend postgraduate education programs and work in the field, and postgraduate theses in this field should be prepared and supported.

References

1. Finlay GD, Rothman MJ, Smith RA. Measuring the modified early warning score and the Rothman Index: Advantages of utilizing the electronic medical record in an early warning system. J Hosp Med. 2014; 9 **(2)**: 116–119.
2. Sensmeier J. Big data and the future of nursing knowledge. Nursing Management (Springhouse): 2015 46(4): 22-27. doi: 10.1097/01.NUMA.0000462365.53035.7d
3. Kulkarni S, Seneviratne N, Baig M.S, Khan A.H.A. Artificial Intelligence in Medicine: Where Are We Now? Academic Radiology 2020; 27(1):62-70. doi.org/10.1016/j.acra.2019.10.001
4. Gandomi A, Haider M. Beyond the hype: Big data concepts, methods, and analytics. International Journal of Information Management. 2015; 35:137-144.
5. Bellazzi R. Big data and biomedical informatics: A challenging opportunity. Yearbook of Medical Informatics. 2014; 9:8-13. doi:10.15265/IY-2014-0024
6. Topaz M, Pruınellı L. Big Data and Nursing: Implications for the Future. Stud Health Technol Inform. 2017; 232: 165-171. doi.10.3233 / 978-1-61499-738-2-165
7. Brennan PF, Bakken S. Nursing Needs Big Data and Big Data Needs Nursing Journal of nursing scholarship 2015;47(5):477-484. doi.org/10.1111/jnu.12159
8. McGrow K. Artificial intelligence Essentials for nursing. Nursing. 2019;49(9): 46–49. doi: 10.1097/01.NURSE.0000577716.57052.8d
9. Robert N. How artificial intelligence is changing nursing. Nurs Manage. 2019 Sep; 50(9): 30–39. doi: 10.1097/01.NUMA.0000578988.56622.21
10. De Momi E, Kranendonk L, Valenti M, Enayati N, Ferrigno G. A neural network-based approach for trajectory planning in robot–human handover tasks. Front Robot AI. 2016; (3):33- 34 doi.org/10.3389/frobt.2016.00034
11. Westra BL, Latimer GE, Matney SA, Park JI, Sensmeier J, Simpson RL, Swanson MJ, Warren JJ, Delaney CW. A national action plan for sharable and comparable nursing data to support practice and translational research for transforming health care. J Am Med Inform Assoc. 2015;22(3):600-607. doi: 10.1093/jamia/ocu011.
12. Westra, BL. Clancy TR, Sensmeier J, Warren JJ, Weaver CD, Connie W. Big Data Science-Implications for Nurse Leaders**.** Nursing Knowledge**.** 2015**;**39(4);304-310**.** doi: 10.1097/NAQ.0000000000000130
13. Joerin A, Rauws M, Ackerman ML. Psychological artificial intelligence service, Tess: delivering on-demand support to patients and their caregivers: technical report. Cureus. 2019; 11(1**): e**3972.
14. Barrera A, Gee C, Wood A, Gibson O, Bayley D, Geddes J. Introducing artificial intelligence in acute psychiatric inpatient care: qualitative study of its use to conduct nursing observations. Evid Based Ment Health 2020;23:34–38. doi:10.1136/ebmental-2019-300136
15. Yang X, Bian J, Fang R, Bjarnadottir RI, Hogan WR, Wu Y. Identifying relations of medications with adverse drug events using recurrent convolutional neural networks and gradient boosting. J Am Med Inform Assoc. 2020; 27(1):65–72. doi: 10.1093/jamia/ocz144
16. Minvielle L, Audiffren J. NurseNet: monitoring elderly levels of activity with a piezoelectric floorSensors (Basel). 2019; 19(18):3851. doi: 10.3390 / s19183851
17. Lee SK, Son YJ, Kim J, Kim HG, Lee JI, Kang BY, et al. Prediction model for health-related quality of life of elderly with chronic diseases using machine learning techniques. Healthc Inform Res. 2014; 20(2):125–134. doi: 10.4258/hir.2014.20.2.125.

18. Son YJ, Kim HG, Kim EH, Choi S, Lee SK. Application of support vector machine for prediction of medication adherence in heart failure patients. Healthc Inform Res. 2010; 16(4):253–259. doi:10.4258/hir.2010.16.4.253.
19. Yu JY, Jeong GY, Jeong OS, Chang DK, Cha WC. Machine learning and initial nursing assessment-based triage system for emergency department. Healthc Inform Res. 2020; 26(1):13–19. doi: 10.4258/hir.2020.26.1.13
20. Song W, Kang MJ, Zhang L, Jung W, Song J, Bates DW, Dykes PC. Predicting pressure injury using nursing assessment phenotypes and machine learning methods. Journal of the American Medical Informatics Association. 2021;28(4):759–765. doi.org/10.1093/jamia/ocaa336
21. Bai X, Wang Q, Cao S. Application of Infusion Control System Based on Internet of Things Technology in Joint Orthopedics Nursing Work. Journal of Healthcare Engineering. 2021 Mar 26; 2021:6691258 doi.org/10.1155/2021/6691258
22. Niu Y. Influence of Standardized Nursing Management of Hospital Based on Smart Electronic Medical Blockchain on Nursing Quality of Digestive Endoscopy Room. Journal of Healthcare Engineering. 2021 Aprıl 27; 2021: 5539901 doi.org/10.1155/2021/5539901
23. Bodur G, Dinçer M, Tutak Z, Ertaş G, Vuran S, Kuvan D. Yapay zekânın sağlığın geleceğine yansımaları: üniversite öğrencilerinin gözünden kalitatif çalışma örneği," 17.Ulusal Hemşirelik Öğrencileri Kongresi, Çanakkale, Turkey 2018;177-178

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Investigation of Public-Oriented Covid-19 Poster Designs Using Artificial Intelligence-Assisted Eye Tracking Method

Emel FİLİZ [1], Sadiye ARSOY [2]

[1] *Selcuk University, Faculty of Health Sciences, Dept. of Healthcare Management , Turkey efiliz2@hotmail.com*
[2] *Selcuk University, Faculty of Health Sciences, Dept. of Healthcare Management, Turkey sadiyearsoy21@gmail.com*

* Corresponding Author: Selcuk University, Faculty of Health Sciences, Dept. of Healthcare Management
E-Mail: efiliz2@hotmail.com

Publication Information

Keywords :
- Eye-tracking,
- Artificial intelligence,
- Health

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Introduction-Purpose The aim of this study is to evaluate health posters using Artificial Intelligence Assisted Prediction Based Eye Tracking method.

Material-Method: Three (3) posters with hand washing theme were selected from among 23 posters presented to the public at the Ministry of Health COVID-19 Information Platform. Heat maps were created on posters using the artificial intelligence eye tracking method. Artificial intelligence eye tracking was done through "Attention Insight Heatmaps". The accuracy of this method is 90% compared to the classical eye tracking method.

Findings: It was visually presented how strongly each piece of poster designs attracted attention. How clear the design was and the percentage of attention paid to the titles and explanations on the posters were demonstrated by this method (Clarity ratio: 66-68%).

Discussion-Conclusion: With this method, without the need to collect data, understanding the most striking areas on health-related posters and educational materials, improving visual interaction and optimizing content visibility can be achieved. The use of artificial intelligence eye tracking method in the preparation of posters and educational materials for health protection and improvement will provide the advantages of analysis in a short time, rapid decision making, improvement of the performance quality of the design and low cost.

1. Introduction

Artificial intelligence technology, whose use is increasing and gaining importance day by day, is used intensively in all areas of life. One of these usage areas is the eye tracking method. Eye tracking refers to examining the condition of the eye movement and pupil, determining where and for how long the individual looks [1]. That is, it is a technique that examines, documents and measures eye movements [2].

Eye tracking includes the process of measuring eye movements in order to analyze a person's attention level [3]. These measurements are made in the traditional eye tracking method by devices or computers that are made up of cameras and projectors and use image processing algorithms an perform eye tracking [4]. As eye tracking technology has developed, it has become a method that is used extensively in automotive, psychology, medicine, product design and many other fields, especially in neuromarketing. In these areas where eye tracking is used, it is important to understand what and how the individual looks at, what he or she pays attention to what he or she thinks [5].

Eye tracking method has become more accessible due to the developments in technology [6]. Eye tracking is more applicable, especially thanks to artificial intelligence. Artificial intelligence-assisted predictive eye tracking refers to a software-based system that is an alternative to traditional eye tracking. It is based on prediction based on previously collected eye tracking data. Heat maps prepared by artificial intelligence technology measure where the attention of the individual is gathered like heat maps prepared in traditional eye tracking method [7].

Heat maps are one of the most used visualization methods when visually analyzing eye tracking data. It is mostly used for the analysis of stimuli such as posters, brochures and photographs. Heat maps are based on creating an eye tracking map and showing the area that attracts the most attention [8]. Heat maps allow access to qualitative data at the point when and where eye tracking data occurred. In terms of quantitative data, it provides access to data such as statistical focus, focus time and pupil growth rate [9].

Artificial intelligence-assisted eye tracking method is the most appropriate method that can be used to predict attention perceptions of screen-based stimuli in areas such as written or visual advertisements, product packages, web pages, public spots [10, 11, 12]. The basic building block of the artificial intelligence assisted eye tracking method is an artificial intelligence algorithm that learns from the data and constantly improves itself. Deep learning algorithms with a complex structure are trained on the basis of thousands of images obtained from eye tracking works. The artificial intelligence algorithm recognizes individuals' perceptions of attention while analyzing the images in question and brings them into a systematic structure. Thus, artificial intelligence is enabled to analyze what and how the studies it analyzes should address [7].

Using the traditional eye tracking method provides the opportunity to constantly follow the visual contents where and when they are formed and changed. Inferences are made about the reactions received in this direction [13]. Likewise, it is stated that the data obtained in studies conducted with traditional methods reveal reliable results [14, 15].

Using the artificial intelligence-assisted predictive eye tracking method has more advantages over the traditional method. The most important of these are as follows;

- It creates a fast decision-making mechanism based on data,
- It provides the opportunity to improve and develop design performance,
- It provides optimization of content visibility,
- It offers a very inexpensive service compared to the traditional eye tracking method,
- It ensures that the work to be done is tested before it is presented to the target audience,

etc. Compromising the accuracy is seen as the disadvantage of artificial intelligence-assisted prediction-based eye tracking method [7].

2. Method

Three (3) posters with hand washing theme were selected from among 23 posters presented to the public at the Ministry of Health COVID-19 Information Platform. Heat maps were created on posters using the artificial intelligence-assisted prediction based eye tracking method. This process was done with the "Attention Insight Heatmaps" tool supported by artificial intelligence (AI). This tool, like real eye-tracking heat maps, shows which areas of visual material are viewed the most and least. It can be evaluated whether there is important information in the area that users can see.There is no need to collect data, as the AI algorithm uses pre-recorded data from real eye tracking studies with a total of 30,800 images and generates heat maps in seconds. Thus, it is a much more economical and faster option with an accuracy rate of 90-94% compared to real eye tracking studies [7].

3. Results

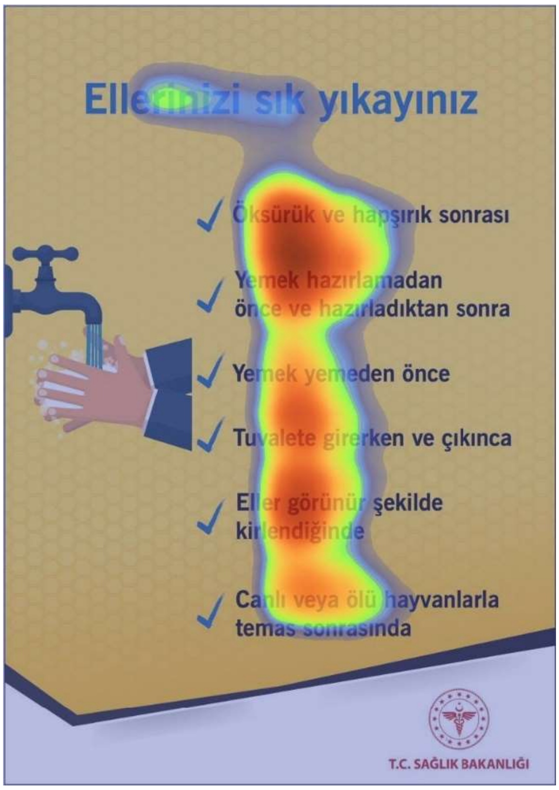
It was visually presented how strongly each piece of poster designs attracted attention. Heat maps are shown to draw attention from green to red, less intense to more intense in regions where eye movements are concentrated [17]. The red regions indicate increased attention and interest levels, while the yellow and green regions indicate less attention and interest [18].

In Figure 1 (a), there is the 'Wash your hands frequently' poster prepared by the Ministry of Health. The poster includes a visual image of washing hands and typography on how to wash hands. The heat map (b) shows that the level of attention is intense in the typography area. The clarity level of the design was 68% with the percentage of attention paid to the title and explanations (typography) on the poster.

In Figure 2 (a), there is the ‘The protection from virus in in our power' poster prepared by the Ministry of Health. The poster includes visual images and explanatory texts on protecting and maintaining hand hygiene. Heat map (b) shows that attention level and interest are intense in the visual image area located under the title typography and title. The clarity level of the design was 66%, with the percentage of attention paid to the title and explanations on the poster.

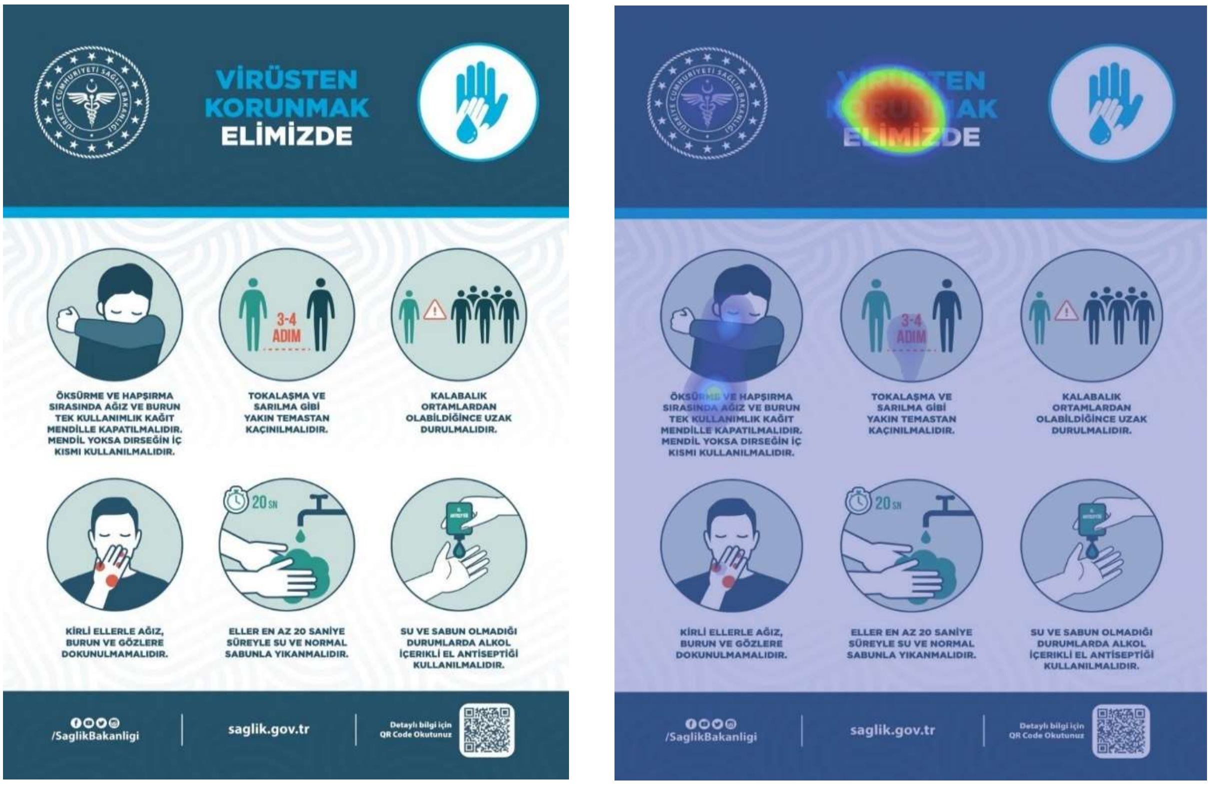
In Figure 3 (a), there is "Let's wash our hands, protect our health" poster prepared by the Ministry of Health. The poster features visual images and typographies related to the symptoms of the coronavirus, ways of protection and proper washing of hands. The heat map (b) shows that the area with the title typography has more intense attention and interest levels. The clarity level of the design was 66%, with the percentage of attention paid to the headline typography on the poster.

(a)



(b)

Figure 1: "Wash your hands frequently" poster



(a) (b)

Figure 2. ‘The protection from virus in in our power' poster

(a) (b)

Figure 3. "Let's wash our hands, protect our health" poster

4. Conclusions and Evaluation

The traditional eye tracking method is a method of determining where and how long the users in the system focus and in which area the instant attention level is concentrated using eye tracking devices in the laboratory environment. In the artificial intelligence-assisted eye tracking method, eye tracking is performed by predicting the previously collected eye tracking data through machine learning and deep learning. With this method, without the need to collect data, understanding the most striking areas on health-related posters and educational materials, improving visual interaction and optimizing content visibility can be achieved.

In this study, the poster designs prepared by the Ministry of Health for the public in order to create awareness about the Covid-19 pandemic were evaluated using the artificial intelligence eye tracking method and presented as a report. Since it was not known which parts of the design were expected to attract attention during the preparation of the posters, an evaluation could not be made as to whether the poster achieved its purpose or not. However, if artificial intelligence assisted eye tracking method had been used during the design of these posters, it could have been determined where they had wanted to draw people's attention, and the information or messages to be emphasized could have been placed in this area.

The use of artificial intelligence-assisted predictive eye tracking method in efforts aimed at increasing health literacy, protecting and improving health, preventing diseases, informing the public, raising awareness and increasing social sensitivity in the society has many advantages such as analysis in a short time, creating a decision-making mechanism in the light of data, improving the performance quality of the design and low cost. The use of artificial intelligence eye tracking method in the preparation of posters and educational materials for health protection and improvement will ensure that the desired messages reach the target effectively.

References

1. Yıldırım N ve Varol A. A Research On Eye Tracking and Eye Tracking Systems. International Engineering, Science and Education Conference, 01-03 December 2016.
2. Tobii Technology AB. Tobii Eye Tracking. An introduction to eye tracking and Tobii Eye Trackers, 2010.
3. Holmqvist K, Nyström M, Andersson R. Eye tracking: a comprehensive guide to methods and measures. 560, 2011.
4. Duchowski AT. Diversity and types of eye tracking applications. In: Eye Tracking Methodology: Theory and Practice: Cham, Springer International Publishing, 2017. pp 247-8.
5. Harezlak K, Kasprowski P. Application of eye tracking in medicine: a survey, research issues and challenges. Comput Med Imaging Graph 2018; 65: 176-90.
6. Ashraf H, Sodergren MH, Merali N, Mylonas G, Singh H ve Darzi A. Eye-tracking technology in medical education: A systematic review. Medical Teacher, vol. 40, no. 1, pp.62-69, 2018.
7. Attention İnsight. Erişim Adresi: https://attentioninsight.com/eye-tracking-vs-predictive-eye-tracking/. Erişim Tarihi: 24.03.2021.
8. Blascheck, T., Kurzhals, K., Raschke, M., Burch, M., Weiskopf, D. & Ertl, T. Visualization of Eye Tracking Data: A Taxonomy and Survey. Computer Graphics Forum, 36(8), 260-284, 2017. https://dx.doi.org/10.1111/cgf.13079.
9. Raschke, M., Blascheck, T. & Burch, M. Visual Analysis of Eye Tracking Data. HumanCentric Chronographics: Making Historical Time Memorable, 391-409, 2013. https://dx.doi.org/10.1007/978-1-4614-7485-2_15.
10. Pieters, R., Warlop, L. & Wedel, M. Breaking Through the Clutter: Benefits of Advertisement Originality and Familiarity for Brand Attention and Memory. Management Science, 48(6), 765-781, 2002. https://dx.doi.org/10.1287/mnsc.48.6.765.192.

11. Radach, R., Lemmer, S., Vorstius, C., Heller, D. & Radach, K. Eye Movements in the Processing of Print Advertisements. The mind's eye: Cognitive and Applied Aspects of Eye Movement Research, 609-632, 2003. https://dx.doi.org/10.1016/B978-044451020-4/50032-3.
12. Yücel, A. & İnan, M. Beyin Tercih Yapar Mı? EEG ve Eye-Tracking İle Tüketici Davranışı ve Beyin Aktivitesi Üzerine Yapılan Çalışmalara Yönelik Bir Analiz. IV. Uluslararası Battalgazi Bilimsel Çalışmalar Kongresi, 29 Şubat-1 Mart, Malatya, 2020.
13. Yeniad, M., Mazman, S. G., Tüzün, H. ve Akbal, S. (2011). "Bir Bölüm Web Sitesinin Otantik Görevler ve Göz İzleme Yöntemi Aracılığıyla Kullanılabilirlik Değerlendirmesi". Ahi Evran Üniversitesi Kırşehir Eğitim Fakültesi Dergisi, 12(2): 147-173.
14. Rayner, K. "Eye Movements in Reading and İnformation Processing: 20 Years of Research". Psychological bulletin, 124 (3): 372-422, 1998.
15. Lohse, G. ve Johnson, E. "A comparison of two process tracing methods for choice tasks". Organizational Behavior and Human Decision Processes, 68(1): 28-43, 1996.
16. Sağlık Bakanlığı, Afişler: https://covid19.saglik.gov.tr/TR-66259/halka-yonelik.html. 21.04.2021.
17. Baş, T., Tüzün, H. Tüketicileri (Kullanıcıları) ve Ürün Kullanımlarını Analiz Etmek İçin Göz İzleme Yönteminin Kullanılması, Tüketici Yazıları (IV) Ocak, ss. 217 – 234, 2014.
18. Toker, A. Seçilmiş Reklam Filmlerinin Nöropazarlama Kapsamında Göz İzleme Yöntemi İle Analizi. Yüksek Lisans Tezi, Süleyman Demirel Üniversitesi Sosyal Bilimler Enstitüsü, Isparta, 2019.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Nursing and Technology: Artificial Intelligence in Women's Health

Duygu TUNA KARABULUT[1,*], Sümeyye BAKIR[2], Özlem DEMIREL BOZKURT[2]

[1]*University of Health Sciences Tepecik Training and Research Hospital, Izmir, Turkey*

[2]*Ege University Faculty of Nursing, Department of Women's Health and Disease Nursing, Izmir, Turkey*

*Corresponding Author: University of Health Sciences Tepecik Training and Research Hospital, Izmir, Turkey

Tel.:05387346829 E-Mail: duygutuna93@gmail.com

Publication Information

Keywords :

- Nursing,
- Artificial Intelligence,
- Technology,
- Women's health

Category : Special Issue

Received :

Accepted : 26.05.2021

A B S T R A C T

Introduction-Objective: New approaches in nursing care can only be achieved by following developments and technological innovations in the healthcare field. Practice of artificial intelligence (AI) applications in the health sector especially in recent years, is an indicator of new inventions to affect future of humanity. Aim of this review is to provide information on robotic surgery and use of AI in the field of women's health and raise awareness of nurses on technological developments.

Material-Method: This study has been planned to be conducted by reviewing the literature.

Findings: Creating and development of new technologies should be considered important, as this positively affects healthcare institution and performance of professionals in healthcare delivery also as it provides more quality service and better cost-benefit ratio. Today, use of robotic surgery is widespread. Operations as hysterectomy, myomectomy, sacrocolpopexy aimed at women's health, can be performed by this technique. Potent AI techniques can detect clinically important information from among a wide set of healthcare data by using complex algorithms and can assist nurses in decision. Fetal heart rate and complications about fetus, can be detected evaluating cardiotocographies by android robots. AI applications are used in intrapartum monitoring in order to prevent diagnosis differences between specialist physicians to be able to provide assessments are consistent, and to reduce perinatal or maternal morbidity. Applications as INFANT and CAFE have been developed against difficulties in proper evaluation of NST. The study called System 8000, records uterus contractions and variations in heart rhythm depending on fetus movements. Additionally, there are studies targeting developing fetal cardiography methods or forming artificial neural network databases to provide accurate categorization and prognosis of premature birth.

Discussion-Conclusion: Adoption of AI and robot use in order to improve how nurses deliver healthcare, is the start of transformation emergent technologies caused in nursing. We require to keep up with technological developments in order to be able to carry women's health nursing to advanced levels.

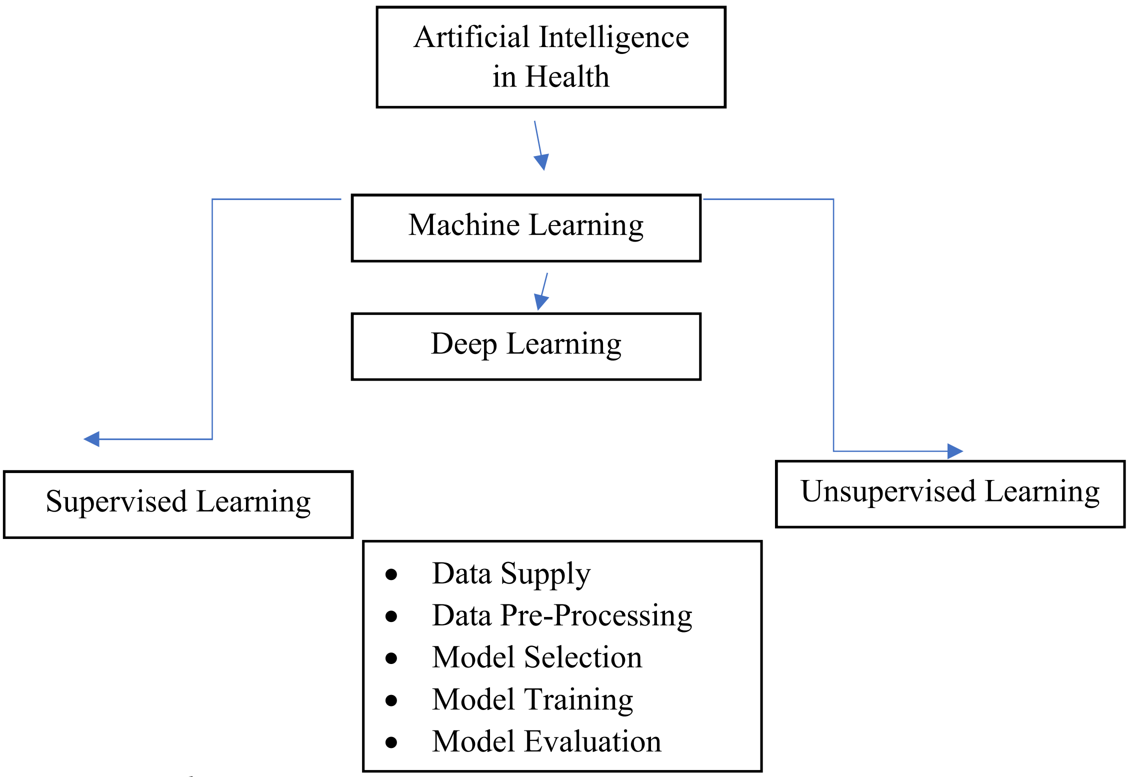
1. Introduction

Artificial intelligence (AI) is a type of digital computer system arranged in a way similar to how neurons in the brain are formed by multiple nerve nodes, which parallels the way the human brain processes information. AI consists of two basic elements such as deep learning and machine learning (Figure 1). While machine learning consists of algorithm categories, artificial neural networks are also included in deep learning [13]. AI is therefore also called neural networks. It is widely used in expert systems, machine learning, fuzzy logic, artificial neural networks, and genetic algorithms [19]. As a result of these developments, health care has undergone various changes with the availability of new tools/equipment or new diagnosis-treatment methods. The use of AI in the healthcare field began approximately in the 1970s. At the point arrived in recent years, many studies can be found in the research made in databases with the keyword artificial intelligence [19]. In earlier studies in the literature, it was stated that medical decision support systems are useful in supporting the clinical decision-making process in heart diseases, the use of algorithms in determining the chance of success in IVF treatment can be successful, the use of artificial intelligence-based cloud service can create a realistic solution for medical imaging and telemedicine, and artificial neural networks can be used to classify cancer cells according to their gene sequences [6,8,21,22]. In this regard, health professionals are expected to have knowledge about changing health technologies and to be able to consult using practices containing evidence-based information.

This review was created by making a literature review to provide information on the use of artificial intelligence and robotic surgery, which emerged with increasing digitalization and research activities in the 21st century, in order to improve patient outcomes and help make diagnostic decisions in the field of women's health. In the meantime, while there are new discoveries in the field of health that will affect the future of humanity, it was aimed to raise awareness for nurses to follow technological developments and to develop new approaches in care.

2. Nursing and Technology

Today, technology creates transformative effects in the health sector. Scientific nursing practices are constantly changing with discoveries and innovations and create an accumulation of knowledge. With the integration of innovative approaches and new technologies, evidence-based care can be realized in nursing practices. It also reveals the desire to develop nursing for the benefit of society and patients. Therefore, scientific research in nursing is extremely important to change the status of the nursing profession [1,4]. With the developments in science and technology, nurses need to use technology and follow the developments in this field in order to be able to apply nursing care and treatments that yield effective results. New discoveries in many areas that will affect the future of humanity, such as health, will be possible with the use of creativity by individuals. In this process, being aware of new developments and bringing new approaches to care are among the professional requirements [10,12].



Kaynak: *Canbay, P. 2020. 'Sağlıkta Yapay Zeka:Makine Öğrenmesi Yöntemleri ve Uygulamaları'.*

Nurses are at the forefront of incorporating technology into healthcare without disregarding ethical aspects. It is necessary to create and develop new technologies of high quality that positively affect the performance of both the institution and the employee in the provision of healthcare services and provide a better cost-benefit ratio. It should be aimed to increase technology production in the field of nursing in our country by increasing the number of studies in the field of technology and ensuring the continuity of research. If future research focuses on information systems and combines with nursing methods, an important gap in nursing will be closed. In addition, following the technological developments in the nursing profession, there is a need to carry out studies using different technologies [1,12].

If we refer to examples from around the world in artificial intelligence practices in the field of nursing, Duke University School of Nursing initiated a pilot project with the Faculty of Engineering, suggesting that the humanoid production robot can be easily trained to perform 23 different nursing tasks. Knowledge and practices in the fields of care, education, management and research are affected by technological developments. This situation makes it necessary to rethink and design the information and practices in all areas of nursing and focus on researches aimed at determining the effect of technology on nursing and patients [4]. Past and future studies on technology in the field of nursing will ensure the development of the health care system and will be useful in terms of raising awareness on the points that need to be improved by increasing knowledge [4]. It is necessary to understand how artificial intelligence and its use can change and improve patient care by taking advantage of the studies on artificial intelligence in the field of women's health. In order to cope with the complexity of artificial intelligence, nurses must know that technology has algorithms at its core.

2.1. Artificial Intelligence in Women's Health

Artificial intelligence (AI) consists of algorithms that aid decision-making. In other words, it makes computers think like humans [13]. It has affected a range of professions, including gynecology and obstetrics [5,9]. It is predicted that AI is generally used in the field of health for staying healthy, diagnosis, treatment, research, early diagnosis, decision making, elderly care and education, and that it will further develop in the future. [19]. With the development of artificial intelligence technology, the practices of this technology in the field of women's health are increasing. These developments are a very new concept in health services, especially in nursing practices. It is expected to follow the changing health technologies in order to develop high-quality care methods that will increase patient safety. Practices especially used by nurses developed with the aim of maintaining and improving health, protecting it from diseases and coping with them, and providing care, mean nursing technology [16].

The rise of AI has led to the development of neural networks consisting of a reliable mathematical system capable of interpreting multifactor data. Artificial neural networks are systems that evaluate reliable, flexible and multi-factor data at the speed of light. These networks are connected through multiple synapses and they send data back and forth to each other. Thanks to this mechanism, AI finds the most likely answer. These multiple connections are achieved by the fact that computers mimic cognitive functions such as the reasoning process while determining the most likely answer to a problem. This sophisticated AI software is now used in medicine to analyze large amounts of data, which can help prevent and diagnose diseases and monitor patients [5,9].

3. Results

3.1. Artificial Intelligence in Fetal Health Assessment

Electronic fetal monitoring is one of the most common obstetric diagnosis methods used in the evaluation of fetal oxygenation. Electronic fetal monitoring (EFM) plays an important role in decreasing fetal deaths due to hypoxia by enabling early determination of risks [20]. Electronic fetal monitoring used to determine fetal well-being in the antepartum period is defined as a nonstress test (NST). Unlike antepartum, electronic fetal monitoring during the intrapartum period evaluates heart rate changes due to contractions [15].

Exemplary benefits of using artificial intelligence are practices for evaluating cardiotocographs during childbirth. Healthcare professionals monitor the fetus with changes in fetal heart rate and diagnose fetal complications. In intrapartum monitoring, there may be differences in diagnosis among obstetricians. AI can make assessment more consistent and reduce perinatal or maternal morbidity [5].

CAFE and INFANT

There are some examples where artificial intelligence tested NST analysis. Some of these algorithms are CAFE (Computer-Aided Fetal Evaluator) program and INFANT (Interpretation of Fetal Heart Rate During Labor) study protocol. Both are highly integrated systems incorporating complex algorithms developed to overcome the challenges in NST analysis [9]. According to the results of a study analyzing the possibility of the CAFE system to interpret data, it was concluded that the AI system read the information at a similar level with the experts in the field and could also detect errors. It was stated that further studies needed to be undertaken to increase reliability in data interpretation [9]. The most striking finding of the INFANT protocol is that AI detects the time required to detect NST abnormalities in the fetus in a shorter time than health professionals. This software was used in all three studies and it was determined that it was as good as obstetricians in interpreting NST and managing labor afterwards, and the system performed better than routine clinical practice. While this software could not predict only one perinatal death, experts in the study were unable to predict multiple deaths. In the studies investigating the INFANT protocol, it was stated that a series of deaths could be prevented if artificial intelligence was used in clinical applications [2].

SYSTEM 8000

The study named System 8000 records NST quality, uterine contractions, basal heart rate of the fetus, and slowing and acceleration variations in heart rhythm due to fetal movements. Thus, it can define the difference by taking into account the episodic changes in fetal heart rate (FHR) and the characteristic movements of the fetal sleep states [5].

In another artificial intelligence project, the aim is to monitor fetal heart rate with several non-invasive sensors and create a database that will be used to develop fetal electrocardiography (ECG) methods. Fetal monitoring during delivery is traditionally performed with fetal heart rate obtained from cardiotocography. There are widespread difficulties in reliably recording the fetal heart rate due to the interference of the rhythms of the mother and fetus, which can lead to unnecessary cesarean sections. The purpose of AI algorithms is to monitor fetal heart rate abnormalities and to distinguish results that reflect fetal bradycardia [11]. Correct classification and prediction of preterm birth is considered a very difficult situation considering various factors. For this reason, the goal of another artificial intelligence developing project is to create an artificial neural network database that will provide accurate classification and prediction of preterm birth. However, the lack of continuity of reliable data on variables reveals that further studies should be conducted [11].

3.2. Artificial Intelligence in Surgery

Today, we consider the use of artificial intelligence in the field of surgery as an aid to the healthcare professional by understanding the preoperative risk estimation, the estimation of postoperative complications and the visual cues of the peroperative robot. It is predicted that as artificial intelligence gains increased access to visual surgical data, its capabilities such as processing signals and recognizing patterns will also increase. In addition, as artificial intelligence models are trained with an increasing number of cases, it is aimed to develop a collective awareness of surgery that will help a surgeon provide optimal intraoperative care to his/her patients [7]. Robotic surgery has become very popular among surgeons since the first day it was introduced, but it is prevented due to its high-cost rates. According to the latest data in the literature, it is emphasized that robotic surgery is developing and may represent standard care for gynecological surgery [18]. In addition, as seen in the literature, it is likely that robotics will become widespread in clinical settings with studies combining it with artificial intelligence practices [17]. Currently, the use of robotic surgery is widespread. With this technique, operations for women's health such as hysterectomy, myomectomy, sacrocolpopexy can be performed [14].

3.3. Reflections on Technology and nursing Profession

The use of technology in the field of nursing has also initiated a process of professional change. In the light of new methods in the field of health technology, it is necessary to carry out studies for the use of technology by the nursing profession and better integrate technology into our profession by closely following information technologies. Only in this way can we professionally advance the nursing profession. At this point; nurse executives and leaders play a crucial role. Training of nursing professionals, regulating the number of nurses, and ensuring that nurses feel comfortable and safe about technology are very important. In addition, executive nurses and leaders should explore the use of technologies in other disciplines to optimize efficiency in the patient care setting [1,4,10,12].

The advancement of the nursing profession is possible through the guidance of changing leadership, evolving health, national health leaders and policy makers, evolving educational standards, workforce designs, and implementation recommendations. In addition, the necessity to cooperate with Health Information Technology developers, manufacturers and nurses in the design, development, purchase, implementation and evaluation of medical devices and products will increase day by day [4]. Nurses should be encouraged to use technology in order to benefit from technology in professional practice. It is considered that it will be beneficial to organize in-service training by determining the areas with technology-related requirements. There is a need for both new technologies developed to increase nursing care and quality, and new studies in the field for their use in care-treatment applications. In addition to descriptive designs, quasi-experimental or experimental study methods should be included in the studies [10].

4. Conclusion and Evaluation

The use of artificial intelligence can significantly improve healthcare services; however, its drawbacks need to be taken into account. Ethical dilemmas, such as cognitive biases, need to be addressed when creating algorithms on the computer. AI predictions can vary by race, genetics, and gender, among other variations. Ignoring the variables can increase or underestimate the risk factors of the disease. At the same time, protecting the privacy of the data owners is also important in this respect. While cooperating in decision-making, artificial intelligence also reduces healthcare costs. In addition, it is promising as it can reduce the workload of healthcare professionals. These artificial intelligence algorithms must be presented under a large database that can adequately reflect real-world conditions. Additionally, AI needs to be flexible in adopting new knowledge so that it continues to learn and change accordingly. In addition, the data should represent a population being evaluated in a realistic clinical setting. Artificial intelligence eases the workload for clinicians as it provides a more accurate diagnosis despite the difficulties. It has the potential to revolutionize patient care by providing a fundamental analysis in testing where interpretative differences between experts are present [9]. Scientific research in the field of nursing is extremely important to change the situation of the nursing profession. As nursing roles expand and nursing research is added to the knowledge base of the discipline, nurses and educators must take the lead in approaching and analyzing this information critically. This effort is important in terms of ensuring social welfare by raising the quality of nursing care practices and education. In this direction, the need for meaningful studies to be carried out in the field of women's health on the basis of artificial intelligence continues, as in all areas of health.

References

1. Aytur Özen, Tangül, and Filiz Kantek. 2020. 'Türkiye'de Hemşirelik ve Teknoloji Alanında Yapılan Çalışmaların İncelenmesi'. *Uluslararası Sağlık Yönetimi ve Stratejileri Araştırma Dergisi* 6(3):395–410.
2. Brocklehurst, Peter. 2016. 'A Study of an İntelligent System to Support Decision Making

in the Management of Labour Using the Cardiotocograph - The INFANT Study Protocol'. *BMC Pregnancy and Childbirth* 16(1):1–15. doi: 10.1186/s12884-015-0780-0.
3. Canbay, Pelin. 2020. 'Sağlıkta Yapay Zeka:Makine Öğrenmesi Yöntemleri ve Uygulamaları'. P. 11 in *Sağlık Bilimlerinde Yapay Zeka*, edited by A. R. Şahin, K. Doğan, and S. Sivri. Akademisyen Kitabevi.
4. Çetin, Belgin, and Nermin Eroğlu. 2020. 'Hemşirelik Bakımında Teknolojinin Yeri ve İnovasyon'. *Acta Medica Nicomedia* 90(October).
5. Desai, Gaurav Shyam. 2018. 'Artificial Intelligence: The Future of Obstetrics and Gynecology'. *Journal of Obstetrics and Gynecology of India* 68(4):326–27. doi: 10.1007/s13224-018-1118-4.
6. Güvenir, H. Altay, Gizem Misirli, Serdar Dilbaz, Ozlem Ozdegirmenci, Berfu Demir, and Berna Dilbaz. 2015. 'Estimating the Chance of Success in IVF Treatment Using a Ranking Algorithm'. *Medical and Biological Engineering and Computing* 53(9):911–20. doi: 10.1007/s11517-015-1299-2.
7. Hashimoto, Daniel A., Thomas M. Ward, and Ozanan R. Meireles. 2020. 'The Role of Artificial Intelligence in Surgery'. *Advances in Surgery* 54:89–101. doi: 10.1016/j.yasu.2020.05.010.
8. Hwang, De Kuang, Chih Chien Hsu, Kao Jung Chang, Daniel Chao, Chuan Hu Sun, Ying Chun Jheng, Aliaksandr A. Yarmishyn, Jau Ching Wu, Ching Yao Tsai, Mong Lien Wang, Chi Hsien Peng, Ke Hung Chien, Chung Lan Kao, Tai Chi Lin, Lin Chung Woung, Shih Jen Chen, and Shih Hwa Chiou. 2019. 'Artificial Intelligence-Based Decision-Making for Age-Related Macular Degeneration'. *Theranostics* 9(1):232–45. doi: 10.7150/thno.28447.
9. Iftikhar, Pulwasha, Marcela V Kuijpers, Azadeh Khayyat, Aqsa Iftikhar, and Maribel DeGouvia De Sa. 2020. 'Artificial Intelligence: A New Paradigm in Obstetrics and Gynecology Research and Clinical Practice'. *Cureus* 12(2). doi: 10.7759/cureus.7124.
10. Konukbay, Dilek, Mürşide Efe, and Dilek Yıldız. 2020. 'Teknolojinin Hemşirelik Mesleğine Yansıması: Sistematik Derleme'. *Sağlık Bilimleri Üniversitesi Hemşirelik Dergisi* 2(3):175–82. doi: 10.48071/sbuhemsirelik.700870.
11. Lee, Kwang-Sig, and Ki Hoon Ahn. 2019. 'Artificial Neural Network Analysis of Spontaneous Preterm Labor and Birth and Its Major Determinants'. *Journal of Korean Medical Science* 34(16):1–10. doi: 10.3346/jkms.2019.34.e131.
12. Merih, Yeliz Doğan, Ayşegül Alioğulları, Meryem Yaşar Kocabey, Çiğdem Gülşen, and Aytül Sezer. 2019. 'Hemşirelikte İnovasyon Kültürü Oluşturma; Bir Başarı Öyküsü'. *Zeynep Kamil Tıp Bülteni* 50(3):175–81.
13. Mevlut Keleş. 2020. 'Ürolojide Yapay Zekanın Yeri ve Önemi'. P. 153 in *Sağlık Bilimlerinde Yapay Zeka*, edited by A. R. Şahin, K. Doğan, and S. Sivri. Akademisyen Kitabevi.
14. Pamir Aksoy, Nuran Ayşen, İlknur İnanır, and Zerrin Kaya. 2010. 'Robotik Cerrahide Hemşirenin Rolü'. *Acıbadem Hemşirelik.*
15. Okumuş, H., Tokat, M. A. (2013). Doğum Eyleminde (İntrapartum) Elektronik Fetal izlem ve Klinik Girişimler. M. A. Tokat, H. Okumuş, & N. Demir içinde, Gebelikte ve Doğum Eyleminde Elektronik Fetal İzlem (s. 57). İstanbul: Deomed Yayıncılık.
16. Demirel Bozkurt, Özlem. 2018. "Hemşirelikte Teknolojiye Uyum." *1. Uluslararası İnovatif Hemşirelik Kongresi Bildiri Kitabı* 192.
17. Şendir, Merdiye, Nesibe Şimşekoğlu, Abdulsamed Kaya, and Kamber Sümer. 2019. 'Geleceğin Teknolojisinde Hemşirelik'. *Sağlık Bilimleri Üniversitesi Hemşirelik Dergisi* 1(3):209–14.
18. Siaulys, Raimondas, Vita Klimasauskiene, Vinsas Janusonis, Viktorija Ezerskiene, Audrius Dulskas, and Narimantas Evaldas Samalavicius. 2021. 'Robotic Gynaecological

Surgery Using Senhance® Robotic Platform: Single Centre Experience With 100 Cases'. *Journal of Gynecology Obstetrics and Human Reproduction* 50(1):102031. doi: 10.1016/j.jogoh.2020.102031.
19. Süleyman Sivri, Özgür Rıza Kayğusuz. 2020. 'Yapay Zeka ve Malpraktis'. P. 68 in *Sağlık Bilimlerinde Yapay Zeka*, edited by A. R. Şahin, K. Doğan, and S. Sivri. Akademisyen Kitabevi.
20. Tokat, M. A., Okumuş, H., & Demir, N. (2011). Elektronik Fetal İzlem Eğitiminin Ebe ve Hemşirelerin Bilgi ve Yorumlama Becerilerine Etkisi. DEUHYO ED, 4(2), 63-66.
21. Westermann, F., J. S. Wei, M. Ringner, L. H. Saal, F. Berthold, M. Schwab, C. Peterson, P. Meltzer, and J. Khan. 2002. 'Classification and Diagnostic Prediction of Pediatric Cancers Using Gene Expression Profiling and Artificial Neural Networks'. *GBM Annual Fall Meeting Halle 2002* 2002(Fall). doi: 10.1240/sav_gbm_2002_h_000061.
22. Yan, Hongmei, Yingtao Jiang, Jun Zheng, Chenglin Peng, and Qinghui Li. 2006. 'A Multilayer Perceptron-Based Medical Decision Support System for Heart Disease Diagnosis'. *Expert Systems with Applications* 30(2):272–81. doi: 10.1016/j.eswa.2005.07.022.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Artificial Intelligence at Teaching Critical Thinking for Diagnostic Excellence

Betül AKBUĞA ÖZEL[1]

[1] *Hacettepe University, Faculty of Medicine, Department of Medical Education and Informatics, Turkey*

* Corresponding Author: Hacettepe University, Faculty of Medicine, Turkey
Tel:+09 530 4900888 E-mail: bakbuga2000@yahoo.com

Publication Information

Keywords :
- Artificial intelligence,
- Critical thinking,
- Medical education

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Introduction: Medical errors are a public health burden. Medical errors are the third cause of death followed by heart disease and cancer. Diagnostic accuracy is an important component of high-quality care. However, diagnostic errors (DE) are more common, costly and harmful than other medical mistakes. Human-driven cognitive errors is more important than system-related and patient-related reasons of DE. Cognitive errors are an irrational thought, due to biases, heuristics.
Goal: This study is a narrative review. It aims to evaluate original articles that contributes to teaching and developing critical thinking (CT) skills through artificial intelligence (AI) for diagnostic excellence between the years of 2010 and 2020.
Material-Method: Scanning was conducted by appropriate key words on Ulakbim, Google Scholar, PubMed, ProQuest, and Wiley Online Library as Turkish and English.
Findings: Any national and international original articles were not found about which were teaching cognitive models preventing DE's via CT and AI.
Discussion: There is the hidden epidemic of DE which has become a serious public health problem nationally and internationally. The researches aiming at improving CT skills by AI are limited by time, money and the complexity level of goal. However, improving patient safety is possible as a result of which CT and metacognition skills reduce DE.
Conclusion: Medical educators, computer scientists and clinicians require multidisciplinary cooperation environments in order to focus the AI searches about teaching of CT for diagnostic excellence within multiple problems belonging to multiple variables under uncertainty circumstances.

1. Introduction

Medical errors are a public health burden (1) Medical errors are the third cause of death followed by heart disease and cancer (2). Diagnostic accuracy is an important component of high-quality care (3). However, diagnostic errors (DE) are more common, costly and harmful than other medical mistakes (4). In addition to this, there is the hidden epidemic of DE which has become a serious public health problem nationally and internationally (5). Critical thinking (CT) skills have attracted attention to itself because there are the evidence about CT skills can prevent at least mitigate DE in order to improve patient safety by providing diagnostic excellence (6,7).

This study aims to evaluate original articles that contributes to teaching and developing critical thinking (CT) skills through artificial intelligence (AI) for diagnostic excellence.

2. Diagnostic Errors

Institute of Medicine identified six aims of high-quality care (8) It's report stated that health care should be safe, effective, efficient, equitable, timely, and patient-centered. There was two explicit emphases at this report. The first one was making accurate and timely diagnoses to patients. This one was one of the most important components of providing high-quality care. The second one was errors in diagnosis were a major threat to achieving high-quality care.

According to World Health Organization, diagnostic errors are missed opportunities to make a correct and timely diagnosis based on available evidence (9). Diagnoses can be completely missed, delayed or wrong and may be overlaps in these situations. DE are a global priority in patient safety because they can lead to patients from wrong or delayed testing or treatment (9).

DE are the bottom of the iceberg of patient safety (10). Society to Improve Diagnosis in Medicine argued that among malpractice claims, diagnostic errors appear to be the most common, most costly and most dangerous of medical mistakes based upon Tehrani at all's study (4,10).

Diagnostic error rate is up to 15% (6). All specialties are vulnerable to diagnostic errors. But, the principal specialties in which diagnostic uncertainty is most evident and in which delayed or missed diagnoses are most likely are; EM, internal, and family medicine (11).

3. Critical Thinking

The meaning and significance of CT in medicine education starts at this point: patient safety. Critical thinking in medicine is a high-level cognitive skill used for understanding and evaluating the phenomena, and ultimately making decision about it, based on reasoning and analyzing.

Human-driven cognitive errors is more important than system-related and patient-related reasons of DE (12). Cognitive errors caused DE define the failures in rational and logical thought, due to biases, heuristics (6). There are fifty known biases and they are universal, predictable, and can be corrected. Contrary to popular belief, peoples in general and doctors in particular use intuitional and instinctive mechanisms-driven thinking rather than rational thinking at the vast majority of daily their decisions. Intuitive thinking is unconscious, fast, associative, automatic, and very old skill but it is in tendency to be conducted by emotions, prejudices, fallacies, and biases in opposition to rational thinking. Therefore, medical education should aim at developing under-graduate and post-graduate students' rational and logical thinking by CT knowledge and skills.

In order to improve CT skills and reduce diagnostic errors, five critical objectives required for learners were identified (7). There are four models for CT education such as general model, infusion model, immersion model, mixed-model (13). There are also many efficient methods used such as didactic lectures, socratic questioning, case-based discussions, problem-based learning, simulated video cases, reflective writing or oral reflection, cognitive autopsy.

Within this framework, Croskerry suggested cognitive debasing strategies for medicine in relation of CT skills such as considering alternatives, developing insight and awareness of heuristics, biases, developing metacognition skills, decreasing reliance on memory, minimizing time pressure, constructive feedback, creating time for thinking, the use of simulation (6).

4. Artificial Intelligence in Healthcare and Medical Education

AI is an umbrella term for several computer-based technologies such as machine learning, natural language processing, convolutional neural network, rule-based expert systems, physical robots, and robotic process automation. In healthcare system, AI is actively used in diagnostics, population health, management, patient engagement, patient adherence promotion, and in administrative activities (14). Medical imaging and clinical decision support systems have been continuing to be the most remarkable application areas for the innovative use of AI.

Use of AI in diagnostic imaging can be included in processes such as acquiring, processing and classification, and interpreting the image, object detection and tracking, determining follow-up care, and selecting convenient data storage (15)

AI in medical education uses for individualized learning management systems, augmented virtuality, virtual reality, and wearable devices in the field of medical simulation, student information systems including portfolios and assessments. Use of AI in medical education has a lot of advantages in terms of immediate feedback, enhancement of problem based learning, recognizing and producing solutions to gaps in students' knowledge, reduced need for teacher supervision, less costs and no potential harm to patients (16).

5. Material-Method

This study is a narrative review. The key words of study were "artificial intelligence, critical thinking, medical education". The inclusion criteria for articles were defined. They were being pertinent to every three key words, being application study related to learning, teaching, assessment, publishing between 2010 and 2020. The study's scanning was conducted by appropriate key words on Ulakbim, Google Scholar, PubMed, ProQuest, and Wiley Online Library as Turkish and English. PRISMA diagram was used for showing the flow of study related to inspected articles (17) (Figure 1).

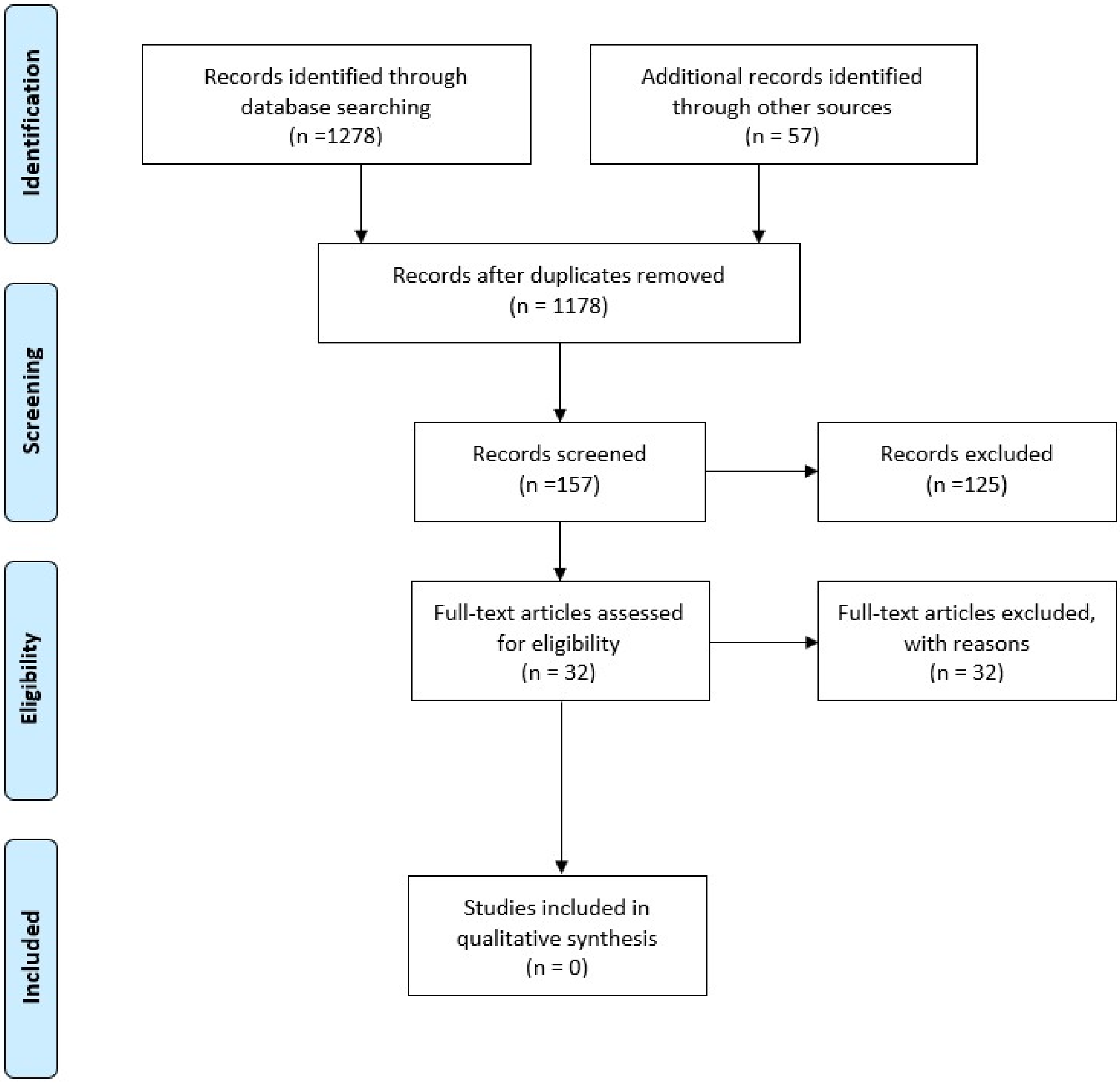


Figure 1. PRISMA flow diagram of the study

6. Results

Any national and international original articles were not found about which were teaching or developing CT via AI. Existing article were predominantly related to the conceptualization the place of AI within medical curriculum or the usage areas of AI in medical education or the interpretation of developments about them.

7. Discussion and Conclusion

There is the hidden epidemic of DE which has become a serious public health problem nationally and internationally. In despite of the importance of DE in terms of both patient safety and financial. The researches aiming at improving CT skills by AI are limited by time, money and the complexity level of goal. However, improving patient satey is possible as a result of which CT and metacognition skills reduce DE.

Clinical decision makers and educators should take into consideration CT skills cannot be acquired simply by osmosis from more experienced medical elders and existing training programs may not provide adequate education regarding diagnostic safety. However, physicians can make diagnosis more reliable by adhering to principles of CT, practicing reflectively, and insisting on follow-up.

Medical educators, computer scientists and clinicians require multidisciplinary cooperation environments in order to focus the AI searches about teaching of CT for diagnostic excellence within multiple problems belonging to multiple variables under uncertainty circumstances.

References

1. Inelmen EM, Sergi G, Enzi G, Toffanello ED, Coin A, Manzato E, Inelmen E. On clinical errors in geriatric medical diagnosis: ethical issues and policy implications. Ethics & Medicine. Int J of Bioethics. 2010;26: 15-24.
2. Makary M, Daniel M. Medical error-the third leading cause of death in the US. BMJ 2016;353:i2139.
3. The Institute of Medicine. Crossing the quality chasm: A new health system for the 21st century. Washington, DC: National Academy Press; 2001.
4. Tehrani ASS, Lee HW, Mathews SC, et al. 25-year summary of US malpractice claims for diagnostic errors 1986-2010: an analysis from the National Practioner Data Bank. BMJ Oual Saf 2013;22:672-680.
5. Graber ML. Diagnostic error: the hidden epidemic. Physician Executive 37(6):12-4, 16, 18-9.
6. Croskerry P. The importance of cognitive errors in diagnosis and strategies to minimize them. Acad Med 2003;78:775–80.
7. Graber ML, Rencic J, Rusz D, Papa F, Croskerry P, Zierler B et al. Improving diagnosis by improving education: a policy brief on education in healthcare professions. Diagnosis 2018;5(3):107-118.
8. Institute of Medicine. Crossing the quality chasm: A new health system for the 21st century. Washington, DC: National Academy Press; 2001.
9. World Health Organization. Diagnostic Errors. Geneva: World Health Organization;2016.https://apps.who.int/iris/bitstream/handle/10665/252410/9789241511636-eng.pdf (January 2021).
10. Society to Improve Diagnosis in Medicine. The Roadmap for Research to Improve Diagnosis, Part 1: Converting National Academy of Medicine Recommendations into Policy Action; 2018. https://www.improvediagnosis.org/wp-ontent/uploads/2018/10/policy_roadmap_for_diagnosti.pdf (January 2021)
11. Leape L.L. The nature of adverse events in hospitalized patients. The Harvard Medical Practice Study II. NEJM, 1991; 377-384.
12. Graber M. Gordon R, Franklin N. Reducing diagnostic errors in medicine: what’s the goal? Acad Med 2002;77:981-992.
13. Tiruneh DT, De Cock M, Elen J. Designing learning environments for critical thinking: Examining effective instructional approaches. Int J of Sci and Math Educ;2017:1065-1090.
14. Davenport T, Kalakota R. The potential for artificial intelligence in healthcare. FutureHealthc J. 2019;6(2):94-98.
15. Pesapane F, Codari M, Sardanelli F. Artificial intelligence in medical imaging: threat oropportunity? Radiologists again at the forefront of innovation in medicine. Eur RadiolExp. 2018;2:35.
16. Masters K. Artificial intelligence developments in medical education: a conceptual and practical framework. MedEdPublish (Open Access), 2020. https://www.mededpublish.org/manuscripts/3752. (February 2021)
17. Moher D, Liberati A, Tetzlaff J, Altman DG, The PRISMA Group (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. PLoS Med 6(6): e1000097.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Towards Federated Learning in Identification of Medical Images: A Case Study

Ruşen HALEPMOLLASI[1,*], Merve ZEYBEL[1], Elif EYVAZ[1], Rabia ARKAN[1],
Ahsen GENÇ[1], İsmail BİLGEN[1], Mehmet HAKLIDIR [1]

[1]*TÜBİTAK Informatics and Information Security Research Center, Information Technologies Institute, Kocaeli, Turkey*

* Corresponding Author: *TÜBİTAK Informatics and Information Security Research Center, Information Technologies Institute, Kocaeli, Turkey*
Tel.: +90 262 648 10 00. E-Mail: rusen.halepmollasi@tubitak.gov.tr

Publication Information

Keywords :
- Federated learning,
- Deep learning,
- Healthcare

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Artificial Intelligence (AI) methods need to learn from adequately large dataset to achieve clinical-grade accuracy and validation, which is vital in the healthcare field. However, sensitive medical data is usually fragmented, and not shared due to security and patient privacy policies. In this context, we aim at classifying abdominal and chest radiographs by applying Federated Learning (FL) with no sharing of the patient data. To perform the analyzes, we use a dataset comprising the abdominal and chest radiographs of patients, derived from Open-i. We implement and evaluate FL framework on distributed data across multiple clients. In the framework, we use multilayer perceptron as a deep learning model for the classification task. FL is a novel approach in which machine learning models are built with the collaboration of multiple clients controlled by a central server or service provider. FL model ensures data privacy and security by retaining the training data decentralized. We compare the performance of FL model against the centralized learning model. According to our results, FL model gives similar results to centralized models. Meanwhile, FL model provides security and privacy for patients by training individual models in distributed clients and sharing merely the model weights. We demonstrate that FL can address classifying private medical data by enabling multiple distributed clients to collaboratively train without the need to exchange or centralize patient records. Consequently, FL is a promising approach to sensitive medical data in terms of security, privacy, and bias.

1. Introduction

Artificial Intelligence (AI) solutions are widely used and result in significant novelties in almost every field such as healthcare, finance, science, network. (Danilevsky et al., 2020; Geiger & Urtasun, 2012; Janai et al., 2020; Wan et al., 2020; Xu et al., 2019). In the data processing workflow in traditional machine learning approaches, the data on which the model is trained should be collected and integrated into a data center, cloud or a central machine. However, centralized data and centralized training for machine learning models are often undesirable due to privacy and security concerns in case of sensitive data (Xu et al., 2021), or due to restricted transmission resources for data transfer in case of large amounts of data (Chen et al., 2020).

In this regard, the term Federated Learning (FL) was introduced by McMahan et al. in 2016 (McMahan et al., 2017) and defined as "the solving of learning tasks by a loose federation of participating devices coordinated by a central server.". FL is a novel approach in which machine learning models are created with the collaboration of multiple clients controlled by a central server or service provider. As FL does not require data to be merged in a server or service provider, it improves the quality of the training model, meanwhile offers security and privacy advantages for users. Although the approach was previously developed for mobile and end device use cases (Aïvodji et al., 2019; Chenet al., 2019; McMahan et al., 2017; Sozinov et al., 2018), in recent years, it has also attracted attention by studies conducted in various fields such as natural language processing (Bernal, 2020; Wang et al., 2020), big data analysis (Zhang et al., 2019), object detection (Liu et al., 2020), environment prediction (Hu et al., 2018), finance (Cheng et al., 2020), medicine and healthcare (Choudhury et al, 2019; Huang et al., 2019).

In the healthcare field, sensitive medical data is often stored in different data sources (e.g. Electronic Health Records (EHRs) of different patient populations are stored in different hospitals) and not shared for concern that it might violate security and patient privacy policies. The limited variety and no accessibility of data constitute an obstacle in terms of effectively training AI models and reaching reliable results, ensuring generalization of the models. Furthermore, when obtaining a dataset from limited data sources or investigating data belonging to a patient population attaching to their demographic environment, unbalanced data structures and therefore biased decisions may occur. Although several studies have addressed the aforementioned issues, the empirical evidence presented so far is still limited in various aspects.

To this end, we apply FL, which ensures data privacy and security by retaining the training data decentralized, to classify abdominal and chest radiographs with no sharing of the patient data. When performing the analyzes, we use a dataset comprising the abdominal and chest radiographs of patients. We implement and evaluate FL framework on distributed data across multiple clients. In the framework, we use multilayer perceptron (MLP) method that is a widely used classifier for medical imaging studies such as image denoising (Burger et al., 2012), segmenting in magnetic resonance images (Chiou & Hwang, 1995; Middleton & Damper, 2004), and computer-aided diagnosis (Stoitsis et al., 2006). We compare the performance of FL model against the centralized learning model. To analyze the results, we evaluate the classification performances of both approaches using the accuracy, precision, recall, and F-1 score metrics.

The structure of the paper: Applications of FL for different domains and for healthcare are mentioned in Section 2. After fundamentals of FL are introduced in Section 3, a case study performed in this paper and the evaluation of the analysis results are provided in Section 4. Conclusion of the paper is discussed in Section 5. Finally, in Section 6, final remarks and future research directions are mentioned.

2. Related Works

2.1 Federated Learning in AI

In our age where both software and hardware technologies are evolving rapidly, the data produced is increasing day by day (Li et al., 2020). It is collected in a central machine, cloud, or data center when being processed according to standard AI approaches (Li et al., 2017). Although the widespread adoption of AI technologies has resulted in significant improvement in many fields, the breach of privacy causes major problems regarding user privacy issues and security threats for both persons and organizations (Comiter, 2019).

FL has been given considerable attention by researchers, recently, as it is an immensely crucial method in terms of the resolution to the issues related to the centralization of data and user privacy that traditional machine learning models are inefficient. Yang et al. have provided a comprehensive study regarding the definitions, architectures, privacy solutions, and various applications of FL from a general point of view. They categorized FL framework as horizontal federated learning *-i.e., for overlapping data in the sample space-* or vertical federated learning *-i.e., for overlapping data in the feature space-* according to partitioning of data from different sources by samples or features. Furthermore, another category in their study is federated transfer learning, which is offered as a solution for challenging scenarios where data from different clients do not completely overlap neither in the sample space nor in the feature space (Yang et al., 2019).

FL has been further advanced and implemented in various mobile applications by several studies since it was first implemented by Google's researchers to predict text input of users from Google's virtual keyboard application, namely Gboard, on devices. For instance, Hard et al. have separately performed a recurrent neural network model both in the server-based environment and in the FL-based environment for the prediction of the next word. They compared the performance of prediction outputs of both experiments and got better results in the recall metric with the FL-based environment (Hard et al., 2018).

Moreover, Leroy et al. have used FL approach based on the idea of an embedded wake word detector to initiate an interaction with a smartphone voice assistant by implementing an adaptive averaging strategy instead of the standard averaging strategy for the weighted model (Leroy et al., 2019). The proposed strategy has decimated the number of communication rounds to gain target output performance. Furthermore, in (Ramaswamy et al., 2019), the authors provided a word level neural language model for estimation of the emoji from the text that the users have typed on a keyboard application (e.g. Gboard) on a smartphone. They have stated that the model trained by applying FL approach performs better than a server-based approach.

Yurochkin et al., have provided a probabilistic FL framework with multilayer perceptron networks by applying Bayesian nonparametric learning approach (Yurochkin et al., 2019). Thus, the model can generate effective matching weights for training neural networks on image datasets. Saputra et al. have applied the clustering-based energy demand learning model as the machine learning method for the prediction problem. However, the need to share data between charging stations and the charging station provider causes the increasing issues about privacy. To deal with this problem, authors have offered an FL approach, namely federated energy demand learning (FEDL), to predict the amount of energy needed by electric vehicle networks at charging stations without disclosing the privacy of both electric vehicles and charging stations (Saputra et al., 2019).

Yang et al. have proposed an FL framework to train a fraud detection model, effectively, based on the behavioral features. They have aimed to minimize the loss of banks and persons who have credit cards or debit cards in their study. They have reported that the FL-based fraud detection model achieves an approximately 10% higher average of Area Under the Curve (AUC) score than the traditional fraud detection model (Yang et al., 2019).

2.1 Federated Learning in Healthcare

In healthcare informatics, different data sources, e.g. pharmaceutical corporations, hospitals, insurance companies, etc., have their own data that belong to varied patient populations and do not share them to perform a centralized ML model. In this context, the application of FL framework is critical as it enables multiple healthcare organizations controlled by a central server or service provider to collaboratively build ML models while keeping training data locally. Therefore, FL framework ensures data privacy and security by retaining the training data decentralized (Kairouz et al., 2019).

Centralized, Localized, and Federated models trained with Support Vector Machine, Logistic Regression, Single-layer Perceptron machine learning algorithms have been evaluated for the prediction of ADR (adverse drug reaction) by Choudhury et al. (Choudhury et al., 2019). According to their results, FL model offers security and privacy advantages for users by training across a population of highly distributed devices, while having better precision, recall, and accuracy metric results than localized models, and having similar results to centralized models. Furthermore, the study has suggested using the perceptron classifier, which has the best performance for ADR detection. In another study, authors have also reported a detailed FL framework for the analysis of distributed healthcare data. Authors have extended the FL framework with a distributed differential privacy mechanism and investigated the effect of different levels of privacy on performing the FL model (Choudhury et al., 2019).

Brisimi et al. have used a binary classification framework to predict future hospitalizations of the patients by using the EHRs of heart diseases during a recent year. Due to privacy concerns of health data used, they have proposed a distributed solution method with a sparse Support Vector Machine (sSVM) algorithm via the soft-margin L1-regularized. They have used Cluster Primal Dual Splitting (cPDS) algorithm to reduce the communication cost brought by the distributed solution method established between agents. According to their results, they achieved similar performance with the central methods in terms of AUC metric. Also, their methods have converged faster compared to alternative distributed algorithms (Brisimi et al., 2018).

Chen et al. have stated that daily activity data produced by wearable health devices can be used in the early diagnosis of various cognitive diseases. In this context, traditional machine learning methods have limitations since users' data is produced by wearable devices of different brands and are isolated from each other. Therefore, they have offered FedHealth Framework, which is suitable for common use based on Federated Transfer Learning. The activity data of users obtained from different brand devices were first trained locally on the user devices and then distributed with the FedHealth Framework. They have used KNN, SVM, RF classification algorithms in this framework. According to the results obtained, the proposed FedHealth Framework has achieved an average of 5.3% accuracy more than the results obtained in models trained locally (Chen et al., 2020).

Huang et al. have proposed a new community-based federated machine learning (CBFL) algorithm, for the problem of health data being non-identically independently distributed (non-IID) which causes the FL method to perform inefficiently. They used Electronic medical records (EMRs) data for the estimation of hospitalization and mortality rate. Authors have implemented the CBFL algorithm in 3 steps: (i) training encoder, (ii) using the K-means clustering for exploring communities depending on similar diagnoses and geological locations, (iii) enabling the model to learn from these clusters. They have reported that CBFL algorithm outperformed the FL framework in AUC score (Huang et al., 2019).

3. Federated Learning

An FL server based FL concept, an innovative solution on the distribution of models to the clients at different locations and the collaborative training on these clients. The successful, reliable, and generalized results of AI solutions are directly related to the training of machine learning models with sufficient data and the attributes selected from the data. However, because of security and privacy issues, sometimes data may not be shared or it may not be possible to transfer and store large data to a central server or data center. In this context, FL can address the concerns of data owners regarding privacy and security issues as they do not share their data and machine learning models are trained decentrally on the framework. Also, it can also offer various additional security measures during transfering parameters. Moreover, big data with different structures that improve model performance are presented to the models, meanwhile, resource and cost issues can be eliminated as data is not stored and aggregated in a data center and machine learning models are not trained centrally.

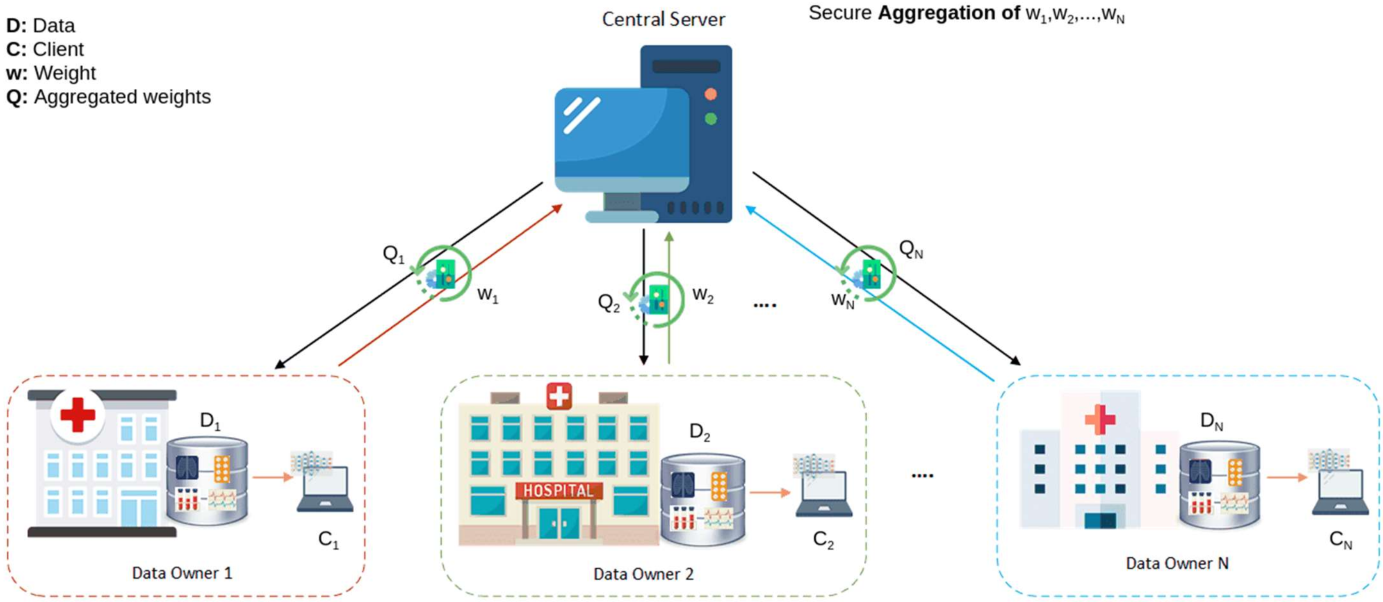


Figure 1. Federated learning flow**.**

Federated learning is basically based on training the models locally on the clients and aggregating updated model parameters globally in the server. As illustrated in Figure 1, in FL procedure, the central server sets the initial parameters and sends a global model to clients of the healthcare organizations in different locations for download. In particular, each client C_i locally trains the model on its own data D_i and sends only model update w_i with no data transfer to the center via a secure protocol tunnel. Finally, the central server performing secure aggregation with model updates of clients sends back the aggregated weight Q_i to clients to update their own local model. Various machine learning algorithms can be used in the flow and the entire process is repeated iteratively till the model converges, with its loss moving towards the minimum.

4. A Case Study

4.1 Dataset

We evaluated our model on a publicly available dataset derived from Open-i[1] (Lakhani et al., 2018). The dataset consists of 74 images in portable network graphics format, of which 37 are abdominal X-rays and 37 are chest X-rays (Figure 2). We split the data into two sets, i.e. training set and test set, with a technique commonly used to assess the performance of a model. When developing models and identifying feature sets, the training set of data is utilized. On the other hand, the test set that has never been used before is utilized to evaluate the performance of the models.

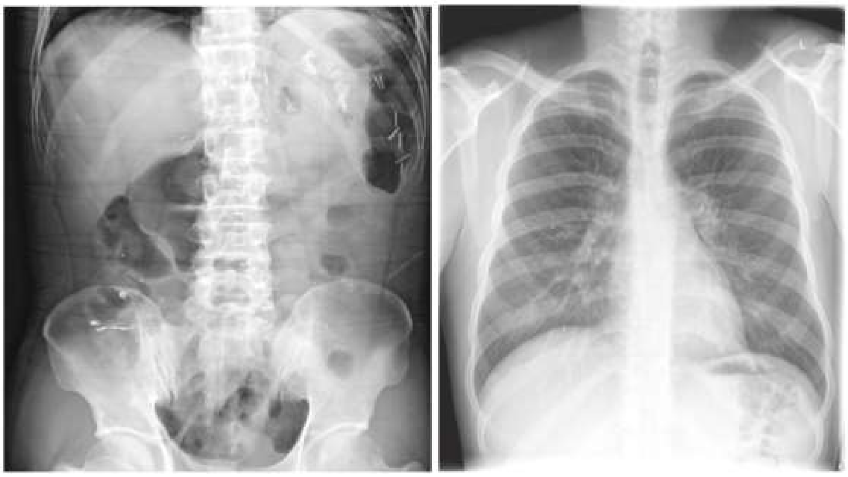


Figure 2. Sample Abdominal (left) and Chest (right) X-rays in dataset (Lakhani et al., 2018).

4.2 Methods

As a case study, we aimed to indicate that FL approach, which does not require sharing of data from different sources, can be applied for our classification problem. Therefore, we used a multilayer perceptron that is a non-complex model. MLP, which is a type of artificial neural networks, consists of the input layer, one or more hidden (intermediate) layers, and an output layer. We used two consecutive layers of deep learning architecture while implementing the model and utilized nonlinear activation functions relu and sigmoid to solve high-level correlations in the data. Also, we used Stochastic Gradient Descent as an optimization function.

In our architecture, we used 2 clients and 1 server. The initial weight values of the model created on the server are sent to the clients. The training of the MLP is started with local data by taking the first weights by the clients. New weights of models trained on clients are sent to the server. The weights of the model in the server are updated with the new average weights from the clients. The weight exchange between server and clients continues until the desired performance criterion is reached. The performance criterion can be an accuracy value as well as the number of epochs. In this study, the number of epochs was determined as success criteria.

4.3 Analysis of Results

There are various evaluation metrics to assess the predictive performance of classification methods. In this study, we calculated some of them, namely, accuracy, precision, recall, and F-measure that are acquired

[1] **Open-i**. https://openi.nlm.nih.gov

from the measures in confusion matrix to evaluate the performance of FL model and centralized model. As seen in Table 1, the confusion matrix is a table layout based on the number of samples classified correctly and incorrectly in the test data. There are four cases for binary classification in a confusion matrix, which contains "actual" and "predicted" dimensions. In this study, TP indicates the cases where both predicted values and actual values are the abdominal images, True Positive. FP, i.e., False Positive, represents the instances, where predicted values are abdominal X-rays but actual values are chest X-rays. TN demonstrates the cases where both predicted value and actual value are the chest X-rays, True Negative. FN, namely False Negative, includes the cases where predicted values are chest X-rays, but actual values are abdominal X-rays.

Table 1. Confusion Matrix

		Actual	
		Positive	Negative
Predicted	Positive	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)

Accuracy is the most common evaluation metric to identify the correct prediction rate of classifiers. However, precision, recall, and F-measure metrics should be used together with accuracy which can be misleading in datasets where the imbalance and predictions belonging to the less class are important.

Precision is important where FP estimation is costly and refers to what percentage of actual positives is estimated as positive. In our results, precision means what percent of the samples estimated abdominally were actually abdominal and is calculated (Eq. 1).

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

Recall is important when the FN estimation is critical and calculated as shown in Eq. 2. This metric shows to what proportion of the classifier identified these images when evaluating all samples in the abdominal class.

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

F-measure The trade-off between recall and precision values is important to achieve optimal results. Therefore, the F-measure score is used to balance between recall and precision and is calculated by the harmonic mean of these metrics (Eq. 3).

$$F - Measure = 2 * \frac{recall * precisio}{recall + precision} \tag{3}$$

When performing the experiments, each training process was continued for 30 epochs. We repeated the experiments 10 times with random sampling on the dataset that is splitted into subsets for training and testing as 70% and 30%, respectively. We measured the performance of each experiment using the aforementioned metrics. Finally, we averaged the overall performance scores. Table 2 shows the classification results of abdominal X-rays and chest X-rays.

According to these results, used DL models manage to distinguish chest and abdominal radiographs successfully, and FL framework obtained almost the same results as centralized learning model (same accuracy and F-measure with a slightly different loss).

Table2. Comparison of evaluation metrics for FL model and centralized learning model.

	Accuracy	Precision	Recall	F-measure	Loss
Federated Learning model	1.0	1.0	1.0	1.0	0.497
Centralized learning model	1.0	1.0	1.0	1.0	0.489

5. Conclusion and Evaluation

Machine learning methods are widely used in the processing and analysis of medical images. However, no acquiring a sufficiently large-scale dataset due to limitations such as security, patient privacy, data storage, and transmission affects the performance of machine learning models negatively. For this purpose, in our study, we offered FL framework with MLP classifier as a deep learning model to address the classification problem. When performing the analyzes, we applied FL model on distributed data across multiple clients controlled by a central server. Also, we repeated the same experimental steps with centralized learning model in which data from all clients are aggregated and stored in a central server. Both learning models are trained with the dataset comprising the abdominal and chest radiographs of patients obtained from an online repository of medical images, OpenI.

We compared FL model with centralized learning model in terms of several metrics including accuracy, precision, recall, and F-measure. The results show that FL model has almost the same performance with centralized learning model while ensuring data privacy and security for patients by training individual models in distributed clients and sharing merely the model weights. After analyzing all experimental results, we found that FL is a promising approach as it can address classifying private medical data without the need to centralize patient records.

6. Final Remarks and Future Work

In this study, we focused on applying FL model to address the identification of medical images without the need to centralize patient records that are into multiple distributed clients. In this context, we plan to extend our study with different perspectives in the future.

Aggregating massive datasets and training the machine learning models in a central server, service provider, or cloud requires sufficient storage and computing resources and causes a burden on the communication of the clients with the server. Hence, we aim at performing FL framework with larger data sets, more classification methods, and more clients. After repeating the same experiments with centralized learning framework, we will also compare the outputs of evaluation metrics and training time performances of both models. Furthermore, in an FL setup, we will analyze the optimization of model weights that different clients train locally when aggregating on the server and investigate the effects of different threshold values.

Moreover, in future studies, we aim to explore the existence of bias in the FL model. Clients included in an FL framework may have different data structures, feature sets, and the number of samples depending on their location. Therefore, in the FL process, even though the data set ratios between clients are adjusted similarly, bias may exist in the ultimate model due to the heterogeneous structure that occurs after aggregation and the bias in their own dataset. On the other hand, if we look up the landscape in reverse, unfair decisions due to bias that arises when data in a single source is trained may be eliminated by training data from different sources together.

References

1. Aïvodji, U. M., Gambs, S., & Martin, A. (2019). *IOTFLA: A secured and privacy-preserving smart home architecture implementing federated learning.* Paper presented at the 2019 IEEE Security and Privacy Workshops (SPW).
2. Brisimi, T. S., Chen, R., Mela, T., Olshevsky, A., Paschalidis, I. C., & Shi, W. (2018). Federated learning of predictive models from federated electronic health records. *International journal of medical informatics, 112*, 59-67.
3. Burger, H. C., Schuler, C. J., & Harmeling, S. (2012). *Image denoising: Can plain neural networks compete with BM3D?* Paper presented at the 2012 IEEE conference on computer vision and pattern recognition.
4. Chen, M., Mathews, R., Ouyang, T., & Beaufays, F. (2019). Federated learning of out-of-vocabulary words. *arXiv preprint arXiv:1903.10635*.
5. Chen, M., Yang, Z., Saad, W., Yin, C., Poor, H. V., & Cui, S. (2020). A joint learning and communications framework for federated learning over wireless networks. *IEEE Transactions on Wireless Communications*.
6. Chen, Y., Qin, X., Wang, J., Yu, C., & Gao, W. (2020). Fedhealth: A federated transfer learning framework for wearable healthcare. *IEEE Intelligent Systems, 35*(4), 83-93.
7. Cheng, Y., Liu, Y., Chen, T., & Yang, Q. (2020). Federated learning for privacy-preserving AI. *Communications of the ACM, 63*(12), 33-36.
8. Chiou, G. I., & Hwang, J.-N. (1995). A neural network-based stochastic active contour model (NNS-SNAKE) for contour finding of distinct features. *IEEE Transactions on Image Processing, 4*(10), 1407-1416.
9. Choudhury, O., Gkoulalas-Divanis, A., Salonidis, T., Sylla, I., Park, Y., Hsu, G., & Das, A. (2019). Differential privacy-enabled federated learning for sensitive health data. *arXiv preprint arXiv:1910.02578*.
10. Choudhury, O., Park, Y., Salonidis, T., Gkoulalas-Divanis, A., & Sylla, I. (2019). *Predicting adverse drug reactions on distributed health data using federated learning.* Paper presented at the AMIA Annual symposium proceedings.
11. Comiter, M. (2019). Attacking Artificial Intelligence. *Belfer Center Paper*.
12. Danilevsky, M., Qian, K., Aharonov, R., Katsis, Y., Kawas, B., & Sen, P. (2020). A survey of the state of explainable AI for natural language processing. *arXiv preprint arXiv:2010.00711*.
13. Garcia Bernal, D. (2020). Decentralizing Large-Scale Natural Language Processing with Federated Learning. In.
14. Geiger, A., Lenz, P., & Urtasun, R. (2012). *Are we ready for autonomous driving? the kitti vision benchmark suite.* Paper presented at the 2012 IEEE Conference on Computer Vision and Pattern Recognition.
15. Hard, A., Rao, K., Mathews, R., Ramaswamy, S., Beaufays, F., Augenstein, S., . . . Ramage, D. (2018). Federated learning for mobile keyboard prediction. *arXiv preprint arXiv:1811.03604*.
16. Hu, B., Gao, Y., Liu, L., & Ma, H. (2018). *Federated region-learning: An edge computing based framework for urban environment sensing.* Paper presented at the 2018 IEEE Global Communications Conference (GLOBECOM).
17. Huang, L., Shea, A. L., Qian, H., Masurkar, A., Deng, H., & Liu, D. (2019). Patient clustering improves efficiency of federated machine learning to predict mortality and hospital stay time using distributed electronic medical records. *Journal of biomedical informatics, 99*, 103291.
18. Janai, J., Güney, F., Behl, A., & Geiger, A. (2020). Computer vision for autonomous vehicles: Problems, datasets and state of the art. *Foundations and Trends® in Computer Graphics and Vision, 12*(1–3), 1-308.

19. Kairouz, P., McMahan, H. B., Avent, B., Bellet, A., Bennis, M., Bhagoji, A. N., . . . Cummings, R. (2019). Advances and open problems in federated learning. *arXiv preprint arXiv:1912.04977*.
20. Lakhani, P., Gray, D. L., Pett, C. R., Nagy, P., & Shih, G. (2018). Hello world deep learning in medical imaging. *Journal of digital imaging, 31*(3), 283-289.
21. Leroy, D., Coucke, A., Lavril, T., Gisselbrecht, T., & Dureau, J. (2019). *Federated learning for keyword spotting.* Paper presented at the ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP).
22. Li, P., Li, J., Huang, Z., Li, T., Gao, C.-Z., Yiu, S.-M., & Chen, K. (2017). Multi-key privacy-preserving deep learning in cloud computing. *Future Generation Computer Systems, 74*, 76-85.
23. Li, T., Sahu, A. K., Talwalkar, A., & Smith, V. (2020). Federated learning: Challenges, methods, and future directions. *IEEE Signal Processing Magazine, 37*(3), 50-60.
24. Liu, Y., Huang, A., Luo, Y., Huang, H., Liu, Y., Chen, Y., . . . Yang, Q. (2020). *Fedvision: An online visual object detection platform powered by federated learning.* Paper presented at the Proceedings of the AAAI Conference on Artificial Intelligence.
25. McMahan, B., Moore, E., Ramage, D., Hampson, S., & y Arcas, B. A. (2017). *Communication-efficient learning of deep networks from decentralized data.* Paper presented at the Artificial Intelligence and Statistics.
26. McMahan, H. B., Ramage, D., Talwar, K., & Zhang, L. (2017). Learning differentially private recurrent language models. *arXiv preprint arXiv:1710.06963*.
27. Middleton, I., & Damper, R. I. (2004). Segmentation of magnetic resonance images using a combination of neural networks and active contour models. *Medical engineering & physics, 26*(1), 71-86.
28. Ramaswamy, S., Mathews, R., Rao, K., & Beaufays, F. (2019). Federated learning for emoji prediction in a mobile keyboard. *arXiv preprint arXiv:1906.04329*.
29. Saputra, Y. M., Hoang, D. T., Nguyen, D. N., Dutkiewicz, E., Mueck, M. D., & Srikanteswara, S. (2019). *Energy demand prediction with federated learning for electric vehicle networks.* Paper presented at the 2019 IEEE Global Communications Conference (GLOBECOM).
30. Sozinov, K., Vlassov, V., & Girdzijauskas, S. (2018). *Human activity recognition using federated learning.* Paper presented at the 2018 IEEE Intl Conf on Parallel & Distributed Processing with Applications, Ubiquitous Computing & Communications, Big Data & Cloud Computing, Social Computing & Networking, Sustainable Computing & Communications (ISPA/IUCC/BDCloud/SocialCom/SustainCom).
31. Stoitsis, J., Valavanis, I., Mougiakakou, S. G., Golemati, S., Nikita, A., & Nikita, K. S. (2006). Computer aided diagnosis based on medical image processing and artificial intelligence methods. *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 569*(2), 591-595.
32. Wan, S., Gu, Z., & Ni, Q. (2020). Cognitive computing and wireless communications on the edge for healthcare service robots. *Computer Communications, 149*, 99-106.
33. Wang, Y., Tong, Y., & Shi, D. (2020). *Federated latent Dirichlet allocation: A local differential privacy based framework.* Paper presented at the Proceedings of the AAAI Conference on Artificial Intelligence.
34. Xu, F., Uszkoreit, H., Du, Y., Fan, W., Zhao, D., & Zhu, J. (2019). *Explainable AI: A brief survey on history, research areas, approaches and challenges.* Paper presented at the CCF international conference on natural language processing and Chinese computing.
35. Xu, J., Glicksberg, B. S., Su, C., Walker, P., Bian, J., & Wang, F. (2021). Federated learning for healthcare informatics. *Journal of Healthcare Informatics Research, 5*(1), 1-19.
36. Yang, Q., Liu, Y., Chen, T., & Tong, Y. (2019). Federated machine learning: Concept and applications. *ACM Transactions on Intelligent Systems and Technology (TIST), 10*(2), 1-19.
37. Yang, W., Zhang, Y., Ye, K., Li, L., & Xu, C.-Z. (2019). *FFD: a federated learning based method for credit card fraud detection.* Paper presented at the International Conference on Big Data.
38. Yurochkin, M., Agarwal, M., Ghosh, S., Greenewald, K., Hoang, N., & Khazaeni, Y. (2019). *Bayesian nonparametric federated learning of neural networks.* Paper presented at the International Conference on Machine Learning.
39. Zhang, J., Chen, B., Yu, S., & Deng, H. (2019). *PEFL: A privacy-enhanced federated learning scheme for big data analytics.* Paper presented at the 2019 IEEE Global Communications Conference (GLOBECOM).

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Genetic Algorithm based Clinical Decision Support System for the Early Diagnosis of Cardiovascular Diseases

Nermin ÖZCAN [1,2] *, Mehmet KUNTALP [2]

[1] *Iskenderun Technical University, Faculty of Engineering and Natural Sciences, Dept. of Biomedical Engineering, Turkey*
[2] *Dokuz Eylul University, Graduate School of Natural and Applied Sciences, Dept. of Biomedical Technologies, Turkey*

* Corresponding Author: Iskenderun Technical University, Faculty of Engineering and Natural Sciences, Turkey
Tel.: +90 326 613 56 00 - 2911. E-Mail: nermin.ozcan@iste.edu.tr

Publication Information

Keywords :

- Cardiovascular disease,
- Clinical decision support system,
- Genetic algorithm

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Cardiovascular diseases are among the main health risks contributing to a global health burden. Prognosis and early diagnosis of cardiovascular diseases can help in reducing the deaths as well as providing quality life span to patients. The hindrances over early diagnosis of diseases such as side effects of current techniques and the high cost of expenditure cause various attempts for developing automatic decision support systems. In this study, a clinical decision support system based on machine learning is suggested, allowing the detection of optimal hyper parameters of classifiers that overcome limitations in medical datasets. The approach comprises three major phases: first, identifying missing values of attributes in datasets; second, the construction of more accurate classifiers by implementing an efficient genetic algorithm method for tuning hyper parameters, and then the evaluation of confidence in the designed classifier by describing the individual predictions and their global behavior. In the end, a large-scale experimental study was implemented on heart disease datasets, demonstrating the feasibility and benefit of the proposed technique for early diagnosis of cardiovascular diseases. Experiments on data from the Cleveland heart disease database obtained a classification accuracy of 86.89%. In addition, we received recall and precision values of 77.78% and 91.30%, respectively, in the diagnosis of heart disease. The proposed clinical decision support system is anticipated to be beneficial and supportive for doctors in correctly and efficiently diagnosing heart disease.

1. Introduction

According to research from the Institute for Health Metrics and Evaluation (IHME) [1], Cardiovascular disease (CVD) prevalence reached for 523 million in 2019 and became one of the leading causes of disease burden. Approximately, 18.6 million deaths due to CVD have occurred. The term of CVD involves mortality and prevalence due to eleven heart diseases, caused by stroke, ischemic heart disease and hypertensive heart disease, as well as heart failure. Moreover, non-atherosclerotic and atherosclerotic coronary disorders also cover.

CVD is a disease that causes heart failure when the heart may not pump the necessary amount of blood to other areas of the body. The main cause for heart disease is blockage of coronary arteries. An abnormal heartbeat, chest pains, breathlessness, swollen ankles or feet, exhaustion and fainting are the early symptoms of CVD. Early diagnosis and prognosis is a way to improve a patient's life-span. The scarcity of services or unavailability of doctors and radiologists in developed and developing countries in a decent proportion of the population is a significant issue. This is one of the main reasons that the mortality rate of approximately 50% of patients with heart disease is in 1-2 years. Risk factors related to CVD are the health history of the patient, age, gender, habits, etc. Lifestyle improvements such as regular exercise and non-smoking can decrease potential risks by regulating the level of cholesterol and blood pressure. Although the examination of these risk factors, life-style shifts and patient evaluation findings by physician's aid in the diagnosis, prognosis cannot be ensured. Most of the studies in recent years have focused on the diagnosis of chest graphs with artificial intelligence methods. In these studies, image processing and deep learning methods were used together. Contrary to these studies, our study aspired to create a decision support system for the early diagnosis of the diseases in question. by using the data obtained from the examinations performed by the specialist physicians. Besides, it was sought to create an example regarding how biomedical data may be processed with deep learning algorithms.

One of the promising approaches for diagnosing the CVD is angiography technique. Nevertheless, one of the key reasons for researchers' propensity towards a predictive approach is the side effects of angiography and the high cost of expenditure. Many researchers have been designed machine learning (ML) techniques based clinical decision support systems (CDSS) over the last decades to reduce the risk of medical assessment [2]–[4]. Nevertheless, there is actually a lack of ML strategies for diagnosing heart disease as the medical datasets may include irrelevant features and missing values. Incomplete values and class balance, for example, pose significant obstacles to the success of the prediction model, and may also cause to pointless predictions. In order to apply machine learning algorithms, an appropriate preparation is required for the preprocessing of data sets.

1.1 Related Works

The current conventional invasive approaches used to detect heart disease are focused on a patient's medical history, a clinical test record, smoking habit, obesity, elevated blood cholesterol, high blood pressure and an evaluation of the signs associated by physicians. Many of these approaches are not adequate and the diagnosis can be delayed. In terms of calculation, the human-oriented process often entails high costs and is complex and requires considerable time for evaluation. Non-invasive clinic decision support systems based on predictive ML models such as Logistic Regression (LR), Naïve Bayes (NB), Support Vector Machine (SVM), Fuzzy Logic (FL), K Nearest Neighbor(KNN), Decision Tree (DT), Random Forest (RF), and many more, have been developed by researchers to resolve the lack of these traditional methods and is widely used for the CVD [5]–[7]. The purpose has been to decrease the cardiovascular mortality rate with the support of these expert systems based on ML. The prediction of heart disease by ML models is frequently used in literature, and significant results have been identified in the Cleveland dataset of UCI heart disease [8]–[12].

The irrelevant, incomplete and class imbalance dataset problems have been concerned in much of the recent research on heart disease prediction, since few medical datasets can specifically fulfill these criteria. To overcome the irrelevant features before applying classification techniques, a number of researchers used feature selection methods. For instance, Saqlain et al. used Fisher Score and Matthews Correlation Coefficient methods to pick subset of features. As a result, the selected features were used by SVM for classifying patients [13]. Researchers in other studies compared to predictive models based on feature selection techniques namely: Relief, Minimal Redundancy Maximal Relevance (MRMR), Least Absolute Shrinkage and Selection Operator (LASSO), etc. [14,15]. Iftikhar et al. suggested a Genetic Algorithm (GA) based system which combined feature selection and classification techniques. SVM techniques were then used for the classification of medical datasets [16]. Similarly, Mohan, Thirumalai and Srivastava have suggested a smart framework that combines RF with a linear model for estimating heart disease [17]. Amin, Chiam and Varathan evaluated numerous learning-based approaches for detecting heart disease, of which SVM and voting (NB + LR) methods are considered to be remarkable [18]. In certain cases, it is difficult or almost impossible to obtain full information from the participant in medical data sets, due to problems such as interruptions in the data flow, safety issues, the patient's reluctance to comply, etc. Therefore data imputation is performed to fill in the missing values of the features with the new labels and render the dataset complete. In literature, certain investigators used only Cleveland dataset, which has several missing data from the database which itself has four different datasets. In the other hand, abundant researchers have removed samples or columns that have missing values from the dataset. However, dropping missing values results in information loss. For the incomplete data, a missing value imputation method based on statistical techniques such as mean, median, mode have been shown as an acceptable prediction accuracy [19]. Similarly, Gupta et al. used feature extraction methods based on Factor Analysis of Mixed Data to predict heart disease, and completed missing values by the majority label [20]. On the other hand, substantial number of researchers developed hybrid algorithms to enhance classification performance in the diagnosis of CVD. Ali et al. successfully predicted the heart failure based on the optimized stacked SVM model and its better performance was also verified through comparison with other popular methods [21]. Similarly, (Venkatesh, Balasubramanian, and Kaliappan developed a data Predictive Analytics model based NB to increase the prediction performance [22]. Samuel et al. have proposed a framework of a hybrid system based FL for the identification of heart failure risk, using ML [23]. Long, Meesad, and Unger suggested a diagnostic method based on the feature reduction of Rough Sets by redefining the dimensions using the Chaos Firefly Algorithm and Interval Type-2 FL [24].

Though researches show acceptable prediction performance, class imbalances and missing values are still unresolved problems. As in existing clinical practice, the dataset for heart disease often suffers from these difficulties. To solve these issues, clinical decision support systems are required in large-scale experimental studies combining the distinct ML methods.

1.2 Our Approach

The approach of CVD prediction in this study mainly consists of three steps. First, Cleveland heart disease datasets are used to predict CVD. There are some weaknesses in the dataset such as incomplete data, limited number of instances, and class imbalances. Iterative Bayesian Ridge techniques are used to impute the missing values according to the characteristics of the datasets. Second, we suggest a genetic algorithm (GA) based hyper parameter optimization approach for class imbalance dataset for heart disease prediction. Finally, once an accurate classifier has been developed by completing the preprocessing steps, this study focuses on evaluating the model's predictions. The aim is to design a CDSS, which inspire confidence to the experts for the prediction of CVD.

2. Material and Method

2.1 Data and Data Preprocessing

The Cleveland Dataset contains data from ML Repository of the University of California, Irvine (UCI) [25]. While dataset has 76 features, only 14 attributes are widely used for scientific purposes. There are 13 features that attribute in prediction of heart disease and one feature performs as the output or the predicted feature for the heart disease presence in a patient. The dataset involves a feature called 'num' to indicate the diagnosis of heart disease in patients of scales ranging, from 0 to 4. In this case, 0 corresponds to the absence of heart failure and all values from 1 to 4 represent heart disease patients.

Incomplete data imputation is a significant task in the preprocessing phase realized by two widely used methods. The first one is to fill a statistical value (i.e. mean, mod and median of attribute). The second way is to impute incomplete data before the classification phase. If the ratio of incomplete attributes is really not huge, the second strategy is especially better than the first, because the imputed values could have a severe effect on the structure of the original data. Nevertheless, it is incredibly difficult to estimate missing data in certain cases by the second method if the correlation between features is poor. Accordingly, in our work, we proposed that different approaches be used and compared with statistical based median approach (M-IA), distance based KNN (KNN-IA) regression approach [26] and iterative Bayes Ridge (BR-IA) regression approach [27].

2.2 Classification

Tree-based classifiers typically have a hierarchical approach in the context of tree structure. It splits down the dataset into smaller subsets and at the same time develops the corresponding tree structure. According to this rule, a tree with the decision and the leaf nodes is obtained. Decision nodes have two or three branches, and the leaf nodes represent a classification. The process is mainly based on partitioning iteratively using the split-and-conquer technique. Decision Tree is a key tree-based classification method; various classifier techniques based on tree such as RF, ADA have been designed by developing decision tree technique. Five distinct tree-based classification approaches were used and compared in this study to test the predictive efficiency of CVD in this work: ADA, DT, ET, GB and RF.

2.3 Hyperparameter Optimization

In the classifier models, the choice of hyperparameters seriously influences the runtime of the model during learning and its success in the validation set. In optimizing hyperparameters, the purpose is to investigate the optimum hyperparameter values that will establish the best results. We used GA in order to find optimal hyperparameters effectively in this work. As the fitness function of GA, the Area Under Curve (AUC) metric was used to determine the effects on the performance of the hyperparameters used. In each implementation, we performed a 5-fold cross validation to determine the best hyperparameters of models. The hyperparameters maximized according to the AUC score were then used in classifiers in test sets. Each classifier model has its own hyper parameters which is depicted in Table 1.

2.4 Performance Evaluation

To analyze the performance of the models' predictions, evaluation metrics were used. Almost all of the metrics are concentrated on a confusion matrix. Confusion matrix is a combination of four distinct values: True Positive (TP) indicates the model correctly predicts CVD patients, False Positive (FP) indicates the model predicts healthy people as CVD patients, True Negative (TN) indicates the model correctly predicts healthy people as healthy, and False Negative (FN) indicates the model predicts CVD patients as healthy. We used 5 metrics to evaluate the efficiency of the model. Accuracy Score is the ratio of the amount of TP and TN to the total number of samples. Recall Score means by dividing the amount of TP by the sum of TP and FN. Precision Score means by dividing the amount of TP by the sum of TP and FP. F1 Score is used to compare models of varying precision and recall scores. The Area Under the Curve (AUC) Score calculates the area under the ROC curve, which is the Receiver Operator Characteristic Curve. The ROC curve is a probability curve and a schematic representation of the diagnostic functionality of the binary classifier system. More simply, it demonstrates how well the model can distinguish between classes.

Table 1: List of hyperparameters used in the optimization process. Comprehensive information on all classifiers and their parameters can be obtained from "https://scikitlearn.org".

Classifier	Hyperparameters and Range	Classifier	Hyperparameters and Range
ADA	algorithm: "SAMME", "SAMME.R" learning_rate: in range [0.1-1] n_estimators: in range [20-100]	*GB*	criterion: "friedman_mse" , "mse" , "mae" max_depth: in range [5-100] max_features: "auto" , "sqrt" , "log2" max_leaf_nodes: in range [5-100] min_samples_leaf: in range [2-10] min_samples_split: in range [2-10] n_estimators: in range [20-100] loss: "deviance", "exponential" learning_rate: in range [0.1-1] subsample: : in range [0-1]
DT	criterion: "entropy" , "gini" max_depth: in range [5-100] max_features: "auto" , "sqrt" , "log2" max_leaf_nodes: in range [5-100] min_samples_leaf: in range [2-10] min_samples_split: in range [2-10] splitter: "best" , "random"		
ET	criterion: "entropy" , "gini" max_depth: in range [5-100] max_features: "auto" , "sqrt" , "log2" max_leaf_nodes: in range [5-100] min_samples_leaf: in range [2-10] min_samples_split: in range [2-10] n_estimators: in range [20-100]	*RF*	criterion: "entropy" , "gini" max_depth: in range [5-100] max_features: "auto" , "sqrt" , "log2" max_leaf_nodes: in range [5-100] min_samples_leaf: in range [2-10] min_samples_split: in range [2-10] n_estimators: in range [20-100]

3. Results

The experimental results were divided into two parts, each of which contained a separate phase of the proposed technique. In the first part, three imputation techniques (two regression-based and one statistical-based) were used to resolve incomplete data issues. KNN-IA and BR-IA were the two regression-based missing data imputation approaches. KNN-IA assigns missing values to each training sample by calculating the nearest k-nearest neighbors (in this work 20 distinct numbers of nearest neighbors were compared). The BR-IA chooses the most appropriate output feature to be imputed and the imputed feature to input another candidate feature, and so on until all missing values are imputed to the dataset. On the other hand, the M-IA is a statistical imputation method that is concerned with the imputation of the median value of the related attribute. The second section of the experimental results focused on the optimum value of hyper parameters, as well as on the creation of correct classifiers, simply by performing a search based on GA of the determined classifier hyper parameters. Five different tree-based learning methods were used in this section, namely ADA, DT, ET, GB and RF. The results of final constructed models (they only use the optimized hyper parameters for each classifier), were compared to three imputation methods. The hyper parameter tuning approach is common in medicine for designing stable classifiers. K fold cross validation (k=5) was conducted when tuning hyper parameter optimization methods. All optimization methods and classifiers were performed on the same instances of the dataset, so that the variations at the time of the final results comparison were not due to data differences.

Once the hyperparameters of classifiers were determined, the best subset of classifier hyperparameters were applied together with the proposed imputation process. Table 2 lists the predictive performance (average AUC achieved by cross-validation) of the ADA, DT, ET, GB and RF classifiers using various imputation approaches. The results indicated that the models built on the BR-IA as using ET classifier obtained a better mean predictive performance than the models built on KNN-IA or M-IA.

Table 2: Average AUC values obtained by classifiers ADA, DT, ET, GB and RF using various approaches. BR-IA, KNN-IA, and M-IA are imputation techniques used in related datasets. For each type of classifier and imputation technique (showed by grid), the best AUC values are highlighted in the bold typeface.

Imputation	ADA	DT	ET	GB	RF
BR-IA	0,9086	0,8274	**0,9135**	0,9030	0,8948
KNN-IA	0,9061	**0,8496**	0,9103	**0,9085**	0,9024
M-IA	**0,9117**	0,8148	0,9092	0,8992	**0,9062**

The BR-IA show consistent AUC test results in the same manner as distinct classifier training results as depicted in Figure 1. ET (AUC 0.906) is best classifier for this dataset followed by RF (AUC 0.898) and ADA (AUC 0.897).

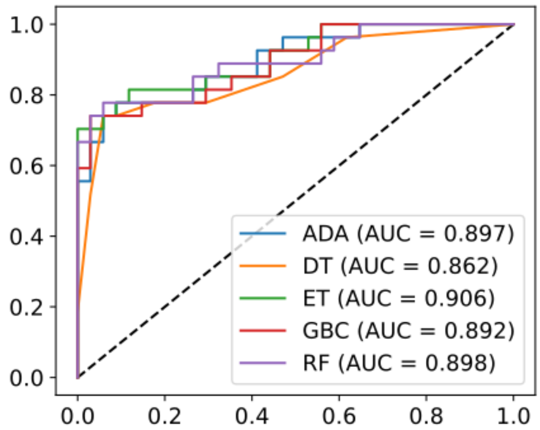


Figure 1: ROC-AUC curve obtained by classifiers ADA, DT, ET, GB and RF for Cleveland data.

Finally, the constructed classifiers by BR-IA were compared by accuracy, recall, precision and F1 score, which are four well-known evolution metrics for classification models to investigate testing efficiency on Cleveland dataset. Based on the results shown in Figure 2, it can be observed that the ET is the better classifier. The accuracy was 87.25%, the recall was 83.48%, the precision was 88.62% and the F1 score is 86.02%. The classifier ADA, had second high results, obtained the performance 86.24%, 82.78%, 87.50%, 84.35% for accuracy, recall, precision and F1score, respectively. While DT and RF had very close results with each other, it can be noted that the DT is the most unstable classifier in this work.

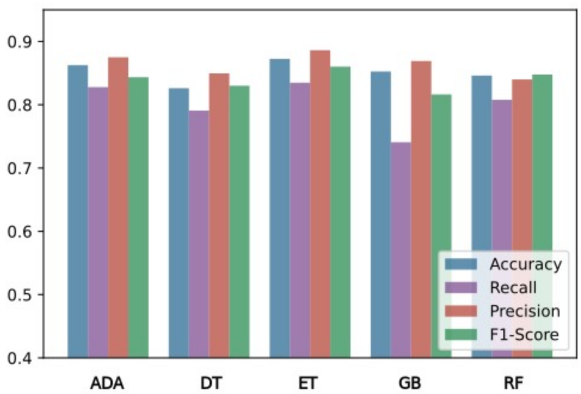


Figure 2: Barplot depicting the testing performance of respective classifiers ADA, DT, ET, GB and RF, in terms of Accuracy, Recall, Precision and F1 score for Cleveland dataset imputed by BR-IA.

5. Conclusion and Evaluation

In this work, an appropriate CDSS was proposed to resolve dysregulations in medical datasets and for early diagnosis of CVD. The proposed methodology consists of two major phases that not only allow to incorporate the expert knowledge and identify missing value of attributes in datasets, but also the construction of very accurate classifiers (by implementing an efficient GA method for tuning hyperparameters). A comprehensive experimental research was performed on the Cleveland dataset. Data imputation results showed the feasibility of filling datasets to enhance classification performance. Furthermore, hyperparameters of classification models were determined through the proposed GA, and classifiers with good performance were consequently constructed based on these hyperparameters.

This study has demonstrated that the proposed approach can help to recognize novel diagnostic and prognostic features, thereby enabling improved clinical techniques to be developed and introduced and a more accurate diagnosis of CVD to be achieved. As a result, this technique can be used in medical area for early detection of heart disease based on CDSS.

References

1. IHME. Global Burden of Disease cause and risk summaries. Lancet. 2020;396:86-87.
2. Anooj PK. Clinical decision support system: Risk level prediction of heart disease using weighted fuzzy rules. J King Saud Univ - Comput Inf Sci. 2012;24(1):27-40. doi:10.1016/j.jksuci.2011.09.002
3. Nazari S, Fallah M, Kazemipoor H, Salehipour A. A fuzzy inference- fuzzy analytic hierarchy process-based clinical decision support system for diagnosis of heart diseases. Expert Syst Appl. 2018;95:261-271. doi:10.1016/j.eswa.2017.11.001
4. Qatawneh Z, Alshraideh M, Almasri N, Tahat L, Awidi A. Clinical decision support system for venous thromboembolism risk classification. Appl Comput Informatics. 2019;15(1):12-18. doi:10.1016/j.aci.2017.09.003
5. Fuster-Parra P, Tauler P, Bennasar-Veny M, Ligeza A, López-González AA, Aguiló A. Bayesian network modeling: A case study of an epidemiologic system analysis of cardiovascular risk. Comput Methods Programs Biomed. 2016;126:128-142. doi:10.1016/j.cmpb.2015.12.010
6. Davari Dolatabadi A, Khadem SEZ, Asl BM. Automated diagnosis of coronary artery disease (CAD) patients using optimized SVM. Comput Methods Programs Biomed. 2017;138:117-126. doi:10.1016/j.cmpb.2016.10.011
7. Dwivedi AK. Performance evaluation of different machine learning techniques for prediction of heart disease. Neural Comput Appl. 2018;29(10):685-693. doi:10.1007/s00521-016-2604-1
8. Das R, Turkoglu I, Sengur A. Effective diagnosis of heart disease through neural networks ensembles. Expert Syst Appl. 2009;36(4):7675-7680. doi:10.1016/j.eswa.2008.09.013
9. Nahar J, Imam T, Tickle KS, Chen YPP. Computational intelligence for heart disease diagnosis: A medical knowledge driven approach. Expert Syst Appl. 2013;40(1):96-104. doi:10.1016/j.eswa.2012.07.032
10. Blokh D, Stambler I. Information theoretical analysis of aging as a risk factor for heart disease. Aging Dis. 2015;6(3):196-207. doi:10.14336/AD.2014.0623
11. Kavitha R, Kannan E. An efficient framework for heart disease classification using feature extraction and feature selection technique in data mining. In: 1st International Conference on Emerging Trends in Engineering, Technology and Science, ICETETS 2016. IEEE; 2016. doi:10.1109/ICETETS.2016.7603000
12. Vijayashree J, Sultana HP. A Machine Learning Framework for Feature Selection in Heart Disease Classification Using Improved Particle Swarm Optimization with Support Vector Machine Classifier. Program Comput Softw. 2018;44(6):388-397. doi:10.1134/S0361768818060129
13. Saqlain SM, Sher M, Shah FA, et al. Fisher score and Matthews correlation coefficient-based feature subset selection for heart disease diagnosis using support vector machines. Knowl Inf Syst. 2019;58(1):139-167. doi:10.1007/s10115-018-1185-y
14. Muhammad Y, Tahir M, Hayat M, Chong KT. Early and accurate detection and diagnosis of heart disease using intelligent computational model. Sci Rep. 2020;10(1):1-17. doi:10.1038/s41598-020-76635-9

15. Haq AU, Li JP, Memon MH, Nazir S, Sun R, Garciá-Magarinõ I. A hybrid intelligent system framework for the prediction of heart disease using machine learning algorithms. Mob Inf Syst. 2018;2018. doi:10.1155/2018/3860146
16. Iftikhar S, Fatima K, Rehman A, Almazyad AS, Saba T. An evolution based hybrid approach for heart diseases classification and associated risk factors identification. Biomed Res. 2017;28(8):3451-3455.
17. Mohan S, Thirumalai C, Srivastava G. Effective heart disease prediction using hybrid machine learning techniques. IEEE Access. 2019;7:81542-81554. doi:10.1109/ACCESS.2019.2923707
18. Amin MS, Chiam YK, Varathan KD. Identification of significant features and data mining techniques in predicting heart disease. Telemat Informatics. 2019;36(November 2018):82-93. doi:10.1016/j.tele.2018.11.007
19. Paul AK, Shill PC, Rabin MRI, Akhand MAH. Genetic algorithm based fuzzy decision support system for the diagnosis of heart disease. In: 5th International Conference on Informatics, Electronics and Vision, ICIEV 2016. IEEE; 2016:145-150. doi:10.1109/ICIEV.2016.7759984
20. Gupta A, Kumar R, Singh Arora H, Raman B. MIFH: A Machine Intelligence Framework for Heart Disease Diagnosis. IEEE Access. 2020;8(Ml):14659-14674. doi:10.1109/ACCESS.2019.2962755
21. Ali L, Niamat A, Khan JA, et al. An Optimized Stacked Support Vector Machines Based Expert System for the Effective Prediction of Heart Failure. IEEE Access. 2019;7:54007-54014. doi:10.1109/ACCESS.2019.2909969
22. Venkatesh R, Balasubramanian C, Kaliappan M. Development of Big Data Predictive Analytics Model for Disease Prediction using Machine learning Technique. J Med Syst. 2019;43(8). doi:10.1007/s10916-019-1398-y
23. Samuel OW, Asogbon GM, Sangaiah AK, Fang P, Li G. An integrated decision support system based on ANN and Fuzzy_AHP for heart failure risk prediction. Expert Syst Appl. 2017;68:163-172. doi:10.1016/j.eswa.2016.10.020
24. Long NC, Meesad P, Unger H. A highly accurate firefly based algorithm for heart disease prediction. Expert Syst Appl. 2015;42(21):8221-8231. doi:10.1016/j.eswa.2015.06.024
25. Heart Disease Data Set. UCI Machine Learning Repository. Accessed November 16, 2021. http://archive.ics.uci.edu/ml/datasets%0A/Heart+Disease
26. Zhang S. Nearest neighbor selection for iteratively kNN imputation. J Syst Softw. 2012;85(11):2541-2552. doi:10.1016/j.jss.2012.05.073
27. Mostafa SM, Eladimy AS, Hamad S, Amano H. CBRL and CBRC: Novel algorithms for improving missing value imputation accuracy based on bayesian ridge regression. Symmetry (Basel). 2020;12(10). doi:10.3390/SYM12101594

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Bursa Faculty of Medicine Medical And Medical Specialty Students' Attitude Towards Artificial Intelligence: Survey Study

Deniz GÜVEN[1*], Elif GÜLER KAZANCI[2], Ayşe ÖREN[3]

[1]University of Health Sciences, Ankara Kecioren Training and Research Hospital, Department of Pediatrics , Kecioren/ Ankara / TURKEY
[2]University of Health Sciences, Bursa Yüksek İhtisas Training and Research Hospital, Department of Pediatric Hematology-Oncology, Yıldırım/Bursa / TURKEY
[3]University of Health Sciences, of Medicine, Bursa Yüksek İhtisas Training and Research Hospital, Department of Pediatrics,Yıldırım/Bursa / TURKEY

* Corresponding Author: University of Health Sciences, Ankara Kecioren Training and Research Hospital, Department of Pediatrics, Kecioren/ Ankara / TURKEY
Tel.: 05076710030. E-Mail: deniz.guven06@hotmail.com

Publication Information

Keywords :
- Artificial intelligence;
- Medical school student;
- Medical education;
- Survey;Bursa

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Objective: Artificial intelligence techniques are used more frequently in medicine. As medical students begin their careers upon completion of their education, there will likely be various artificial intelligence software tools. We aimed to evaluate the knowledge levels and attitudes of medical faculty students towards artificial intelligence in medicine.

Material-method: A web-based survey was designed using Google forms and sent online to students studying medicine in 2020-2021 at the University of Health Sciences, Bursa Training and Research Hospital. The survey consists of departments that were evaluating the demographics properties and the attitudes towards artificial intelligence in medicine.

Results: The questionnaire was answered by 50 medical school and 35 pediatric medical specialty students. The age range of medical students was 18-25 years, while the age range of medical specialty students was 26-30 years. All of the participants said they knew about artificial intelligence. While 37.1% of assistants are familiar with the use of artificial intelligence in medicine; 24% of the students were knowledgeable. The greater involvement of artificial intelligence in our lives was very excited in both groups; a third were concerned. All participants wanted education on artificial intelligence in medical school.

Conclusion: Medical students who will be the physicians of the future look positively to artificial intelligence applications. They want to gain education and experience in this subject with deep curiosity. Artificial intelligence will open completely different doors in medical education and applications in the field of medicine; future physicians will also be supportive and practitioners of this technology.

1. Introduction

Artificial intelligence (AI) is a technique created by machines and systems that automatically solve complex problems and imitate human intelligence activities. The term AI was first coined by Mc Carthy in 1955 as the science and engineering of making smart machines [1]. The purpose of these systems is to be able to process data from a large database and imitate human decisions based on a specific set of instructions. Medicine, as a complex scientific discipline, is constantly faced with the problems of acquiring, processing, and applying large amounts of knowledge [2]. The integration and use of methods that generate big data in the medical field has become necessary. There are also persistent expectations of improving patient access to services, lowering operating costs, and improving treatment outcomes.

The use of AI in medicine has the potential to improve many aspects of healthcare. The burden of adapting the workflow to ever-changing norms and guidelines increases the frustration of healthcare professionals and forces highly trained professionals to spend more hours on paperwork rather than focusing on patient care [3]. Operations are almost impossible for humans to do, such as monitoring patients 24 hours a day, can also be performed safely by AI systems. It can reduce the number of erroneous errors in clinical practice and the differences in judgment among medical professionals. New models discovered by AI through analysis of big data from clinical practice could enable the development of new biomarkers for diagnosis and treatment.

AI tools for medicine often play the role of a virtual assistant for doctors and healthcare systems, helping them provide more accurate and efficient patient care. AI can be designed and used as a virtual assistant for patients and the public in common chronic diseases or primary health care [4]. Counseling on simple health problems or rewriting of chronic drug prescriptions may be possible. If simple but time-consuming work processes are taken care of by AI, it significantly reduces the fatigue of healthcare providers. Doctors can take more care of patients and spend more time concentrating on more complex medical tasks.

Various AI software tools will likely be used in clinical practice as current medical students begin their careers as medical professionals. When applying AI technology to patients, medical professionals are people who should sit in the driver's seat, not in the back seat [5,6]. In this study, we aimed to evaluate the knowledge levels and attitudes of the students of medicine and the students of medical specialty education at University of Health Sciences, Bursa Yüksek İhtisas Training and Research Hospital, towards AI in medicine.

2. Material and Method

A web-based questionnaire was designed using Google forms and sent online to 80 students of medicine (MS) and 45 students of medical specialty education studying in the field of pediatrics (MA) between 2020-2021 at the University of Health Sciences, Bursa Yüksek İhtisas Training and Research Hospital. Participation in the survey is voluntary and consent of the participants has been obtained. 50 MS and 35 MA answered the questionnaire. The questionnaire was prepared based on the literature. The first 15 questions of the questionnaire were evaluating the demographic characteristics, technology-related attitudes, and skills of the students. The last part of the questionnaire consisting of 15 questions was aimed to evaluate their knowledge, experience in artificial intelligence and their attitudes towards artificial intelligence in medicine. Statistical analysis was performed using descriptive statistics in SSPE 22.00 program. In order to conduct the study, consent was obtained from the ethics committee of University of Health and Science, Bursa Faculty of Medicine.

3. Results

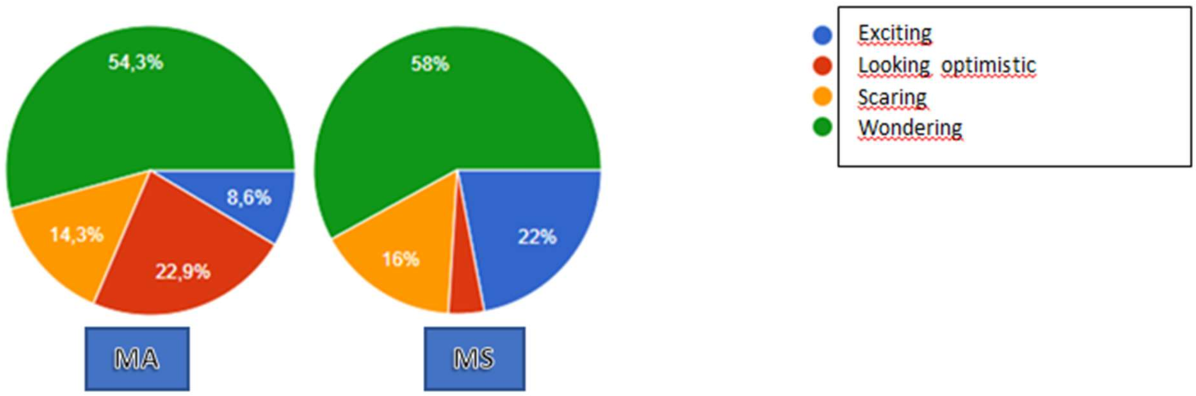
50 MS and 35 MA answered the questionnaire. While gender distribution of MS is homogeneous, 88.6% of MA is female. While the majority of MS was in the 18-25 age range, MA was in the 26-30 age range. Participants in both groups were in their 1st or 2nd year of education. While the family income level was medium in both groups, the education level of parents was high in both groups. Most of the mothers were working. While most of the MA stayed in their own home; MS lived with their families. Almost all of the participants had internet access where they lived. While the average time spent on the internet was 2 (1-5) hours on the MA; it was 5 (1-16) hours at MS. Computer knowledge status was average and only one fourth of those in both groups received computer-related training **(Table 1).**

Table 1. Demographic features of students

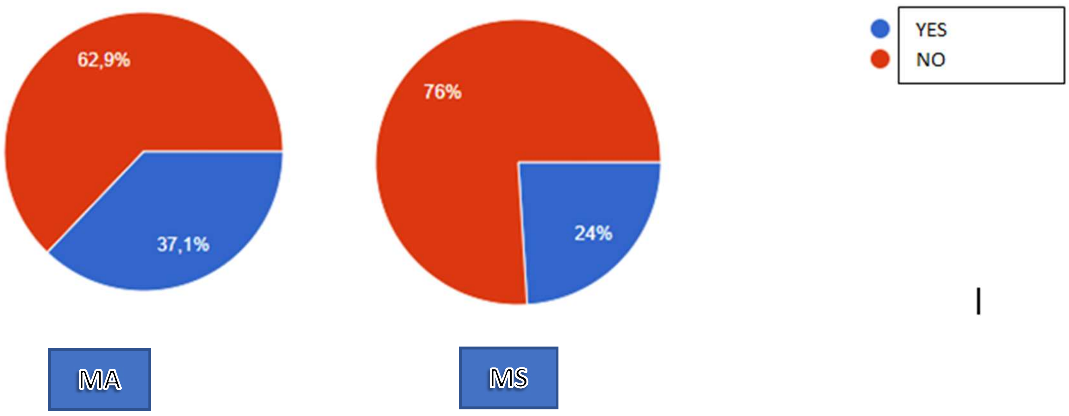
Demographics		Students of medical specialty education(MA) n=35	Students of medicine(MS) n=50
Gender	Female	88.6%	52%
	Male	11.4%	48%
Age	18-25 years	22.9%	94%
	26-30 years	62.9%	
	>30 years	14.3%	
Education year	1	28.6%	68%
	2	48.6%	6%
	3	8.6%	2%
	4	14.3%	24%
	5	0%	0%
	6	28.6%	0%
Family income	High	42.9%	28%
	Medium	57.1%	68%
	Low		4%
Mother education	Can't read / write		4%
	Primary school	20%	28%
	High school	22.9%	28%
	University	54.3	40%
Father education	Can't read / write		2%
	Primary school	14.3%	20%
	High school	11.4%	24%
	University	80%	54%
Mother work	Yes	40%	38%
	No	60%	62%
Father work	Yes	74.3%	74%
	No	25.7%	26%
Living place	Dorm		4%
	Own hause	77.1%	14%
	Family hause	22.9%	82%
Access to the internet	Yes	97.1%	98%
	No	2.9%	2%
Time spent on the internet (average)		2 saat	5 saat
Computer knowledge level	1	2.9%	6%
	2	20%	8%
	3	37.1%	44%
	4	31.4%	32%
	5	8.6%	10%

All of the participants knew about AI. Those who worried about artificial intelligence doing many things today were in the minority; it was about a third in both groups. The inclusion of artificial intelligence in our lives aroused a high level of curiosity and excitement in both groups **(Graphic 1).** 37.1% of the MA and 24% of MS were knowledgeable on AI use in medicine **(Graphic 2).** The mostly known applications of AI in medicine were in the fields of microsurgery, robotic surgery, radiology and genetics. While 8% of the MS participated in the project / study related to AI; none of the MA participated **(Graphic 3).** On the contrary, while the use of AI in medicine was 95.7% in the MA it was never possible in MS **(Graphic 4).** Over 90% of the participants in both groups stated that they would like to use AI in medicine in the future. Although almost all of both groups think that hospitals using AI was more advantageous in diagnosis and treatment; those who believed in this were much more in MS. While the majority of those who want artificial intelligence education in the medical faculty were same in both groups; the rate of those who did not want was higher in the MA (11.4%) than in the MS (6%)**(Graphic 5).** MS thought that AI should be used much more in medicine **(Graphic 6).** The majority of both groups found the use of AI to be reliable in the medical field. The proportion of those who found it unsafe was equal in both groups at a rate of approximately one quarter. While the majority thought that artificial intelligence couldn't replace the state of doctors in the future; the rate of those who thought it could be was much higher in MS (32%) than in MA (6.7%)**(Graphic 7).** In the subgroup analyzes, it was found that; MS were more confident in the benefits of AI in medicine. It might be because of MS was consisted of much more male gender and early age participants who were more open to training and use of these technologies.

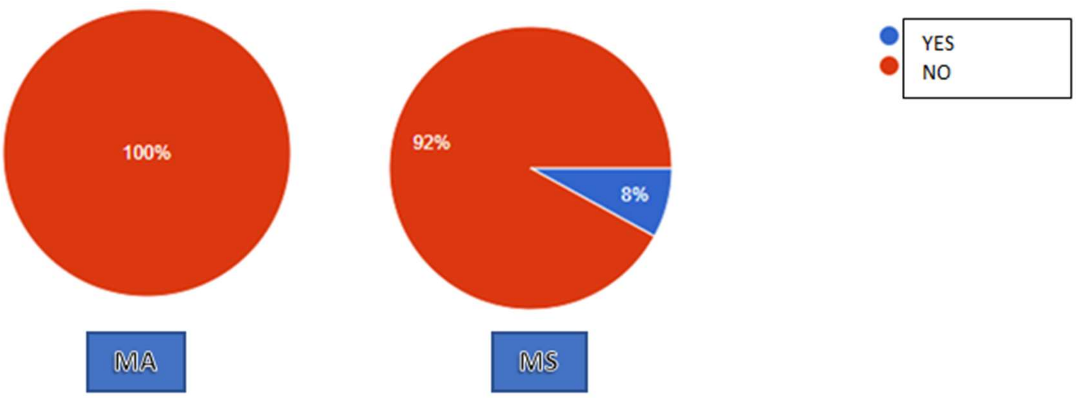
Graphic1. Emotional state about artificial intelligence



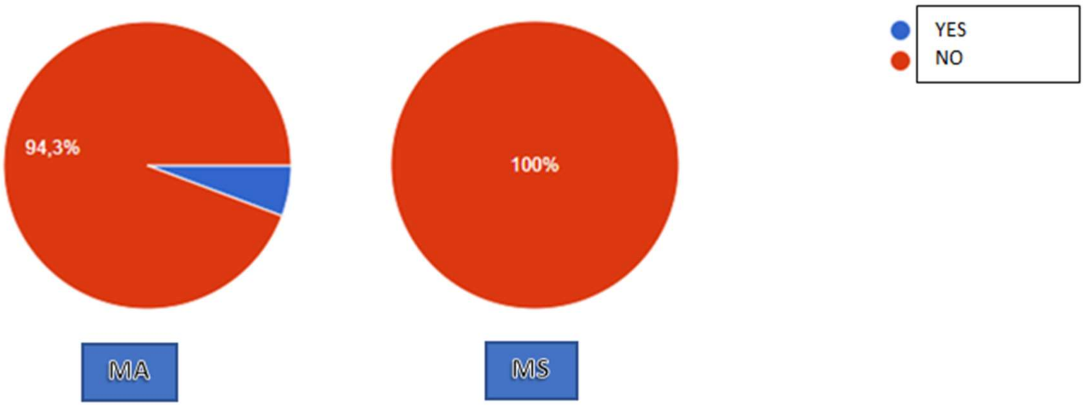
Graphic2. The situation of hearing artificial intelligence in medicine



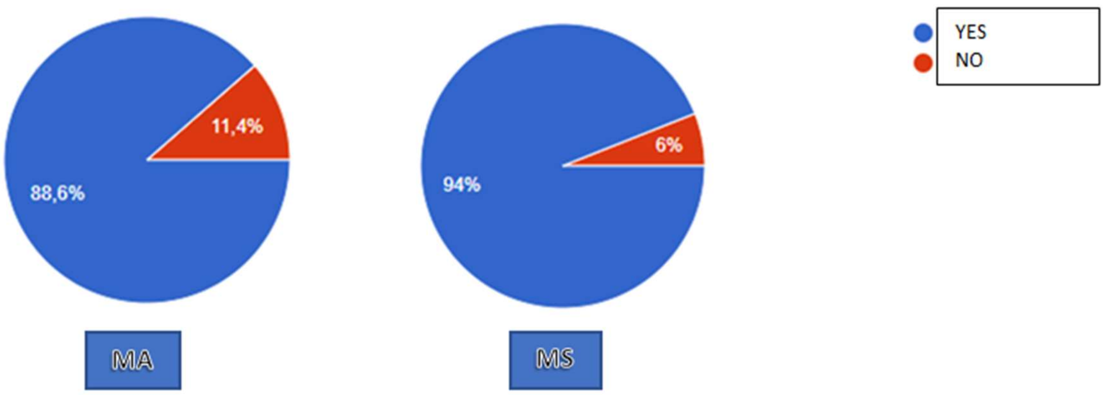
Graphic3. Participation in a project / study related to artificial intelligence in medicine



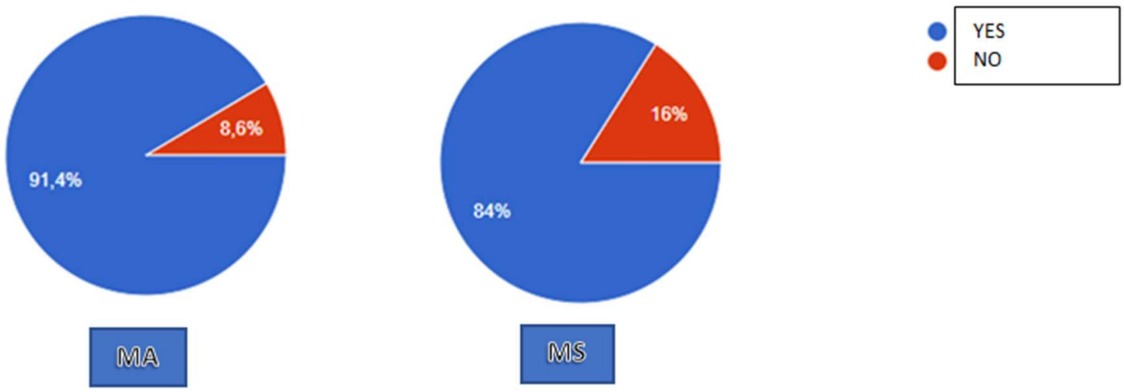
Graphic4. The situation of having used artificial intelligence in medicine



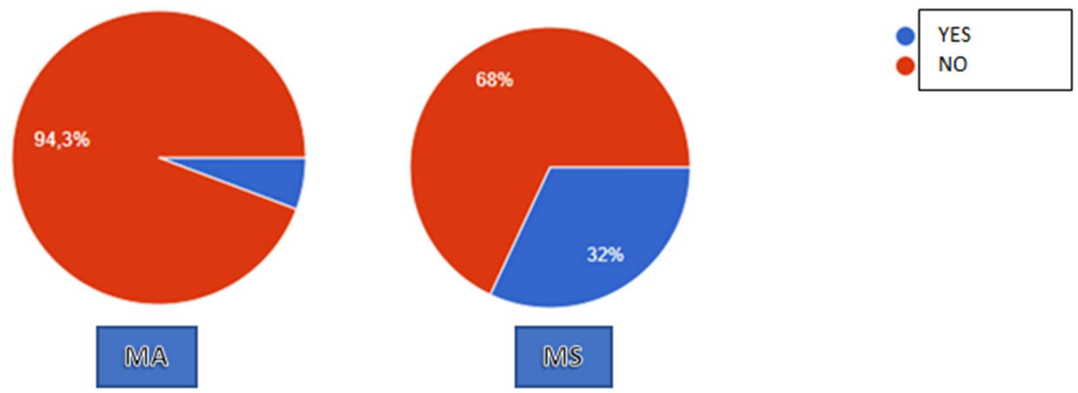
Graphic5. The situation of requesting artificial intelligence training in medicine



Graphic6. The situation of thinking that artificial intelligence should be used more in medicine



Graphic7. The situation of thinking that robots may be doctors profession in the future as a result of the use of artificial intelligence



4. Discussion

Recently, studies on the use of AI in medicine have been carried out all over the world. In a multi-centered survey of medical school students in Germany, most of the participants stated that they were unaware of AI, but admitted that this technology would revolutionize medicine. The majority of the participants disagreed with the idea that AI would replace people. Those who wanted to study AI were in the majority. In subgroup analyzes, male and tech-savvy participants were more confident in the benefits of AI and less afraid of these technologies [7]. In our study, male and early age participants were much more in MS similar to the study conducted in Germany, and those who believed in the benefits of artificial intelligence and wanted to benefit from it were in the majority. In our MA group, the average age was more higher and most of them were women. The gender distribution was more homogeneous in MS. Technology interest and the time spend on the internet were found to be significantly higher in MS. Accordingly these differences, the state of interest in AI might be changed.

Again, in a survey of medical school students in Canada, those who believe AI will replace doctors in the future were found as one-third of the participants. Despite this, most of them thought that the need for physicians might decrease [8]. Almost all of our participants stated that they were aware of the benefits of using artificial intelligence in the field of medicine while they thought that hospitals using artificial intelligence would be more successful in diagnosis and treatment. Most of them said that they want to use artificial intelligence much more in their future medical lives. The rate of those who wanted AI training in medicine was found to be very high in both groups, but those who wanted AI applications in medical education applications were much higher in MA. Those who thought that these applications should be more in medicine were found much more in the MS than in the MA. The reason for this can be attributed to the fact that there were much more men and technology enthusiasts in MS. The reason for the high number of people who wanted AI applications in medicine were in MA group was they were more interested in practical training after 6 years of theoretical training. It can be attributed to their adoption of approaches that made their job easier.

In a recent survey made to the students of the Eskisehir Faculty of Medicine; all of the participants said that they heard AI, almost the majority of them were not worried about artificial intelligence [9]. Despite this, most of the students stated that they did not have information about artificial intelligence applications in medicine. More than two-thirds of them declared that they would like to use artificial intelligence in their medical life in the future [9]. Yet in a survey conducted on dentistry students in Turkey; the participants had insufficient knowledge of AI, although it was found that they were willing to improve their knowledge in this area. Participants thought that artificial intelligence would have a positive impact on future dental practice [10]. Although the majority of our participant group had a high level of knowledge about AI, it had been observed that there were very few people who had knowledge about the applications in the medical field. In our study participants from MS participated in the projects related to AI in medicine, but not in the MS. This might be attributed to the recent initiation of studies in this newly developing field or to the fact that MS were more open to technology due to their age. There were much more participants who had the opportunity to use AI in medicine in the MA group. This means that AI applications have started in clinics. In our study, the importance of the use of AI in medicine in the education curriculum of medical faculty students was revealed, because they will be the healthcare providers in the future.

Although modern AI technologies such as deep learning are known to have high accuracy in finding patterns compared to past technologies, they have a strong dependence on training data. The accuracy of their algorithms cannot go beyond the information specific to the datasets they are trained in and cannot avoid errors in their data. This strong data dependency poses a particular concern in the medical field [11]. In our study, most of the participants found AI safe in the medical field. Although the general opinion was that the robots cannot replace physicians, the younger generation believed much more that this might happen.

5. Conclusion

As a result; medical students, who will be the physicians of the future, regarded AI applications positively and they wanted to gain education and experience in this subject with deep curiosity. Already, among the MS group there were participants who took part in projects related to artificial intelligence in medicine, and among the MA there were participants who were participated in applications in this field. It is a fact that; artificial intelligence will open completely different doors in medical education and medical applications; future physicians will also be the supporter and practitioner of this technology.

References

1. Hamet P, Tremblay J. Artificial intelligence in medicine. Metabolism 2017; 69S: S36–S40. doi: 10.1016/j.metabol.2017.01.011
2. Sniecinski I, Seghatchian J. Artificial intelligence: A joint narrative on potential use in pediatric stem and immune cell therapies and regenera-tive medicine. Transfus Apher Sci 2018: S1473–0502(18)30172–1. doi: 10.1016/j.transci.2018.05.004.
3. Lan K, Wang DT, Fong S, Liu LS, Wong KK, Dey N. A survey of data mining and deep learning in bioinformatics. J Med System 2018; 42 (8): 139.
4. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med. 2019;25:44–56. doi: 10.1038/s41591-018-0300-7.
5. Horgan D, Borisch B, Richer E, Bernini C, Kalra D, Lawler M et al. Propelling Health Care into the Twenties. Biomed Hub. 2020 May 27;5(2):15-67. doi: 10.1159/000508300. PMID: 32775335; PMCID: PMC7392387.
6. Park SH, Do KH, Kim S, Park JH, Lim YS. What should medical students know about artificial intelligence in medicine? J Educ Eval Health Prof. 2019;16:18. doi: 10.3352/jeehp.2019.16.18. Epub 2019 Jul 3. PMID: 31319450; PMCID: PMC6639123.
7. Pinto Dos Santos D, Giese D, Brodehl S, Chon SH, Staab W, Kleinert R et al. Medical students' attitude towards artificial intelligence: a multicentre survey. Eur Radiol. 2019 Apr;29(4):1640-1646. doi: 10.1007/s00330-018-5601-1. Epub 2018 Jul 6. PMID: 29980928.
8. Gong B, Nugent JP, Guest W, Parker W, Chang PJ, Khosa F et al. Influence of Artificial Intelligence on Canadian Medical Students' Preference for Radiology Specialty: A National Survey Study. Acad Radiol. 2019 Apr;26(4):566-577. doi: 10.1016/j.acra.2018.10.007. Epub 2018 Nov 11. PMID: 30424998.
9. Öcal E , Atay E , Önsüz M , Algın F , Çokyiğit F , Kılınç S et al.Tıp Fakültesi Öğrencilerinin Tıpta Yapay Zeka ile İlgili Düşünceleri. TÖAD. 2020; 2(1): 9-16.
10. Yüzbaşıoğlu E. Attitudes and perceptions of dental students towards artificial intelligence. J Dent Educ. 2021 Jan;85(1):60-68. doi: 10.1002/jdd.12385. Epub 2020 Aug 26. PMID: 32851649.
    Park SH, Kim YH, Lee JY, Yoo S, Kim CJ. Ethical challenges regarding artificial intelligence in medicine from the perspective of scientific editing and peer review. Sci Ed. 2019 Jun 13; doi: 10.6087/kcse.164.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

The Effect of Mirror Therapy on Upper Extremity Functionality in Children with Obstetric Brachial Plexus Injuries

Rabia Nur ATA [1,*], Tülay TARSUSLU ŞİMŞEK [2]

[1] *Dokuz Eylül University, School of Physiotherapy and Rehabilitation, Turkey*
[2] *Dokuz Eylül University, School of Physiotherapy and Rehabilitation, Turkey*

* Corresponding Author: Dokuz Eylül University, Turkey
Tel.: +90 5512463366. E-Mail: rabianurata@gmail.com

Publication Information

Keywords :

- Obstetric brachial plexus injuries,
- Mirror therapy,
- Physiotherapy,
- Rehabilitation

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Introduction-Purpose: The aim of this study is to evaluate the effects of mirror therapy on upper extremity functionality in children with Obstetric Brachial Plexus Injury (OBPI).

Material-Method: Thirty-two children between the ages of 4-16 who were diagnosed with OBPI were included in the study. Children were randomly divided into 2 groups (study group n = 16, control group n = 16). Upper extremity functions; Raimondi's hand functions evaluation system was evaluated using Gilbert's elbow motion evaluation system, Raimondi's shoulder movement evaluation system, Modified Mallet Scoring, QUEST and Narakas sensory evaluation system. The study was conducted for 12 weeks and 2 days a week. The study group received a 40-minute traditional physiotherapy program and an additional 20 minutes of mirror therapy to the rehabilitation program. A traditional physiotherapy and rehabilitation program of 40 minutes was applied to the control group. Evaluations were made before the treatment, at the 4th, 8th and 12th weeks of the treatment. The data obtained were used in statistical analysis.

Results: There was no statistically significant difference between the study group and the control group ($p > 0.05$).There was no difference between the groups in any measurement time ($p > 0.05$). However, it was found that there were positive gains in the study group regarding that mirror therapy improved upper extremity functionality between measurement times ($p < 0.05$).

Discussion-Conclusion: Our study has shown that mirror therapy improves upper extremity functionality in children with 0BPI. It is recommended to apply mirror therapy in addition to physiotherapy and rehabilitation programs.

1. Introduction

Obstetric brachial plexus injuries (OBPI) is a clinical picture that occurs due to injury in C5, C6, C7, C8 and T1 nerve roots, truncuses, divisions, cords or terminal branches during delivery, and various degrees of unilateral and bilateral paralysis occur. Accordingly, it is seen with secondary problems (1,2).

Children diagnosed with OBPI are followed up regularly and surgical and conservative treatment options are decided (3,4). Physiotherapy and rehabilitation programs are among the most important conservative treatment options. Various rehabilitation methods are available to improve upper extremity functions and motor control. In recent years, it has been stated that mirror therapy can be used to increase the functions of the upper extremity as a reliable method in patients with OBPI, due to its cheapness, non-invasiveness, absence of any complications and ease of application (5).

The aim of the study is to examine the effect of mirror therapy on upper extremity functional skills in individuals with OBPI.

2. Material-Method

The research was planned as a randomized controlled study.

Participants

In our study, 32 children who met the inclusion criteria were randomly divided into two groups (study group n = 16, control group n = 16).

Inclusion criteria; According to the Narakas classification, those in Group 2-3, to have the communication skills to understand and execute the given commands, to have no other neuropsychological, orthopedic, neuromuscular disorders, to be willing to participate in the study, to be 4-16 years old.

Exclusion criteria; loss of sensation and motor in the intact extremity, presence of neglect, visual problems, medical complications, and lack of ability to perceive and apply commands.

The treatment program was applied to the study group for 12 weeks, 2 days a week and 60 minutes session duration. Traditional physiotherapy and rehabilitation exercises were applied in the first 40 minutes of the session, and mirror therapy was applied in the last 20 minutes. A traditional physiotherapy program was applied to the control group for 12 weeks, 2 days a week and a session duration of 40 minutes.

Data Collection Tools

Socio-demographic Data Registration Form

All children participating in the study and their families were informed verbally and in writing about the purpose of the study, the method of application and the evaluations to be made, and their consent was obtained. First of all, age, gender, affected extremity and dominant hand of children with OBPI were questioned. Later, the mothers (first degree caregivers) were asked about some birth information (number of births, birth type, height and birth weight, etc.), socio-demographic characteristics and recorded.

Raimondi's Hand Functions Evaluation System

It is a scale developed by Raimondi et al. to evaluate hand function. Those with total paralysis, no grip, little or no sensation '1', limitation of the fingers, unable to perform active flexion and extension but " 2 " thumb lateral grip, active wrist extension and passive flexion of the fingers and thumb those with weak lateral grip "3", strong flexion, extension and supination restricted in the wrist and fingers, "4" with thumb movements, strong flexion-extension movement in the wrist and fingers, full pronation-supination movement and thumb use the good ones got the score "5" (6).

Modified Mallet Scoring

The Modified Mallet Classification System provides important information in evaluating the functional competence of the upper extremity functional skill assesment in global abduction, global external rotation, moving the hand to the mouth, on the head and spine, and in the movements of carrying the hand on the abdomen (internal rotation). Scoring between 0-5 is made according to the location and the amount of strain. A score of "1" indicates that there is no desired movement, and a score of "5" defines full movement (7).

3. Results

The age, gender, affected side and dominant side values of the children included in the study are shown in Table 1.

Table 1: Age, gender, dominant side and affected side values of the groups

	Study Groups (*n*=16) X±SD	Control Groups (*n*=16) X±SD
Age	9.68± 3.45 (4 – 15)	10.68± 4.04 (4 – 16)
Gender		
Male	11 (68.8 %)	11 (68.8 %)
Female	5 (31.2 %)	5 (31.2 %)
Affected Side		
Right	11 (68.8 %)	9 (56.3 %)
Left	5 (31.3 %)	7(43.8 %)
Dominant Side		
Right	6(37.5 %)	9(56.3 %)
Left	10(62.5 %)	7(43.8 %)

X: mean, SD: standard deviation, n:

Comparison of the Raimondi hand functions evaluation system used for hand measurements between groups was evaluated using Mixed-ANOVA analysis. In the statistical analysis performed, hand measurement values did not differ between the groups at the 4th week, 8th week and 12th week (F_{Group} = 0.07, p = .800, partial η^2 = 0.002) (Table 2). However, in the in-group evaluations, it was found that the measurement values made at the 4th, 8th and 12th weeks in the study group created a statistical difference compared to the baseline values before the treatment (respectively F_{Time} = 16.41, p <.001, partial η2 = 0.354; $F_{Time \times Group}$ = 7.27, p <.001, partial η2 = 0.195) (Table 3). In the control group, no difference was found in terms of the values of Raimondi's hand function evaluation system in terms of the initial measurement, the findings obtained in the 4th week, 8th week and 12th weeks (Table 3).

Table 2: Raimondi's Hand Functions Assesment System working and control group values and comparison between groups

Evaluation times	Study Groups X ± SD	Control Groups X±SD	Comparison Between Groups				
			Mauchly's W	*p*	*F*Group	*p*	partial η^2
Before treatment	2.50 ± 1.63	2.88 ± 1.67	0.75	.136	0.07	.800	0.002
4. th week	2.56 ± 1.63	3.00 ± 1.51					
8. th week	3.00 ± 1.63	2.94 ± 1.61					
12. th week	3.31 ± 1.49	3.13 ± 1.45					

p <0.05, X: mean, SD: standard deviation,, η2: effect size value, F_{Group}: Test statistics for groups

Table 3: Raimondi's Hand Functions Assesment System working and control group values and comparison before and after treatment within the group

Groups	Evaluation times	X ± SD	Comparison within groups					
			F_{Zaman}	*p*	partial η^2	$F_{Zaman \times Group}$	*p*	partial η^2
Study Groups	Before treatment	2.50 ± 1.63	16.41	<.001	0.354	7.27	<.001	0.195
	4. th week	2.56 ± 1.63						
	8. th week	3.00 ± 1.63						
	12. th week	3.31 ± 1.49						
Control Groups	Before treatment	2.88 ± 1.67	-	-	-	-	-	-
	4. th week	3.00 ± 1.51						
	8. th week	2.94 ± 1.61						
	12. th week	3.13 ± 1.45						

$p < 0.05$, X: mean, SD: standard deviation,, η^2: effect size value, F_{Time}: test statistics for measurement times, $F_{TimexGroup}$: Test statistics for measurement times and group interaction

Comparison of the measurement values of the subtest steps of the Modified Mallet scoring between groups was evaluated with the Mann-Whintey U test. As a result of the statistical analysis, no statistical difference was found between the groups in the initial measurement, 4th week, 8th week and 12th week measurement values for the sub-scores of Modified Mallet scoring (p> 0.05) (Table 4). Within-group evaluations of the sub-scores of the Modified Mallet scoring were made using the Friedman test. In the study group, a statistical difference was found in terms of the Modified Mallet Scoring Global Abduction baseline measurement value and the measurement values at the 4th, 8th and 12th weeks (χ^2 Study = 20.14, p <001) (Table 5). In the control group, no statistical difference was found in terms of the Modified Mallet Scoring Global Abduction values in the baseline measurement, at the 4th, 8th, and 12th weeks (Table 6). A statistical difference was found in the study group in terms of the Modified Mallet Scoring global external rotation initial measurement value, and the measurement values at the 4th, 8th and 12th weeks (χ^2 Study = 18.56, p <001) (Table 5). In the control group, no statistical difference was found in terms of the Modified Mallet Scoring global global external rotation values in the initial measurement, 4th week, 8th week and 12th week measurement findings (Table 6). In the study group, a statistical difference was found in terms of the Modified Mallet Scoring initial measurement value for taking the hand to the neck, and the measurement values at the 4th, 8th and 12th weeks (χ^2 Study = 26.44, p <001) (Table 5). In the control group, no statistical difference was found between the baseline measurement, 4th week, 8th week and

12th week measurement findings in terms of Modified Mallet Scoring values of taking the hand to the neck (χ^2 Control = 6.00, p = .112) (Table 6). In the study group, a statistical difference was found in terms of the Modified Mallet Scoring initial measurement value for bringing the hand to the spine, and the measurement values at the 4th, 8th and 12th weeks (χ^2 Study = 22.463, p <.001) (Table 5). In the control group, a statistical difference was also found in the Modified Mallet Scoring values in terms of taking the hand to the spine in the initial measurement, 4th week, 8th week and 12th week measurement findings (χ^2 Control = 8.571, p = .036) (Table 6). In the study group, a statistical difference was found in terms of the Modified Mallet Scoring initial measurement value for putting the hand to mouth, and the measurement values at the 4th, 8th and 12th weeks (χ^2 Study = 27, p <.001) (Table 5). In the control group, no significant difference was found in terms of the values of the Modified Mallet Scoring hand-to-mouth values in the initial measurement, 4th week, 8th week and 12th week measurement findings (χ^2 Control = 7.20, p = .066) (Table 6). Study group, Modified Mallet Scoring internal rotation initial measurement value, to get reading information at 4th, 8th, and 12th weeks (χ^2 Study = 19, p <.001) (Table 5). In the control group, no significant difference was found in terms of Modified Mallet Scoring internal rotation values in the initial measurement, 4th week, 8th week and 12th week measurement findings (χ^2 Control = 3, p = .392) (Table 6).

Table 4: Modified Mallet Evaluation System study and control group values and comparison between groups,

Modified Mallet Assessment Sub-scores	Study Groups Median (min-max)				Control Groups Median (min-max)				Comparison Between Groups							
	Before treatment	4. th week	8. th week	12. th week	Before treatment	4. th week	8. th week	12. th week	Before treatment		4. th week		8. th week		12. th week	
									z	p	z	p	z	p	z	p
Global Abduction	3 (2- 4)	3 (1-5)	3 (2-5)	4 (2-5)	3 (2-5)	3 (2-5)	3 (2-5)	3 (2-5)	116	.634	123	.850	111	.502	99	.254
Global External Rotation	3 (1-4)	3 (1-4)	3 (2-5)	3 (2-5)	3 (2-4)	3 (2-4)	3 (2-4)	3 (2-4)	126.50	.967	126.50	.967	118.50	.701	97.5050	.209
Hand to neck	3 (1-4)	3 (1-5)	3 (1-5)	3 (2-5)	3 (1-4)	3 (1-4)	3 (1-4)	3 (2-4)	125	.921	126	.953	111	.511	91.5050	.154
Hand to spine	2 (1-4)	3 (1-5)	3 (1-5)	3 (1-5)	2.50 (1-5)	2.50 (1-5)	3 (1-5)	3 (1-5)	127	.984	120	.767	98	.247	104.50	.369
Hand to mouth	3 (2-5)	3 (2-5)	3 (3-5)	3 (3-5)	3 (1-5)	3 (1-5)	3 (1-5)	3 (1-5)	117	.675	126.50	.968	94.5050	.180	97.5050	.237
Internal Rotation	4 (1-5)	4 (1-5)	4 (2-5)	4 (2-5)	4 (1-5)	4 (1-5)	4 (2-5)	4 (2-5)	120.50	.779	123	.859	115	.619	97	.220

p <0.05, z: Mann-Whitney U test min: minimum, max: maximum

Table 5: Modified Mallet Evaluation System study group values before and after treatment within-group comparison

$p < 0.05$, $\chi 2$: Friedman, min: minimum, max: maximum,

Table 6: Modified Mallet Evaluation System control group values before and after treatment within groups comparison

Modified Mallet Assessment Sub-scores	Before treatment Median (min-max)	4. th week Median (min-max)	8. th week Median (min-max)	12. th week Median (min-max)	χ^2	p
Global Abduction	3 (2-5)	3 (2-5)	3 (2-5)	3 (2-5)	-	-
Global External Rotation	3 (2-4)	3 (2-4)	3 (2-4)	3 (2-4)	-	-
Hand to neck	3 (1-4)	3 (1-4)	3 (1-4)	3 (2-4)	6.00	.112
Hand to spine	2.50 (1-5)	2.50 (1-5)	3 (1-5)	3 (1-5)	8.57	.036
Hand to mouth	3 (1-5)	3 (1-5)	3 (1-5)	3 (1-5)	7.20	.066
Internal Rotation	4 (1-5)	4 (1-5)	4 (2-5)	4 (2-5)	3	.392

$p < 0.05$, $\chi 2$: Friedman, min: minimum, max: maximum

4. Discussion

The results of the study conducted to evaluate the effects of mirror therapy on upper extremity functionality in children with OBPI showed that mirror neuron therapy significantly increased upper extremity functional abilities.

In the study conducted by Summer et al on mirror neuron therapy, it was reported that after the treatment program, the simultaneous movements of the hemiplegic and the intact limb improved, increased motor cortex activation and improved motor functions of the affected extremity (8). One of the aims of our study is to evaluate the effect of mirror neuron therapy on hand functions in children included in the study. The results of our study showed that mirror neuron therapy applied twice a week for 12 weeks caused a significant change in the results of the Raimondi hand functions evaluation system. In the outcome evaluations, it was observed that the individuals included in the study caused an increase in the range of motion, especially in finger flexion and wrist flexion and extension. It has been observed that this increase in the range of motion of the patients is important in increasing the comprehension ability.

Proximal joint stabilization and full and active range of motion are important for good upper extremity function. In addition, coordinated functioning in the musculoskeletal system from proximal to distal is also important for an effective activity (9,10). Our study shows that the range of motion, muscle strength and joint stabilization of the proximal region should be emphasized in order to increase and support distal movements. Mirror neuron therapy and applications that will ensure the development of structures related to the shoulder and its periphery should be included in the treatment programs.

5. Conclusion and Recommendations

The results obtained from our study showed that the upper extremity functional skills of the group who received mirror neuron therapy in addition to the traditional physiotherapy and rehabilitation program significantly increased. The results obtained suggest that mirror neuron therapy will make significant contributions to the quality of life in patients with OBPI by increasing upper extremity functional skills.

References

1. Gilbert, A. (Ed.). (2001). *Brachial Plexus Injuries: Published in Association with the Federation Societies for Surgery of the Hand*. CRC Press.
2. Arzillo, S., Gishen, K., & Askari, M. (2014). Brachial plexus injury: treatment options and outcomes. *Journal of Craniofacial Surgery*, *25*(4), 1200-1206.
3. Bahm, J., Ocampo-Pavez, C., Disselhorst-Klug, C., Sellhaus, B., & Weis, J. (2009). Obstetric brachial plexus palsy: treatment strategy, long-term results, and prognosis. *Deutsches Ärzteblatt International*, *106*(6), 83.
4. Zuckerman, S. L., Allen, L. A., Broome, C., Bradley, N., Law, C., Shannon, C., & Wellons, J. C. (2016). Functional outcomes of infants with Narakas grade 1 birth-related brachial plexus palsy undergoing neurotization compared with infants who did not require surgery. *Child's Nervous System*, *32*(5), 791-800.
5. Yavuzer, G., Selles, R., Sezer, N., Sütbeyaz, S., Bussmann, J. B., Köseoğlu, F., ... & Stam, H. J. (2008). Mirror therapy improves hand function in subacute stroke: a randomized controlled trial. *Archives of physical medicine and rehabilitation*, *89*(3), 393-398.
6. Yeves-Lite, A., Zuil-Escobar, J. C., Martínez-Cepa, C., Romay-Barrero, H., Ferri-Morales, A., & Palomo-Carrión, R. (2020). Conventional and Virtual Reality Mirror Therapies in Upper Obstetric Brachial Palsy: A Randomized Pilot Study. *Journal of clinical medicine*, *9*(9), 3021.
7. Van der Sluijs, J. A., van Doorn-Loogman, M. H., Ritt, M. J., & Wuisman, P. I. (2006). Interobserver reliability of the Mallet score. Journal of Pediatric Orthopaedics B, 15(5), 324-327.
8. Michielsen, M. E., Selles, R. W., van der Geest, J. N., Eckhardt, M., Yavuzer, G., Stam, H. J., ... & Bussmann, J. B. (2011). Motor recovery and cortical reorganization after mirror

therapy in chronic stroke patients: a phase II randomized controlled trial. *Neurorehabilitation and neural repair*, *25*(3), 223-233.
9. Nordin, M., & Frankel, V. H. (Eds.). (2001). *Basic biomechanics of the musculoskeletal system*. Lippincott Williams & Wilkins.
10. Pöyhiä, T. H., Koivikko, M. P., Peltonen, J. I., Kirjavainen, M. O., Lamminen, A. E., & Nietosvaara, A. Y. (2007). Muscle changes in brachial plexus birth injury with elbow flexion contracture: an MRI study. *Pediatric radiology*, *37*(2), 173-179.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Big Data, AI and Machine Learning in Plastic Surgery: a New Horizon in Surgical Innovation

Hasan BUYUKDOGAN [1, *]

[1] *University of Health Sciences, Gazi Yasargil Training and Research Hospital, Department of Plastic, Reconstructive and Aesthetic Surgery, Turkey*

* Corresponding Author: University of Health Sciences, Gazi Yasargil Training and Research Hospital, Turkey
Tel.: +90 412 258 0060 e-Mail: buyukdogan@gmail.com

Publication Information

Keywords :

- Aesthetics,
- Breast,
- Burn,
- Craniosynostosis,
- Hand surgery,
- Microsurgery,
- Plastic surgery,
- Reconstruction

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Machine learning and artificial intelligence applications are used in many sub-disciplines of plastic surgery as a guide to the surgeon in solving clinical problems. Artificial intelligence-supported imaging systems are used in hand surgery, 3D surgical navigation, breast implant-associated anaplastic large cell lymphoma studies, wound and burn care, microsurgery, craniofacial surgery, skin cancer surgery, aesthetic surgery, facial reanimation surgery, surgical training, and robotic surgery. Although it seems unlikely that a well-trained surgeon will be replaced by A.I. systems in the near future, machine learning and artificial intelligence applications will be very powerful tools that will help decision-making processes in the plastic surgery discipline.

1. Introduction

Although modern plastic surgery has laid its foundations in the last 100 years due to the development of modern anesthesia, microsurgery materials, and biomaterial technologies, it is possible to follow the principles of plastic surgery 3000 years ago to ancient India. Throughout the ages, the most striking point is that plastic surgery is the main medical discipline that adopts innovative technologies most swiftly.

Computer vision, machine learning, and robotics will be the most important breakthroughs in the future of modern medicine (1, 2). Today, stem cell and 3D printing technologies are the most popular novel subjects in plastic surgery. In a study conducted with plastic surgery specialists, the most development and breakthrough are expected to occur in the field of stem cells; and the least in smart drugs (3). In this study, we wanted to shed light on the issues that will be studied and practiced even more in the coming years.

2. AI in Plastic Surgery

Due to its nature, plastic surgery is the most relevant surgical discipline about visuality. Although the branches where artificial intelligence is the most successful up to now are visual branches such as radiology and pathology, the use of artificial intelligence in plastic surgery is still in its infancy and most of the projects are still in the concept phase. However, artificial intelligence-based studies are rapidly continuing in many subdisciplines of plastic surgery.

Hand Surgery:

Hand surgery is a branch based on giving form and function to the hand, which is basically a complex machine. Artificial intelligence will guide the surgeon in such matters as closed hand fractures, where the diagnosis of non-displaced fractures that are too small to escape from the surgeon's or radiologist's eye. The algorithm will help the surgeon to decide whether a surgical intervention will be required for these fractures, and how to place the Kirschner wires or mini-plates (4).

Novel proximal upper extremity neuroprosthesis are being developed to provide much more precise fine motor movements for patients with C5 / C6 spinal cord damage and the data that will be collected will help developing even better prostheses to ultimately replace hand transplantation surgeries and prevent the need for immunosuppressive medication.

Breast Implant-Associated Anaplastic Large Cell Lymphoma:

Processing data from the central data portals will help clinicians to identify disease pathogenesis and assess genotype risks in situations where concrete evidence is still lacking, such as breast implant-induced anaplastic large cell lymphoma.

3D Surgical Navigation:

Pre-operative 3D planning, per-operative anatomical localization, and surgical navigation can assist the surgeon's decision-making processes in real-time during the operation. Thus, they may help reduce the duration of both operation and anesthesia.

A.I. can direct the surgeon not only in the surgery of hard tissues such as bones but also in the interventions on soft tissues such as liposuction. It may prevent entering the abdominal area and excessive thinning of the abdominal skin which may lead to skin necrosis (5, 6).

Wound and Burn Care:

Artificial intelligence-supported imaging systems are used in burn surgery to determine the width of the burn area, the depth of the burn, and to predict the possible healing time. Algorithms that detect and follow the hemostasis of skin wounds, will predict how many days are required for the wound to heal by monitoring wound healing sequences and provide an opinion on whether surgical intervention is required for both wound and burn patients. They will present objective data to the clinician to calculate the burned surface area rather than empirical methods such as the rule of nines (7).

Microsurgery:

Flap monitoring algorithms continue to be developed to monitor the circulation of the transplanted tissue after microsurgery, which will warn the clinician in the case of arterial or venous insufficiency.

Craniofacial Surgery:

Computer tomography scanning is currently the gold standard method for the diagnosis of craniosynostosis which can manifest with skull deformity and damage to the central nervous system. Artificial intelligence will be able to evaluate the skull shapes of young children, provide a diagnosis without the need for tomography, and protect patients from the ionizing effects of radiation. Another benefit of machine learning will be in the detection of pathological genes in patients with non-syndromic cleft lip and palate (8, 9).

Skin Cancer:

Although there are successful results of artificial intelligence-assisted diagnostic methods in dermatology and pathology, the surgical treatment of skin cancers is ultimately performed by plastic surgeons. Artificial intelligence technologies will also assist plastic surgeons in determining surgical borders and in patient follow-up.

Aesthetic Surgery:

Facial aesthetic surgery is based on careful pre-op planning and careful examination of the patient's facial proportions. Artificial intelligence-supported glasses and imaging systems will assist the surgeon in evaluating the facial proportions of the patients more objectively. In aesthetic breast surgery, it will inform the surgeon how the breast will look after the operation and possible changes in its shape and size.

Although beauty is relative, human beings have an intuitive decision-making mechanism about what is beautiful and what is not. Algorithms have been developed to determine whether the photo of a subject is beautiful or not by examining the data from faces. The algorithms have been successful by making the same decisions as human subjects, which may be called an "Aesthetic Turing Test" (10-14).

Facial Paralysis:

Following facial paralysis reanimation operations, A.I. can objectively determine the level of functional return and assist the clinician in monitoring the recovering process (15, 16).

Surgical Training:

One minute of a surgical video contains more data than twenty-five high-resolution tomography scans. With the help of artificial intelligence-based processing of such rich data, the audience may be better informed with the analysis of surgical decisions and techniques (17, 18).

Robotic Surgery:

Robotic systems can provide guiding information to the surgeon during surgery and help decision-making mechanisms. Although robots can already display simple surgical skills, an average of twenty thousand steps is performed during a standard surgical procedure.

Further studies are required for an autonomous robotic system to overcome this complexity. Henceforth, it seems unlikely that artificial intelligence will replace surgeons in the near future (19).

3. Conclusion and Evaluation

According to Dr. William Mayo, the founder of the Mayo Clinic, medicine aims to prevent disease and prolong life, and the ideal of medicine is to eliminate the need for a physician. Developing technology and advanced applications of artificial intelligence help bring Dr. Mayo's view to get closer to reality with each passing day.

But in the future of surgery, particularly of plastic and aesthetic surgery, the role of artificial intelligence seems to be a valuable tool to assist the surgeon, not to replace him/her (4, 20-22).

References:

1. Jovic TH, Combellack EJ, Jessop ZM, Whitaker IS. 3D Bioprinting and the Future of Surgery. Front Surg. 2020;7:609836.
2. Gumbs AA, Perretta S, d'Allemagne B, Chouillard E. What is Artificial Intelligence Surgery? Artificial Intelligence Surgery. 2021;1(1):1-10.
3. Ozturk S, Karagoz H, Zor F. The Future of Plastic Surgery: Surgeon's Perspective. J Craniofac Surg. 2015;26(8):e708-13.
4. Jarvis T, Thornburg D, Rebecca AM, Teven CM. Artificial Intelligence in Plastic Surgery: Current Applications, Future Directions, and Ethical Implications. Plast Reconstr Surg Glob Open. 2020;8(10):e3200.
5. Ayoub A, Pulijala Y. The application of virtual reality and augmented reality in Oral & Maxillofacial Surgery. BMC Oral Health. 2019;19(1):238.
6. Kazan R, Cyr S, Hemmerling TM, Lin SJ, Gilardino MS. The Evolution of Surgical Simulation: The Current State and Future Avenues for Plastic Surgery Education. Plast Reconstr Surg. 2017;139(2):533e-43e.
7. Yeong EK, Hsiao TC, Chiang HK, Lin CW. Prediction of burn healing time using artificial neural networks and reflectance spectrometer. Burns. 2005;31(4):415-20.
8. Kanevsky J, Corban J, Gaster R, Kanevsky A, Lin S, Gilardino M. Big Data and Machine Learning in Plastic Surgery: A New Frontier in Surgical Innovation. Plast Reconstr Surg. 2016;137(5):890e-7e.
9. Mendoza CS, Safdar N, Okada K, Myers E, Rogers GF, Linguraru MG. Personalized assessment of craniosynostosis via statistical shape modeling. Med Image Anal. 2014;18(4):635-46.
10. Borsting E, DeSimone R, Ascha M, Ascha M. Applied Deep Learning in Plastic Surgery: Classifying Rhinoplasty With a Mobile App. J Craniofac Surg. 2020;31(1):102-6.
11. Bouguila J, Khochtali H. Facial plastic surgery and face recognition algorithms: Interaction and challenges. A scoping review and future directions. J Stomatol Oral Maxillofac Surg. 2020;121(6):696-703.
12. Dedhia R, Hsieh TY, Tollefson TT, Ishii LE. Evidence-based Medicine in Facial Plastic Surgery: Current State and Future Directions. Facial Plast Surg Clin North Am. 2016;24(3):265-74.
13. Gunes H, Piccardi M. Assessing facial beauty through proportion analysis by image processing and supervised learning. International Journal of Human-Computer Studies. 2006;64(12):1184-99.
14. Singh R, Vatsa M, Bhatt HS, Bharadwaj S, Noore A, Nooreyezdan SS. Plastic Surgery: A New Dimension to Face Recognition. IEEE Transactions on Information Forensics and Security. 2010;5(3):441-8.
15. Guarin DL, Dusseldorp J, Hadlock TA, Jowett N. A Machine Learning Approach for Automated Facial Measurements in Facial Palsy. JAMA Facial Plast Surg. 2018;20(4):335-7.
16. Jiang C, Wu J, Zhong W, Wei M, Tong J, Yu H, et al. Automatic Facial Paralysis Assessment via Computational Image Analysis. Journal of Healthcare Engineering. 2020;2020:2398542.
17. Grenda TR, Pradarelli JC, Dimick JB. Using Surgical Video to Improve Technique and Skill. Ann Surg. 2016;264(1):32-3.
18. Kim Y, Kim H, Kim YO. Virtual Reality and Augmented Reality in Plastic Surgery: A Review. Arch Plast Surg. 2017;44(3):179-87.
19. Hashimoto DA, Rosman G, Rus D, Meireles OR. Artificial Intelligence in Surgery: Promises and Perils. Ann Surg. 2018;268(1):70-6.
20. Chandawarkar A, Chartier C, Kanevsky J, Cress PE. A Practical Approach to Artificial Intelligence in Plastic Surgery. Aesthet Surg J Open Forum. 2020;2(1):ojaa001.
21. Liang X, Yang X, Yin S, Malay S, Chung KC, Ma J, et al. Artificial Intelligence in Plastic Surgery: Applications and Challenges. Aesthetic Plast Surg. 2021;45(2):784-90.
22. Shay P, Taub PJ, Silver L. Improved Techniques and Future Advances in Plastic Surgery in Global Health. Ann Glob Health. 2016;82(4):644-8.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN** : 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Evaluation of Future Doctor's Knowledge and Attitude About Artificial Intelligence

Ömer Faruk AKÇAY[1 *], Sevil ALKAN[2], Sinem SEFER[1], Zeynep İdil DURMUŞ[1]

[1]Çanakkale On Sekiz Mart University Faculty of Medicine, Çanakkale, Turkey
[2]Çanakkale On Sekiz Mart University Faculty of Medicine, Department of Clinical Microbiology and Infectious Diseases, Çanakkale, Turkey

** Corresponding Author: [1]Çanakkale On Sekiz Mart University Faculty of Medicine, Çanakkale, Turkey*
Tel.: +90 05459604265, E-Mail: drfarukakcay@outlook.com

Publication Information

Keywords :
- Artificial intelligence,
- Medical school only,
- Knowledge-attitude

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Introduction-Aim: Artificial intelligence (AI) applications have started to be used in many diagnostic and therapeutic areas in medicine, such as (radiology, cardiology, oncology, infectious diseases, orthopedics, etc.). These global applications have started to be put into practice in our country as well. In this study, we aimed to evaluate the knowledge and attitudes of medical faculty students, who are the doctors of the future, about AI.

Materials and Methods: This cross-sectional study was applied as an online questionnaire on social media between March 28 - April 1, 2021. The sample of the study consisted of volunteer participants from medical faculty students who can be reached throughout our country. Customers were asked to answer the questions on the form made by the researchers.

Results: 260 students, 55.7% female, aged between 17-27 years (mean: 21.08) participated in the study. 26% of the semesters was 5, and it was the class with the highest attendance. 99.6% had heard of AI, and the rate of acquiring school with this information was only 5%. 80% of the students stated that the educational practices of medical education about AI qualifications, only 9.6% of the Turkish healthcare system was enough to cope with the difficulties that AI will bring.

Discussion-Conclusion: According to the opinion of the future doctors; for AI to be applied in field of medicine in our country, necessary infrastructure arrangements should be made on this subject in medical education.

1. Introduction

Nowadays medical artificial intelligence (AI) applications have started to be used in many diagnostic and therapeutic areas (radiology, cardiology, oncology, infectious diseases, orthopedics,etc.) These global applications have started to be put into practice in our country as well. There are already multiple applications in healthcare, ranging from automated administrative tasks to clinical decision aids, automated imaging, intelligent drug design, and AI-powered surgical robots (1). AI technology may also reduce the number of inadvertent errors in clinical practice and may decrease differences in judgments among medical professionals (2). As AI continues to advance, its functionalities will potentially transform the healthcare space (1).

At the time when the current medical students will commence their career as medical professionals after completion of studies and training, various AI software tools will likely be used in clinical practice (2). Medical students should acquire the appropriate knowledge and experience required for them to act as ones who take the ultimate responsibility for their patients when applying the AI technology to them (2).

In this study, we aimed to evaluate the knowledge and attitudes of medical faculty students, who are doctors of the future, about AI.

2. Materials and Methods:

This cross-sectional study was applied as an online questionnaire on social media between March 28 - April 1, 2021. The sample of the study consisted of volunteer participants from medical faculty students who were reached throughout our country. Participants were asked to answer the questions on the form made by the researchers.

3. Results

260 students, 55.7% female, aged between 17-27 years (mean: 21.08) participated in the study. 26% of the semesters was 5, and it was the class with the highest attendance. 99.6% had heard of AI, and the rate of acquiring school with this information was only 5%. 80% of the students stated that the educational practices of medical education about AI qualifications, only 9.6% of the Turkish healthcare system was enough to cope with the difficulties that AI will bring. The answers to the questionnaire are summarized in tables.

Table 1. Knowledge of Artificial Intelligence

Question (Positive answers)	**%**
Analyze patient information to reach diagnoses.	80
Read and interpret diagnostic imaging.	83
Formulate personalized medication prescriptions for patients.	66
Monitor patient compliance to prescribed medications, exercise and dietary recommendations.	79
Perform surgery (e.g. robotic surgery).	80

Table 2. Perceptions of Artificial Intelligence

Question	**%**
Question (Positive answers)	**%**
Have you ever heard about AI? (1.Yes)	99,5
Where did you first encounter with AI? (Internet)	55,4
Have you taken any training in artificial intelligence? (No)	95
I understand what the term “artificial intelligence” means. (Yes)	80
I understand what the term “machine learning” means. (Yes)	44

Table 3. The Impact of Artificial Intelligence on Health Systems, Medical Profession, Ethics and Medical Education

Question (Positive answers)	%
Assist hospitals in capacity planning and human resource management.	77
Artificial Intelligence will reduce the number of jobs available to me.	78
Artificial Intelligence will impact my choice of specialty selection.	40
AI in medicine will raise new ethical and social challenges.	22
The Turkish healthcare system is currently well prepared to deal with challenges having to do with AI.	9
Medical training should include training on AI competencies. (e.g. what is AI, how will it impact us, what are the challenges it raises)	80

4. Discussion

In this study, we analyzed medical students' knowledge and attitude of artificial intelligence in medicine. Most of the students (99,6%) stated that they had already heard about it. A recent study in Turkey also found that 93,6% of the students had heard about AI (5). In our study, we found that a majority of the students had heard of AI from the internet (55,4%) and the media (45%). This might be because of the increased usage of social media and the increased projection of AI on social media. Although students have heard about AI, almost half of them were unstable about the meaning of the term 'machine learning'.

An overwhelming majority thought that AI would be able to operate, follow-up patient's treatment, and interpret specific imaging examinations in the future. A study in Germany found that most students were convinced that AI will be able to automatically detect pathologies in imaging examinations and even automatically indicate appropriate examinations (6). In another study in Canada, most of the students (71%) thought that it was likely that AI would be able to use patient information to reach diagnoses. Some believed this capacity would be attained within 11-25 years (4). As a result, in our country, students' expectations are that artificial intelligence will be more effective in the field of medicine in the coming years.

In our study, most students (77%) thought that AI would reduce the workload of doctors. More than half (60%) stated that AI would not affect their choice of specialty selection. This maybe because students' interest in technology has increased recently. Besides, 40% of them stated that AI would impact their choice of specialty selection. This result shows that they worry about AI would be able to reduce the number of jobs in certain medical specialties. In order to reduce the concerns of students in this regard, it may be important to increase their knowledge and focus on the benefits of AI in medicine. We also found that, although almost all of them are aware of artificial intelligence, their level of knowledge is average. Nowadays when technology is developing rapidly, increasing the level of knowledge about AI will have many positive effects on students' professional lives.

When we asked students whether the Turkish healthcare system was sufficient to deal with artificial intelligence, only a very few (9%) of them confirmed this. Most (80%) stated that the medical curriculum should include content related to AI and machine learning. A recent study in Canada found that the vast majority of students (79%) disagreed that their medical education is adequately preparing them to work alongside AI tools (4). It also reached the same conclusion in another study conducted in Turkey (5). We think that it is time for the medical education system to integrate with technology and artificial intelligence in our country.

According to the opinion of future doctors; in order to apply AI in the field of medicine in our country, this subject should be included in medical education and necessary infrastructure arrangements should be made.

References

1. Hazarika I. Artificial intelligence: opportunities and implications for the health workforce. Int Health. 2020 Jul 1;12(4):241-245. doi: 10.1093/inthealth/ihaa007. PMID: 32300794; PMCID: PMC7322190.
2. Park SH, Do KH, Kim S, Park JH, Lim YS. What should medical students know about artificial intelligence in medicine? J Educ Eval Health Prof. 2019;16:18. doi: 10.3352/jeehp.2019.16.18. Epub 2019 Jul 3. PMID: 31319450; PMCID: PMC6639123.
3. Imran, N., & Jawaid, M. (2020). Artificial intelligence in medical education: Are we ready for it?. Pakistan Journal of Medical Sciences, 36(5). https://doi.org/10.12669/pjms.36.5.3042
4. Mehta N, Harish V, Bilimoria K, Morgado F, , et al. 2021, 'Knowledge and Attitudes on Artificial Intelligence in Healthcare: A Provincial Survey Study of Medical Students', MedEdPublish, 10, [1], 75, https://doi.org/10.15694/mep.2021.000075
5. Öcal EE, et al , "Tıp Fakültesi Öğrencilerinin Tıpta Yapay Zeka ile İlgili Düşünceleri.," 1. Uluslararası Sağlıkta Yapay Zeka Kongresi , 2020
6. Pinto Dos Santos D, Giese D, Brodehl S, Chon SH, Staab W, Kleinert R et al. Medical students' attitude towards artificial intelligence: a multicentre survey. Eur Radiol. 2019 Apr;29(4):1640-1646. doi: 10.1007/s00330-018-5601-1. Epub 2018 Jul 6. PMID: 29980928.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Creating Innovation Culture in Nursing; Butterfly Effect

Yeliz DOĞAN MERİH [1,*], Ayşegül ALİOĞULLARI [2], Aytül SEZER [2], Semra KESKİN [2]

[1] *Turkey Institutes of Health Presidency / SBÜ Hamidiye Nursing Faculty / Innovative Nursing Association, Turkey*
[2] *Turkey Institutes of Health Presidency / Innovative Nursing Association, Turkey*

* Corresponding Author: Turkey Institutes of Health Presidency/ SBÜ Hamidiye Nursing Faculty / Innovative Nursing Association, Turkey
Tel.: +90 5445219151. E-Mail: yelizmrh@gmail.com

Publication Information

Keywords :

- Nursing, Innovation,
- Butterfly Effect,
- Culture Creation

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Nurses have to keep up with constant change and integrate the innovation process into their services in order to achieve effective and desired results in service delivery.

In order to activate the process of innovation in nursing services provided at our country, a number of steps were completed. In the first step, nurses' level of knowledge was improved through regular training, individual counseling was initiated using the coaching system, competitions were organized for making the process more interesting, and participation rate was increased with rewards. These implementations produced an innvoation culture.

During the process of activating innovation at our country, which was initiated in 2012, competitions and scientific meeting were held. In the 8 year period, nurses wurking at our country completed 512 innovative product. Each of these projects had an inventive quality and through these products, the nurses were able to support novel and creative activities which increased the quality of care. The patenting process of 100 innovative products was completed and studies were activated for producing new inventions.

As Society in Nurses, we have made innovation a corporate culture. Our process has always started with support, our nurses have been role models, guided, encouraged, motivated, given training, and a guiding book named "Roadmap of Innovative Nurses" was published in this field. In this sense, we established "Innovation Academy in Nursing", which is the first in our country.

Regular training, role modeling, and scientific activities that introduce the process, make the process more interesting, and guide nurses are crucial for activating the innovation process in nursing.

1. Introduction

In a world where technology is growing fast, investment of countries in innovation and research and development activities are the most important factors for them to increase their competitive power. Innovation is of great importance for countries to increase their basic development power. As a concept, innovation expresses both a process and a result. In the EU and the USA literature, innovation, as a process, is defined as “turning an idea into a marketable product, into a new or improved production or distribution method, or into a new social service method” (Yıldırım, 2007; Acıbozlar, 2006; Doğan Merih, 2018; Denat and Memis, 2006).

In recent years, it has been noticed that there is a wide consensus, both among academicians and practitioners, about the necessity of being innovative in order to be effective and to survive. In this context, it is generally agreed that innovation is an important paradigm that can be used in the face of dynamic conditions. On the other hand, hospitals, which are major institutions of health sector, need to be innovative so as to provide sustainability and competitive power to better respond to the needs of health care workers and their partners. In view of this approach, during the last decade the importance of innovation with respect to the health sector has come to the fore, and academicians and practitioners have started to take more interest in this respect (Denat and Memis, 2006; Feldman, Ruthes, Cunha, 2008).

In the light of the developments, nurses, who hold an important position among health care workers, have taken on an active role in the innovation process over time. This is because one of the most important building blocks of nursing education is to develop creativity in individuals. One of the first principles which is taught to nursing students at the first stage of their vocational education is “a nurse is creative” approach (Khorshid, 2010; Herdman and Yazıcı, 2009; Clement, Polit, Fitzpatrick 2011). When changing health care requirements are taken into consideration, nursing profession needs members who are creative and investigative and who can produce and use knowledge. New inventions in many fields, such as health, will be possible by means of individuals using their creativity and starting the innovation process. In this process, bringing new approaches to innovation and care ranks among the requirements of the profession (Clement, Polit, Fitzpatrick 2011; Best and Thurston, 2006; Yamaç, 2001). Innovation is of vital importance in improving and maintaining guality in nursing care. As stated in ICN (2009) report, innovation in nursing practices plays an important part in coming up with information, methods and services to promote health, prevent diseases, identifying and preventing risk factors, increase health promoting behaviours, and provide better care and treatment (Herdman and Yazıcı, 2009; Dil, Uzun, Aykanat, 2012).

This part, which was planned considering the necessity of innovation in nursing, will include the place and importance of innovation in nursing, how innovation will be activated in nursing profession, the stages of establishing innovation culture in nursing and successful examples of innovative products.

2. Materıal And Methods

The type and place of the research

This study was conducted as a semi-experimental study at the SBÜ Zeynep Kamil Obstetrics and Pediatrics Training and Research Hospital between May 2012 and December 2020.

The universe and sample of the research

The universe of the study was composed of all the nurses working in the hospital. The sample of the study; formed 260 nurses who actively worked in the relevant hospital and agreed to participate in the study during the study period.

Data collection tools of the research

The data were collected with a 30-question survey form created by the researchers within the literature. Within the scope of the questionnaire, there were questions determining the demographic and professional characteristics of the nurses and the participation of the participants in innovative processes.

Ethical aspect

Necessary permissions from the hospital administration and ethics committee approval were obtained for the study. It was explained in writing that the identities of the participants will be kept confidential and that the information will only be used for this study, and consent was obtained.

3. Results

It was determined that 40% of the participants in our study were in the age group of 26-31 years, 63.7% received undergraduate education, 67.2% had professional experience over 10 years, and 90% worked in departments such as clinical, emergency and ICU.

Table 1: Findings of Nurses Regarding the Innovation Process

Features	2012 year		2020 year		Total	
Criteria	**Number**	**%**	**Number**	**%**	**Number**	**%**
Knowledge and awareness of innovation						
Yes	12	9.8	136	98.5	148	56.9
No	110	90.2	2	1.5	112	43.1
			$\chi 2$ = 7.187		P=0.022	**P<0.05**
Participation in innovation training						
Yes	2	1.6	131	94.9	133	51.2
No	120	98.4	7	5.1	127	48.8
			$\chi 2$ = 6.167		P=0.036	**P<0.05**
Developing innovative ideas						
Yes	5	4.1	98	71.0	103	39.6
No	117	95.9	40	29.0	157	60.4
			$\chi 2$ = 5.132		P=0.042	**P<0.05**
Participation in innovation competitions						
Yes	2	1.6	78	56.5	80	30.3
No	120	98.4	60	43.5	180	69.2
			$\chi 2$ = 5.256		P=0.046	**P<0.05**
Innovative product prototype development						
Yes	0	0.0	36	26.1	36	13.8
No	122	100.0	102	73.9	224	86.2
			$\chi 2$ = 6.653		P=0.035	**P<0.05**
Innovative product certification (patent and utility model)						
Yes	0	0.0	40	28.9	40	15.4
No	122	100.0	98	71.1	220	84.6
			$\chi 2$ = 6.277		P=0.036	**P<0.05**
Total	**122**	**100.0**	**138**	**100.0**	**260**	**100.0**

When the participation of the participants in the innovation processes is evaluated on a yearly basis; It was determined that the rates increased significantly over the years, the participation of nurses in innovation processes increased significantly in 2020, and the difference was significant (Table 1).

Table 2: Views of Nurses on the Contribution of Innovation to Nursing

Features	2012 year		2020 year		Total	
Criteria	**Number**	**%**	**Number**	**%**	**Number**	**%**
Innovation studies increase the quality of nursing service						
Yes	30	24.6	129	93.5	159	61.2
No	92	75.4	9	6.5	101	38.8
Innovation studies increase the quality of nursing service						

Yes	25	20.5	130	94.2	155	59.6
No	97	79.5	8	5.8	105	40.4
Innovation studies support continuous change						
Yes	12	9.8	125	90.6	137	52.7
No	110	90.2	13	9.4	123	47.3
Innovation studies increase professional motivation						
Yes	16	13.1	108	78.3	124	47.7
No	106	86.8	30	21.7	136	52.3
Innovation studies provide visibility of nursing						
Yes	10	8.2	136	98.5	146	56.2
No	112	91.8	2	1.5	114	43.8
Innovation studies add strength and value to nursing						
Yes	15	12.3	123	89.1	138	53.1
No	107	87.7	15	10.9	122	46.9
Total	**122**	**100.0**	**138**	**100.0**	**260**	**100.0**

When the opinions of the participants about the contribution of innovation studies to the nursing profession are evaluated; It was determined that they expressed that innovation adds value to the profession, provides visibility, increases motivation and increases the quality of service with the increase of their participation in innovation activities in 2020. (Table 2).

4. Activation Process Of Innovation In Nursing: A State Hospital Example

Especially, the innovations in the field of health make taking on more responsibilities and developing themselves obligatory for health care workers. In this process, bringing new approaches to innovation and health care is one of the vocational requirements. Nursing profession also gets its share from innovation and development processes.

Considering all these requirements, a project in SBU Zeynep Kamil Woman and Child Diseases Education and Research Hospital was started in 2012 to activate the innovation process in the nursing profession. An "Innovation Team" of 6 proficient people was established to take an active role in the process of innovation and of training and consultation of the nurses and to motivate them. The team consisted of innovative nurses who supported this process and aimed to provide the best service to our patients through their professional vocational approaches. The chair of the team was the director of the nursing services of the hospital. Thus, the support of the high executives was provided throughout the innovation practices and periods of change. The process started with the trainings. The trainings were prepared primarily for ZKH nurses. Trainings were integrated into in-service training programs. Web site announcements, training posters and guides and trainings were made visible. All of the nurses were provided with efficient and applied trainings about the innovation process. In the workshops, innovative ideas were developed, prototyping the innovative idea, patent application process for the product, promotion and advertisement of the certified product were applied. Nurses who have received first level training in this field participated in the application trainings. A total of 300 people participated in the trainings in groups of ten people. Through applied workshops, the process was consolidated. At the second step, with the mentality of "The One Who Does Knows The Best", a project team was established, and it included nurses who provided service for 24/7 in this field. The project development team consisted of 7 people, the head of which was the director of nursing services, and the assistant was a research nurse and 5 other nurses competing in innovation training. Under the coordination of this team, clinical innovation mentor nurses were formed from ten nurses who received formal and workshop trainings. These mentor nurses mentored their colleagues in their clinics in order to activate their innovation work individually and as a group in their innovation work. Thanks to these nurses, mentorship was provided not only in trainings but in all of the clinical processes as well. Integration of all innovation processes at work was achieved. Involvement of the nursing services director in coordination and in the innovative processes made the activation of the the project in nursing services easier. Identifying the medical products that our patients and we needed and developing them were the major steps in the project. Our main objective was to increase the quality of our services and to provide an accretion value for our country. This project, which was started in Zeynep Kamil Hospital, got the attention of many nurses in a short time and so many innovation trainings were conducted in different universities, schools and hospital with our project team. Many of our colleagues were made aware of the innovation process. This innovation light which started at Zeynep Kamil Hospital spread to many nurses throughout our country. After increasing the awareness about the topic, in order to make the process attractive competitions and symposiums were held under the coordination of Zeynep Kamil Hospital.

As part of the celebration events of the 150th year of ZKH, a prize competition, and a symposium called "Innovation in Nursing", which was the first in the field and which had the purpose of activating the process in the nursing profession were organised. Trainings, competitions, and symposiums were organised traditionally by this hospital for eigth years. "1st International Innovative and Nursing Congress", which had the characteristic of being a pioneer in our country, was organised in 2018. The "2nd International Innovative Nursing Congress" was held in 2020. After the evaluations carried out during competitions and scientific meetings, some of the projects and papers were awarded, participating nurses were motivated and awareness about the topic was ensured.

During the innovation practices of the nurses in ZKH, 512 medical inventions which were beneficial for the health of mothers and babies were developed. We didn't want these inventions to stay on paper. In order to put the projects into practice, we set out on a challenging journey, but the result was positive. In 8 years, there were applications for patents and useful models in order to protect the innovative inventions that were developed by nurses in the hospital. During this period, about 100 certificates for patents were acquired Certification process for some others are still going on. Some of these products are: Surgical instruments, Surgical needles with different protection mechanisms, Labour tracking devices, A post-natal anti-bleeding device, Newborn intensive care products-formula milk preparation device, A bed that teaches how to breathe, Crying sensor, Special blood collecting needles for the newborn, Blood tranfusion devices, sliding beds to increase patient comfort, A bed that can change positions and give massage, A wearable iv holder and foley-catheter holder that will support patient mobilization, Specific milking devices, Drug navigators, Testing pens for drug safety, Multi purpose wheel chairs and controlled waste collecting devices. One of our biggest goals for the future is to be able to use the products that we have developed.

Figure 1: Patent pictures of nurses

The number of patents is an important criterion that shows the development level of countries. These innovations lead to an increase of value and have an important part in reaching the goals for evolution in Turkey. The nurses of this hospital, see how they have been supporting this process well by obtaining patent specifications for inventions. Prototypes of some of the innovative products of our nurses were developed. After getting permission, trial processes were started for some of the products. Then, we joined the team of Istanbul Aggregation of Health Industry (ISEK) for the products for which the process of certification was completed. Nurses from ZKH are the only ones, became members of this scientific team. Thanks to this participation, we got invitations from Istanbul Research and Development Fairs many times and we demonstrated the inventions so as to be able to put them into practice. In this way, nursing profession was made to be visible in the innovation process (Figure 2).

Our endeavors also caught the attention of media. After the news in media about the successful practices of nurses in the field of innovation, both motivation of our colleagues for the innovation processes was increased throughout the country and the inventions were publicized. At present, we are about to start to produce some of the inventions. We have received many awards for our achievements. We may start to use the inventions of our nurses in our service deliveries in a few years.

Figure 2: Exhibitor picture

It was a tough but well-ending journey to activate the innovation process within nursing services. The nurses of Zeynep Kamil Hospital turned innovation into a culture into the hospital. However, not all hospitals are so lucky as ours. In fact, a lot of nurses in different institutions have innovative ideas but as they do not have guiding role models they cannot make their ideas come true and they limit themselves, and their inventions continue to stay as dreams. Our process started with continuous support. Innovative nurses of Zeynep Kamil Hospital became role models for our nurses and guided them. They were encouraged and motivated, trainings were provided, and a guide book called "Roadmap for Innovative Nurses" was written. The aim was to provide better service to our patients, support manufacturing process in our country, and provide vocational development by spreading this innovation light to all our colleagues. In this process, professional trainings and implementation workshops are very important. We established the "Innovation Academy in Nursing", which is a pioneer in our country. Thanks to this academy, trainings in the innovation process became more professional, and prototype processes of innovative practices and inventions became more effective. Nurses from ZKH believe that the success in innovation will increasingly go on in this way.

Figure 4: Nursing innovation academy studies

Lockable Stretcher For Patıent Bed

Electropneumatic Smart Bed With Micro Cushions

Crying Sensor

Self-Servıce Table

It is important to adopt an organizational culture in order for innovative practices in nursing to be widespread. Organizational culture is the combination of traditions and beliefs which differentiates an organization from another and which encompasses its life style. The more organizational values and beliefs are accepted and adopted by employees, the stronger the organizational culture may become. In this context, national societies and associations of nurses play an important role. This is because with their organizational culture national societies and associations of nurses are the key institutions that can best reflect organizational culture and support innovation. In order to make innovative practices in nursing more common, national societies and associations of nurses should structure their practices so that they can develop organizational innovation.

As the nursing innovation development team, we have expanded the innovation work further. After making innovation in nursing an institutional culture, in order to become role models for nurses, to encourage and motivate them, and to train them the "Innovative Nursing Association" was established on 18.05.2016. It was the first one in the sense of innovation in nursing and the headquarters was in Istanbul. The purpose of the association is to enable nurses to achieve effective and desired results, counseling them how to keep up with the changes, and integrate innovation process into their work, to promote health in nursing practices, to prevent diseases, to identify and prevent risk factors, to increase health-improving behaviors and to support innovation in order to provide better care and treatment. Through this association, the work will be maintained and spread the success of ZKH to other nurses across the country.

5. Conclusion

In order to be able to continue its existence in today's ever changing and developing world, nursing profession should be open to change and development, form a firm unity, be stronger through continuous professional training, and increase the quality of service by making all existing information accessible to each member of the profession. At this stage, nurses should activate the innovation process, and they should shape the future of their profession by initiating professional change and development process.

Putting innovative nursing endeavors into practice through a national integrated strategy, determining which subsectors and value chain stages should be focused on in short, medium and long term through analyses, creating global supportive domains in health sector, cooperating with international actors, and encouraging commercialization of research outputs will contribute to increase the competitive power of health sector and to establish the innovation culture in nursing.

References

1. Yıldırım, E. (2007). The importance of creativity in the information age and the management of creativity. Selcuk University Karaman Journal of Faculty of Economics and Administrative Sciences, 12 (9): 109-120.
2. Acıbozlar, Ö. (2006). Decision making strategies and creativity levels of executive nurses. Master Thesis, Marmara University Institute of Health Sciences. Istanbul.
3. Doğan Merih Y. (2018). İnovatif bir hemşirelik buluşunun hayata geçirilmesi; giyilebilir askı sistemleri. Hemşirelikte Eğitim ve Araştırma Dergisi, 15(4): 215-21.
4. Denat, Y., Memis, S. (2006). Developing creativity in nursing education. Ege University Journal of the School of Nursing, 22 (1): 245-252.
5. Feldman, LB., Ruthes, RM., Cunha, IC. (2008). Creativity and innovation: competences on nursing management. Rev Bras Enferm. 61(2):239-242.
6. Khorshid, L. (2010). Creativity and innovation in nursing. 1. Basic Nursing Care Congress Book. Izmir, 1-4.18.
7. Herdman, AE., Yazıcı, KÖ. (2009). Nursing and innovation. Journal of Nursing Education and Research, 6: 2-4.
8. Clement O-Brien, K., Polit, FD., Fitzpatrick, JJ. (2011). Innovativeness of nurse leaders. Journal of Nursing Management.19:431-438.
9. Yamaç, K. (2001). What is this innovation? Journal of Science Education and Thought, 1: 6-8.

10. Best, M., Thurston, E. (2006). Canadian public health nurses' job satisfaction. Public Health Nursing, 23(3): 250-255.
11. Dil, S., Uzun, M., Aykanat, B. (2012). Innovation in nursing education. International Journal of Human Sciences, (9) 2, 1217-1228.
12. Cohen, S. (2002). Don't overlook creative thinking. Journal of Nursing Management, 33(8):9-10.
13. Şengün, H. (2016). Innovation in health care delivery, Med Bull Haseki, 54: 194-8.
14. Turanlı, R., Sarıdogan, E. (2010). Science-Technology-Innovation Based Economy and Society, Istanbul, Academic Publications.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Unfairness of Deep Learning Methods Arising Gender Bias in Covid-19 Diagnosis of Medical Images

Havvanur DERVIŞOĞLU[1, *], İsmail BILGEN[1], Ruşen HALEPMOLLASI[1], Barış CAN[1], Mehmet HAKLIDIR [1]

[1] *TÜBİTAK Informatics and Information Security Research Center, Information Technologies Institute, Kocaeli, Turkey*

* Corresponding Author: *TÜBİTAK Informatics and Information Security Research Center, Information Technologies Institute, Kocaeli, Turkey*

Tel.: +90 262 648 10 00. E-Mail: @tubitak.gov.tr

Publication Information

Keywords :

- Bias,
- Artificial intelligence,
- COVID-19,
- Medical image

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

The decisions made by Artificial Intelligence (AI) systems are critical due to their growing usage in sensitive areas such as recruitment, criminal justice, and healthcare. It is dramatically significant to detect and measure AI bias to mitigate the effects of bias by making these systems more transparent, explainable, and auditable. In this study, we focus on gender bias to investigate the effect of gender imbalance in medical imaging dataset when applying AI models to detect Covid-19. We perform an analysis to measure gender bias in the diagnosis of medical imaging data using deep learning-based methods. We primarily examine the distribution of samples based on metadata and target labels. In the training phase, we conduct experiments to reveal that gender imbalance produces a biased model. For this purpose, we train a model using both a fully gender-balanced and immensely imbalanced dataset unique to a specific gender. To show that the inferences are generalizable, we apply several deep learning-based solutions including pre-trained models. We compare the performance of different models for exploring gender bias. We observe a significant difference in classification performances between trained models using the imbalanced dataset and balanced dataset in terms of gender. We confirm a similar tendency when using different deep learning methods. Consequently, our experimental results show that gender-imbalance in medical imaging data produces biased decisions in Covid-19 detection. In this study, we explore a gender bias in the deep learning aided Covid-19 diagnosis of the gender-unbalanced medical image data.

1. Introduction

Artificial intelligence (AI) systems, which have the potential to make decisions like experts in many fields, learn to depend on the quality and size of the training data used. The decisions made by these systems are critical due to their growing usage in sensitive areas such as recruitment, criminal justice, and healthcare. In recent years, through the successful results and advances of machine learning and deep learning techniques, AI systems in medicine are also adopted in a wide range from disease diagnosis to radiology screening, drug side effect predictions. Therefore, it is extremely significant that AI solutions that reflect the data structure and individual perceptions are fair with no prejudice towards a certain group.

Although researchers have intensively performed for developing computer-aided systems to assist medical experts, experimental studies on the structure of the data and how it affects the performance of machine learning and deep learning algorithms is still limited (Larrazabal et al., 2020). Considering the consequence of unfair decisions towards a certain underrepresented group, the decisions of these algorithms are vital in healthcare and need to learn from a balanced dataset representing various populations (Kaushal et al., 2020). Thus, it is dramatically significant to detect and measure bias in AI systems to mitigate the effects of unfairness by making these systems more transparent, explainable, and auditable.

AI bias is a concept that emerges as a consequence of a machine learning algorithm systematically producing biased results depending on cognitive perception and/or data structure(ref). It can exist in many shapes and forms such as sampling, exclusion, aggregation, population, behavioral, observer, measurement, algorithmic (Mehrabi et al., 2019, Suresh and Guttag, 2019, Olteanu et al., 2019), however, usually depends on two major sources: (i) the datasets from which the machine learning algorithms learn and/or (ii) the algorithms themselves (Zou and Schiebinger, 2018).

Due to the obstacles in collecting sensitive medical data from different sources, researchers often cannot obtain large and balanced dataset that allow machine learning models to achieve reliable and valid results. Therefore, the models may unintentionally result in biased and unfair predictions against a certain class/group in terms of race, ethnicity, gender, geography, etc. because of the heterogeneous and unbalanced structure of the dataset, which is the first major source of bias (Mehrabi et al., 2019). The other source of bias is related to the design of machine learning models that may include the cognitive biases of the designers.

Gender bias is one of the most common types of bias in healthcare (Bolea-Alamanac et al., n.d.), as well as in other areas such as natural language processing (Prates et al., 2019, Stanovsky et al., 2019), image processing (Serna et al., 2020), recruitment (Bolukbasi et al., 2016). Gender imbalance in the medical dataset is stated as a key cause of gender bias, which causes computer-aided systems to produce biased predictions (Larrazabal et al., 2020).

The detection and measurement of bias has been the subject of many researches. Dixon et al., introduced and illustrated a novel approach to measuring and mitigating unintended bias in text classification problems, they used common demographic features to measure bias and in order to mitigate bias they used an unsupervised approach based on balancing training dataset. They used the Wikipedia Talk Pages dataset to classify text into two classes; toxic or not toxic. They observed that unbalanced numbers of toxic samples constitute a bias (Dixon et al., 2018).

Another study (Serna et al., 2020) conducted to show that bias can be detected in deep learning methods with a few samples. They have come up with a solution that shows that bias is detectable depending on how the models represent information rather than how they perform. Researches in another study that teaches the system what should not be learned, they showed that the existence of bias depends on features such as age, gender and class (Kim et al., 2019) In order to demonstrate this, they added bias to the data to be used in education and conducted various experiments.

In this study, we investigate the existence of gender bias in AI-model- based diagnosis of COVID-19 by examining the effect of gender imbalance in medical imaging dataset. We conduct several experiments to infer gender bias produced by gender-unbalanced medical images. We found that significant bias exists in diagnosis when trained models using different gender groups.

The rest of the study is structured as follows: In section 2, the purpose of measuring bias in machine learning models, the techniques used to measure it are mentioned. In section 3, the methodologies used to detect gender bias, deep learning models utilized and performance metrics used to assess model outputs are explained. In section 4, the steps of the study design including the dataset preparation, preliminary data analysis of gender bias and experimental details are described. In section 5, the results of the experiments conducted are presented. Finally, the results of the study are discussed in section 6.

2. Bias in Machine Learning

The increase in using AI in healthcare in the last few years has brought the issues of researching the reliability of the decisions taken with these models to the forefront. In the last year, it has been observed that research on the using AI models in the diagnosis of COVID-19 has increased. The use of AI models in the diagnosis of COVID-19 is important for rapid diagnosis, and with rapid diagnosis, measures can be taken early for the spread of this disease. The correct diagnosis of this disease is important to start the necessary treatment. The effort of researching the best diagnosis model brings with it the need for the understanding of prediction errors, finding the causes of these errors, and finding out the solution.

The increasing AI studies in healthcare have also boosted the effort of finding the source of inaccurate predictions. There are three main sources of inaccurate predictions of an AI model: (i) The first one is the noise, which is the characteristic of the data used in the training phase of the model, and such errors are generally considered as irreducible errors. (ii) The second is the variance that measures how much the training model varies from one data set to another. If this change is significantly high, the estimates will be unreliable. (iii) The last one is the bias that results from the tendency of the predictions to some aspects (class, feature, etc.). In this study, we focus on the source of bias in AI models which highly affects the quality of the model predictions and can likely be overlooked. In particular, we investigate gender bias in the diagnosis of COVID-19 caused by the unbalanced distribution of medical images belonging to different genders in classes.

2.1 Bias Detection and Measuring

Bias is considered being an excessive tendency or prejudice against an aspect (Flaugher et al., 1978). In machine learning, bias is the error of prejudiced assumptions in a learning algorithm (Nelson et al., 2019). According to the definitions, we can say that we need to understand the bias if we want to get an excellent model, and in order to detect bias, we must be aware of its existence.

In machine learning models, bias is caused by not being able to capture the relationship between the model's input features and the class belonging to it, which is the reason for the model underfitting as well. Therefore, high bias means the model is underfitting (Pavlovski et al., 2018). This can likely be detected when the model does not perform better on the train set than on the test set. In general, to avoid bias, one needs to train a convenient model with a high-representative-power data set. Bias can occur in various cases, such as a dataset that poorly reflects the problems, a model that does not fit well with existing data. Therefore, the detection of the bias should be conducted in several stages of model development from data preparation to model training. The bias can be caused by one or multiple of the steps explained below.

Data Collection step is where bias is most encountered. Dataset based bias may occur if the data is created by people with a certain tendency or the equipment where the data is collected is distorted.

Data Preprocessing is preparing the data for the model. The processes applied at this stage may cause bias. For example, data which represents missing values can cause bias or data filtering operation can be the reason for the break in data integrity.

Modeling is the training process to recognize patterns at this step, the reason for the bias may be due to the parameters of the model.

When developing a model we must be aware of the existence of bias, and that's why we must detect it if we want to have an unbiased model. In order to measure bias, we need to know which type of bias can occur in our model, and then with some experiments we can measure prediction errors which show us the model's consistency.

3. Methodology

We perform an analysis to measure gender bias in the diagnosis of medical imaging data using deep learning-based methods. To detect gender bias encountered in the diagnosis of COVID-19 from chest X-ray images, we initially compose highly gender unbalanced training and test sets. We trained different prediction models on each combination of datasets. Consequently, we analyze the outputs of each model setup to explain existing bias.

Since, one of the most important reasons for bias is the imbalance in data, we force the model to be trained with highly gender unbalanced data to reveal the bias. Although gender is not part of features of labels of subjects and it is solely metadata of them, we hypothesize that it still causes a bias in the diagnosis model. To validate this hypothesis, we introduced a test set comprising samples of a completely different gender to the model than the used for training. We also test with data of the same gender as the one used for training and compared the results. We keep the label distribution balanced for all subsets of the data to get rid of other effects except the gender.

In this study, we used well-known pre-trained models which are proven to be successful in image recognition tasks in literature. To carry out model agnostic and fair bias analysis, we used a substantial number of deep learning models. In section 3.1, we explain pre-trained deep learning methods we exploited in this study, and in section 3.2 we explain the evaluation method and used performance metrics.

3.1 Deep Learning Methods

Deep learning is part of the machine learning family, which is based on artificial neural networks (Stegbauer et al., 2009). And transfer learning is a machine learning method. Due to the small number of samples in the data set, transfer learning was used in the study. Transfer learning is to use previous models or data after solving a problem, instead of solving another similar problem from scratch. Pre-trained models are pre-trained with a large dataset, and weights represent the trained dataset of this model's weights. The features are transferred to different data with transfer learning. Thus, we get a good model where our sample number is low.

In our study, we investigated the existence of gender bias that occurs when training is done with gender imbalance in the problem of classifying COVID-19. To address the classification problem, we used pre-trained models including DenseNet121, DenseNet169, ResNet18, ResNet50, VGG16, EfficientNet.

DenseNet: Dense Convolutional Network (DenseNet), is a CNN (convolutional neural network) architecture. CNNs can cause loss of information when networks go deeper and with DenseNets a solution was introduced for solving this problem. DenseNets solved the loss of information problem by connecting each layer to every other layer in a feed-forward fashion and this solution providing usage of the network's reusing features potential (Huang et al., 2017).

ResNet: Residual Networks is a powerful model that is used for many computer vision tasks. In a deep neural network, we use more layers for reducing error rate, but that causes gradient problems. ResNets has a skip connection technique to solve gradient problems (He et al., 2016).

VGG Neural Networks: VGG networks are developed to increase the depth of networks, which provides better accuracy by having small-size convolution filters and small filters (Simonyan and Zisserman, 2014).

EfficientNet: EfficientNet is a CNN architecture and scaling method that scales dimensions using a compound coefficient. CNNs require many trials to provide better accuracy, which take time and resource and often yields models with sub-optimal accuracy. Because of this issue, EfficientNet is introduced. These CNNs not only provide better accuracy but also reduce the parameters (Tan and Le, 2019).

3.2 Performance Metrics

When evaluating the performance of the models and the datasets used, we employ metrics such as accuracy, area under the curve, precision, and recall. We compare the performance of different models for exploring gender bias. The area under the roc curve is a metric used in bias studies in the literature, while precision and recall are two important metrics used in healthcare. In Figure 1, there is a confusion matrix used in the study.

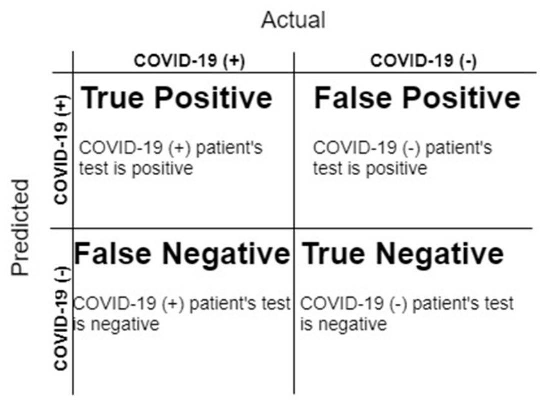


Figure 1. Confusion matrix.

In Equation (1), the recall shows the proportion of patients who have not been diagnosed with COVID-19 despite having COVID-19.

$$Recall\ (True\ Positive\ Rate) = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{1}$$

In Equation (2), the precision shows the proportion of patients diagnosed with COVID-19 when they were not a COVID-19 patient.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{2}$$

Calculation of false positive rate is shown in Equation (3).

$$False\ Positive\ Rate = \frac{False\ Positive}{True\ Negative + False\ Positive} \tag{3}$$

4. Study Design

In this section, we present the design steps of the complete map of gender bias analysis performed in this study. In section 4.1, we mention the collection and preparation of the COVID-19 dataset used in section 4.2, we introduce a preliminary analysis to explore gender bias throughout the data. In section 4.3, we explain the experiments conducted to reveal the reflection of the gender bias on the learning model as further analysis.

4.1. Datasets

For the experiments we utilized two different datasets which contain COVID-19 x-ray images and non-COVID-19 x-ray images respectively:

- *COVID-ChestXRay (Cohen et al., 2020):* this dataset includes CXR and CT images from various websites and publications. This dataset includes images of patients which are COVID-19 or other viral and bacterial pneumonias (MERS, SARS and ARDS). Number of images for COVID-19 patients, 521 and 175 of them are images of female patients, 346 of them are males. This dataset has metadata of the images, which includes gender information.

- *NIH Chest-XRay (Wang et al., 2017):* this dataset is used for non-COVID-19 x-ray images and the dataset includes 112,120 X-ray images from 30,805 patients. There are 14 different diseases in this dataset which are atelectasis, consolidation, infiltration, pneumothorax, edema, emphysema, fibrosis, effusion, pneumonia, pleural thickening, cardiomegaly, nodule mass, hernia. Labeling was done according to the natural language processing analysis of the radiology reports. The dataset provides demographic information which includes gender information.

In our experiments, we kept the number of images of male and female patients in each class equal in order to show the bias that occurs when male and female patients in our classes contain an unbalanced number of samples. The total number of images in the COVID-19 class is 330, half of which are male and half are female patients. For non-COVID-19 class the number of medical images is 360 and this class also has the same number of images for both genders.

4.2. Preliminary Data Analysis of Gender Bias

In this analysis, we aim at exploring gender tendency encoded in the subjects' features by inspecting their representations in lower feature space where the differences can be observed. We examine the differences in medical images in terms of gender metadata.

First, we use VGG16, a pre-trained convolutional neural network model, to extract a feature vector from images. VGG16 is a well-known successful model for image recognition tasks. We use the penultimate layer of the model as the feature vector. The penultimate layer is a fully connected layer with a 4096 number of nodes. Hence, we obtain a feature vector of length 4096 for each subject image.

We further reduce the dimensionality using the PCA algorithm. PCA provides to reduce the number of variables while preserving as much information as possible from the original set. We reduce the dimension to 2 to plot the projections. In order to cluster the samples, we empirically choose 100 numbers of dimensions. We use the K-means algorithm for clustering tasks and empirically determine the number of clusters as 18 to obtain more evident analysis results. In figure 2, the left plot shows distribution of samples in two-dimensional space by remarking genders in different colors and the right plot indicates the numbers of samples of different genders in clusters obtained using 100-dimensional space.

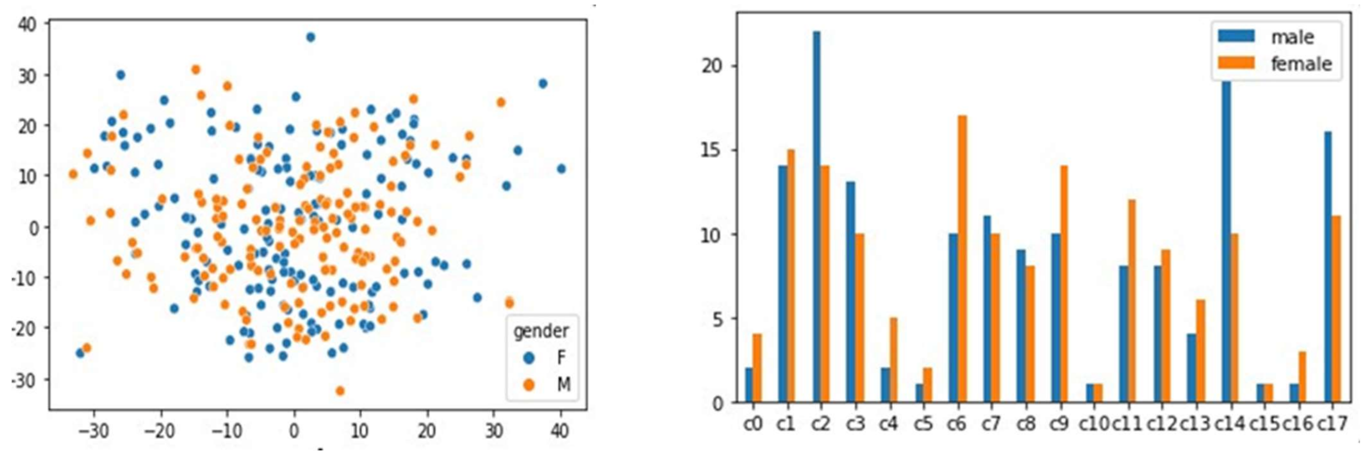


Figure 2. Distribution of samples in two-dimensional space (left) and resulting numbers of genders in clusters obtained using 100-dimensional space (right)

According to this analysis result, we observe that the numbers of samples belonging to different genders are not evenly distributed when clustered based on image features (Figure 2, right plot). Also, it can be observed that the samples of same genders stand close to each other when represented in two-dimensional space (Figure 2, left plot). This shows that the representative features differentiate for different genders, which can lead the machine learning model to have a tendency towards a gender if not trained gender balanced samples. It is worth noting that the gender information of the images is neither a feature nor label of the subject but only its metadata.

4.3. Experimental Setup

In section 3, the proposed methodology to infer gender bias is explained. In this section we detail the preprocessing and training processes as well as the experiments conducted.

Pre-processing Some preprocessing operations were carried out before training the model. First, the images were resized and then normalized using the mean and standard deviation values, because all pre-trained models expect input images at 224 size and normalized to the range [0, 1]. Then, horizontal flip and crop operations were applied for augmentation.

Hyperparameters which is used for pre-processing are:

- Mean for normalize: [0.485, 0.456, 0.406]
- Standard deviation for normalize: [0.229, 0.224, 0.225]
- Resize: 256

- Scale parameter for crop: (0.5, 1.0)

Training As we mentioned, in section 3.1 we used six different pre-trained models for this study. These models in the PyTorch framework were used in order to observe the effect of bias in different models during the training phase.

Hyperparameters which are used for training are:
- Parameters: Pre-trained models are used with default parameters
- Batch size: 10
- Optimizer: Adam
- Learning rate: 0.0001
- Scheduler: Cosine annealing learning rate

Experiment Strategy We conduct experiments to reveal that gender imbalance produces a biased model. For this purpose, two different training policies are used: (i) training models only with male x-ray images and (ii) training models only with female X-ray images. Models trained in both policies are evaluated over male-only and female-only X-ray images.

The experiments conducted are summarized in Table 1. Since one of the most common sources of bias is the imbalance in data, we design experiments such that train models on extremely gender unbalanced datasets in order to elucidate whether a bias towards gender.

We examine the effect of gender bias by comparing male-only and female-only test results. We use multiple pre-trained models to get model agnostic results and repeat each experiment 5 times using randomly split 5 folds to generalize the analysis.

Table 1. The summary of experiment strategy.

Experiments	Trained	Tested
1	male samples	female samples
2	male samples	male samples
3	female samples	male samples
4	female samples	female samples

5. Results

We test models on both gender groups separately. We repeat each experiment using randomly split 5-folds. We measure the precision, recall, and AUC scores for each trial and report the average scores. We conduct the aforementioned processes for each selected pre-trained deep learning model.

Training models only with male x-ray images: We performed model training with male-only medical images (male-only model) and we tested with both gender groups separately. Figure 3, Figure 4 and Figure 5 shows the average AUC, precision and recall scores respectively.

In Figure 3, male trained AUC results are shown.

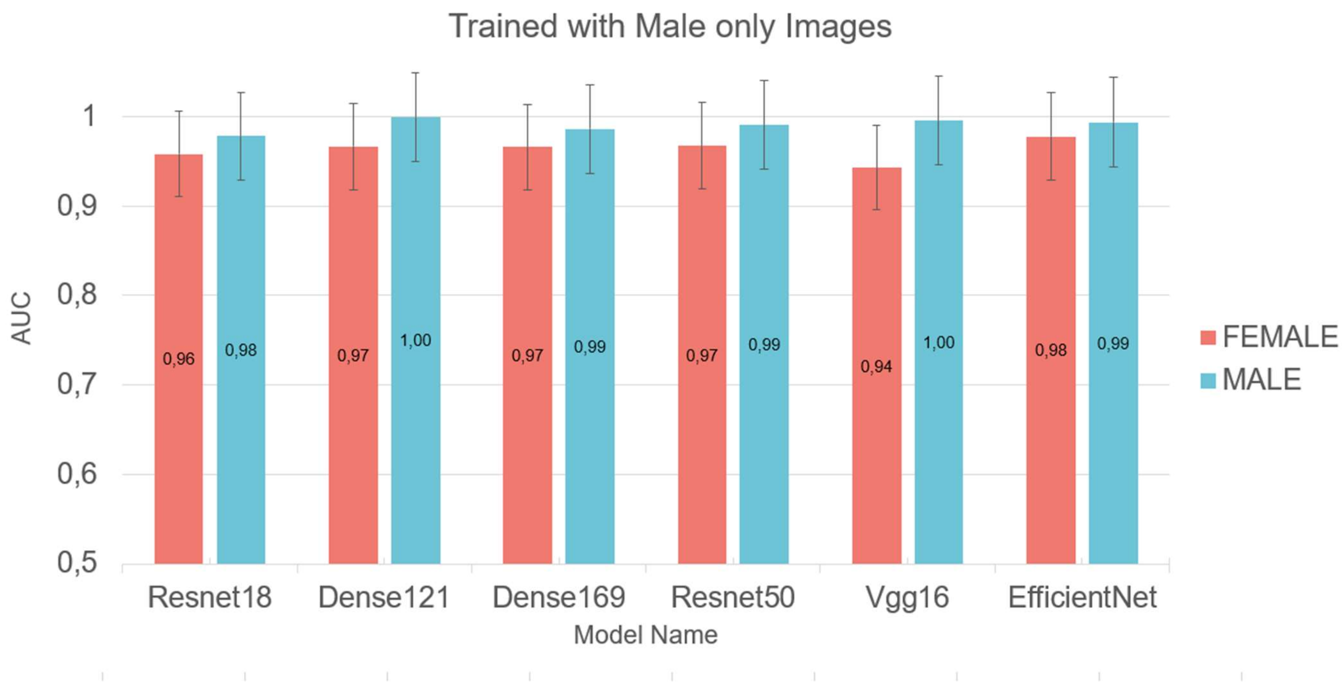


Figure 3. AUC results of male-only models on male-only (blue) and female-only (red) test sets.

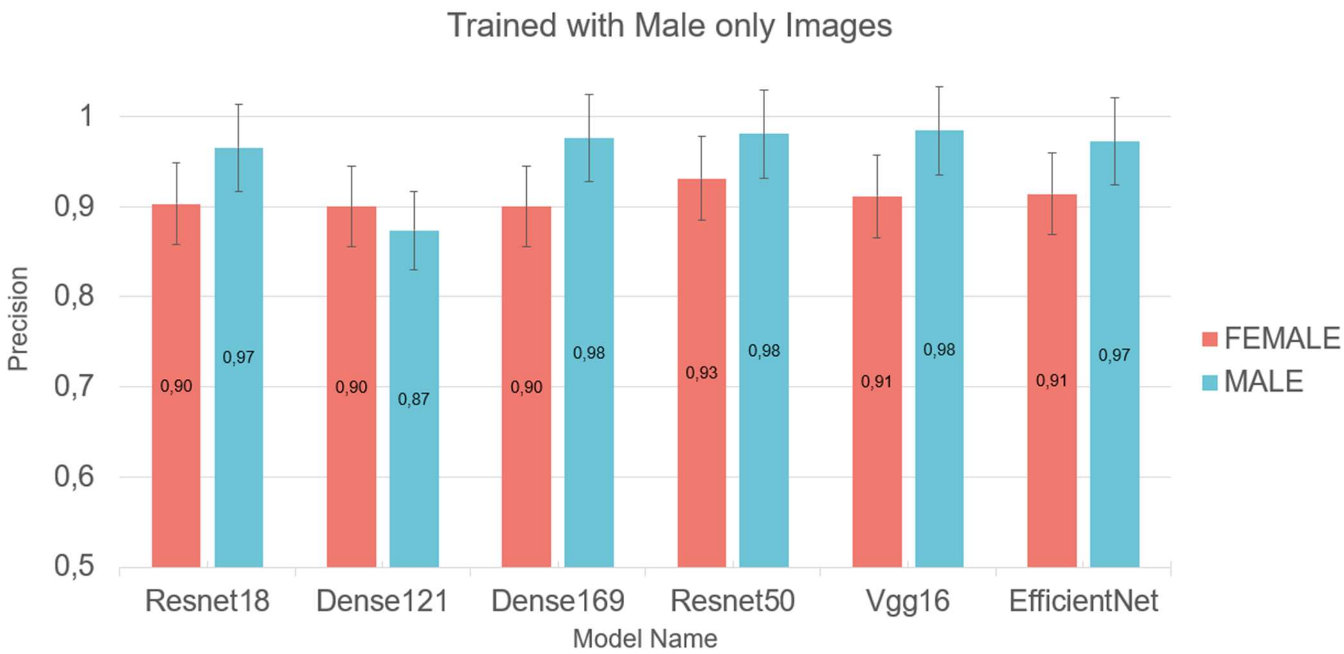


Figure 4. Precision results of male-only models on male-only (blue) and female-only (red) test sets.

Figure 5. Recall results of male-only models on male-only (blue) and female-only (red) test sets.

Training models only with female x-ray images: We performed model training with female-only medical images (female-only model) and we tested with both gender groups separately. Figure 6, Figure 7 and Figure 8 shows the average AUC, precision and recall scores respectively.

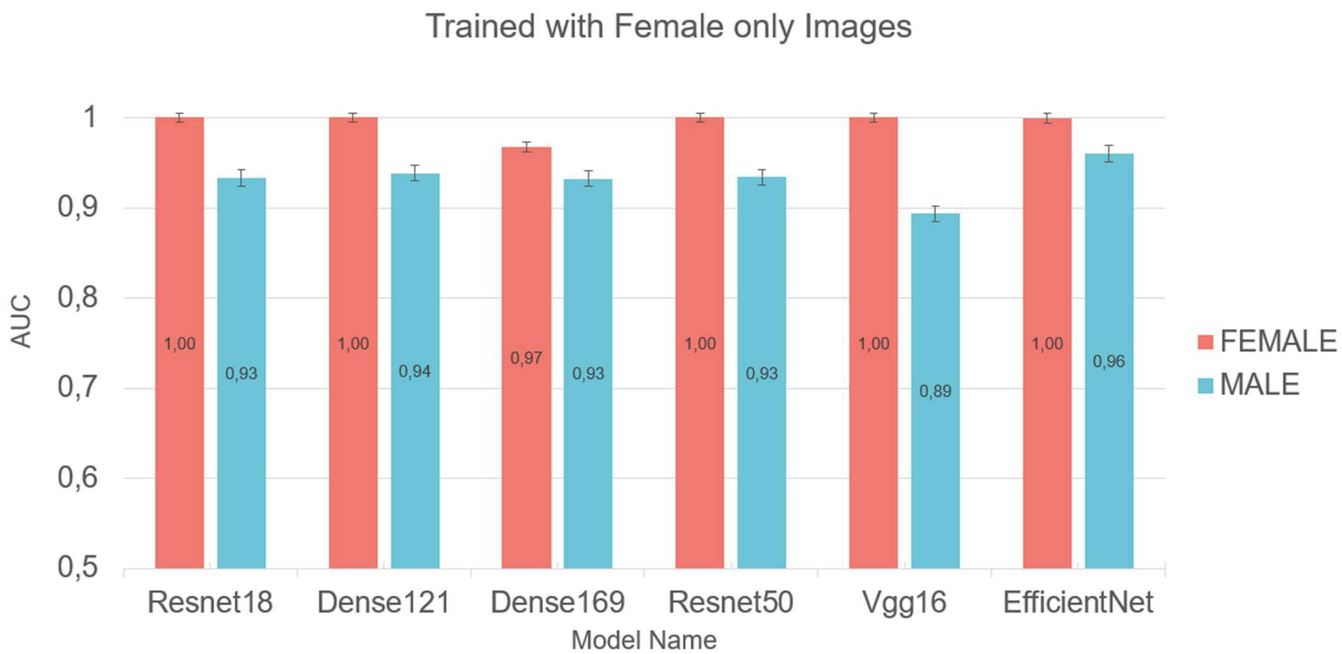


Figure 6. AUC results of female-only models on male-only (blue) and female-only (red) test sets.

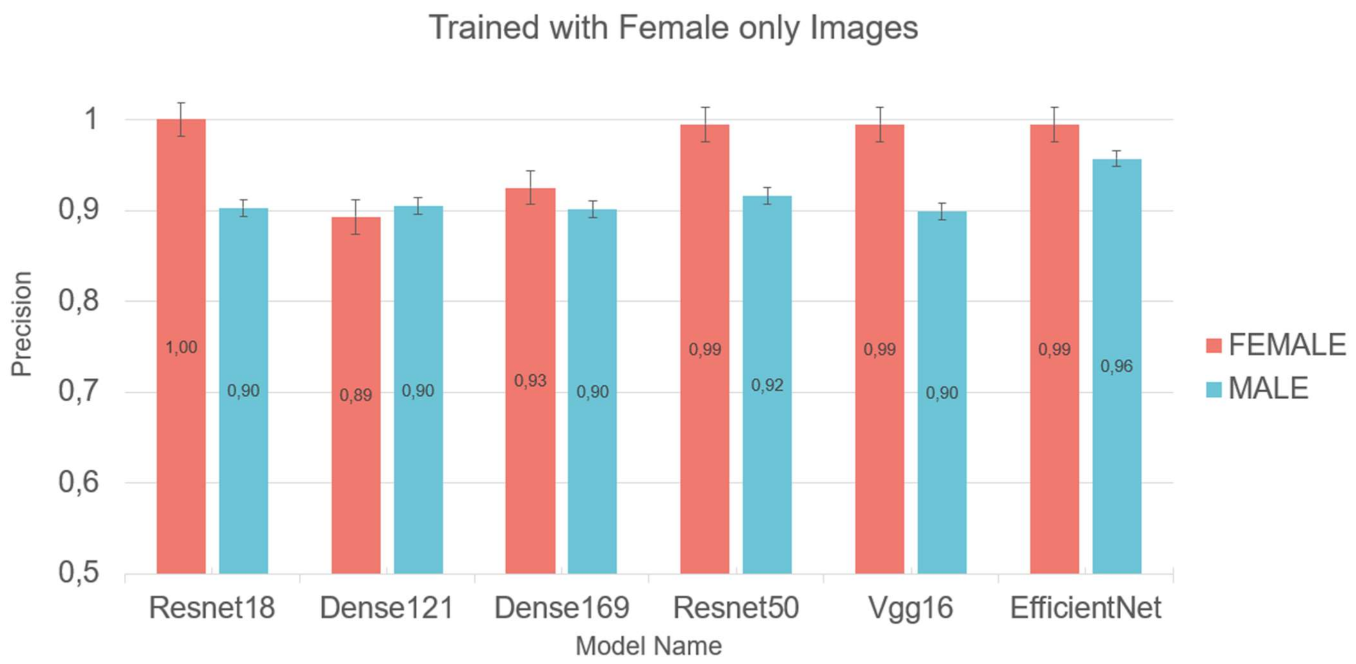


Figure 7. Precision results of female-only models on male-only (blue) and female-only (red) test sets.

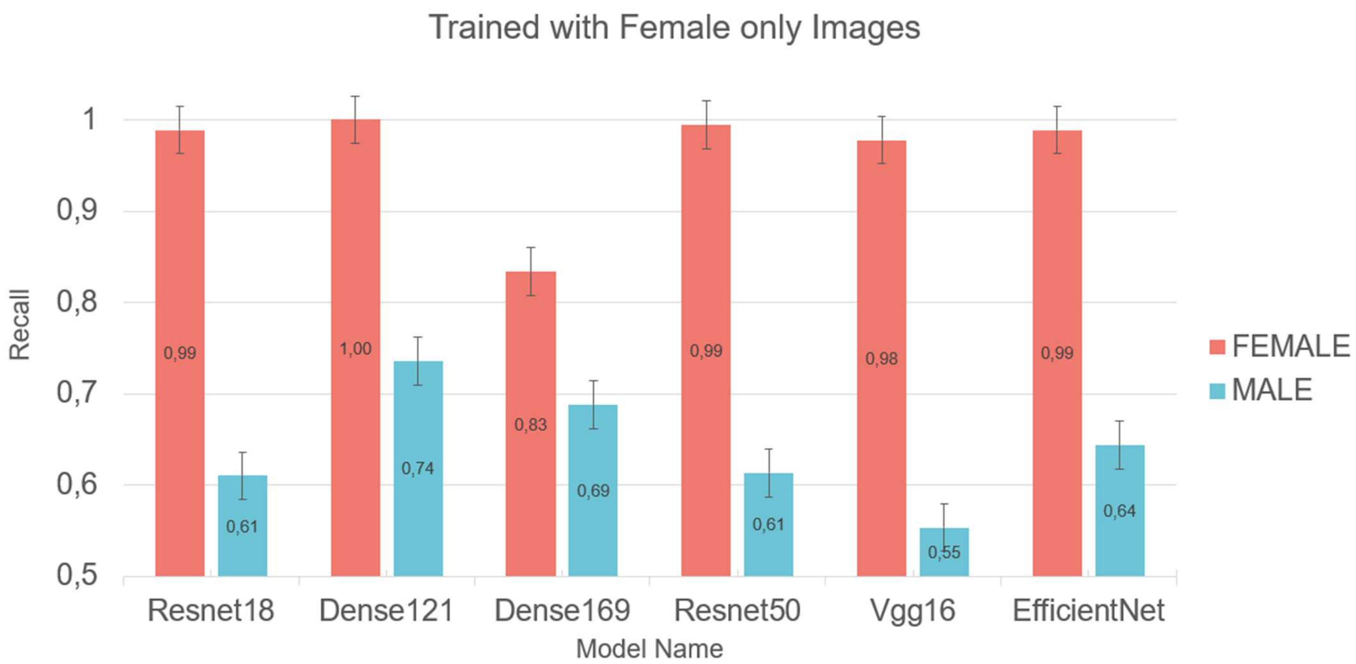


Figure 8. Recall results of female-only models on male-only (blue) and female-only (red) test sets.

Models trained with male-only images get highly near AUC scores with both female-only and male-only test sets (slightly higher on male-only test sets). This indicates that male-only trained model performs well on both gender groups. However, the differences in AUC scores of models trained with female-only images are notably more important than of male-only models.

AUC results of both experiment policies show that models trained with male-only chest X-ray images are much more comprehensive in COVID-19 diagnosis than that of trained with female-only. The greatest AUC differences between test sets of different gender groups is observed in VGG16 model.

In most of the models, the precision scores are observed higher when tested on the same gender group as the train set.

The recall scores of male-only models often differs for male-only and female-only test sets. In more detail, the difference of recall values between two genders is observed higher in VGG16 model. Surprisingly, male-only trained Resnet18 and Dense121 models' recall values are higher on female-only test sets than male-only test sets. On the other hand, the recall scores of female-only models are drastically different between gender groups. While recall value of female-only model is quite high with female-only test sets, it is dramatically low with male-only test sets. The results indicates that training with female-only data induce an great bias whereas training with male-only models behaves fairer against genders in terms of recall.

The results indicate that Dense Networks are the most robust model against gender bias compared with other pre-trained models used in this study.

Although the same train and test set configuration is used, bias severity changes from models to models. This shows that the choice of models is paramount to mitigate bias effects caused by data.

According to these results, gender unbalanced data X-ray images can cause biased decisions in AI-based diagnosis models.

6. Conclusion and Future Work

Bias in ML algorithms can arise from several reasons existing in training data such as unbalanced class distributions, unrepresentative or incomplete data. ML algorithms usually rely on the collection of information that reflects past inequalities. Hence, an algorithmic bias can occur toward any unfair sight of the data. In this study, we explore a gender bias in the deep learning aided COVID-19 diagnosis of medical images. We identify a gender bias due to the unbalanced medical image data.

The accuracy of decisions made with AI systems is crucial for early treatment of the disease that can affect the rest of the patient's life. In this context, the prediction model must be explainable, transparent, and auditable. To this end, it is very important to examine the erroneous decisions made with AI systems and to improve the model performance.

One of the most important reasons for bias is the imbalance in data. In this study, we explore the gender bias in COVID-19 diagnosis models using chest X-ray images. First, we tried to observe gender bias by performing various analyses of data. Second, we conducted various experiments to measure the effect of gender bias in diagnosis performance. Consequently, our experimental results show that gender-imbalance in medical imaging data produces biased decisions in COVID-19 detection, which affects the diagnosis performance significantly.

The imbalance in data is generally sought in the labels of the samples. It is worth stating that gender information, the subject of this study, is neither a label nor a feature of the sample used by the prediction model, but metadata. For this reason, the adverse impact of gender bias on prediction accuracy has a high potential of being overlooked. Furthermore, it has a worse impact on individuals rather than general prediction accuracy. Although the data is completely balanced in terms of the COVID-19 disease labels, the existing unbalance in the gender of subjects may cause another type of bias.

References

Bolea-Alamanac, B., Bailey, S., Lovick, T., & Scheele, D. (n.d.). Valentino, r.(2018).female psychopharmacologymatters! towardsa sex-specificpsychopharmacology. journal of psychopharmacology, 32 (2), 125-133. https://doi.org/10.1177/0269881117747578.

Bolukbasi, T., Chang, K.-W., Zou, J., Saligrama, V., & Kalai, A. (2016). Man is to computer programmer as woman is to homemaker? debiasing wordembeddings. *arXivpreprintarXiv:1607.06520*.

Cohen, J. P., Morrison, P., Dao, L., Roth, K., Duong, T. Q., & Ghassemi, M. (2020). Covid-19 image data collection: Prospective predictions are thefuture. *arXivpreprintarXiv:2006.11988*.

Dixon, L., Li, J., Sorensen, J., Thain, N., & Vasserman, L. (2018). Measuringand mitigating unintended bias in text classification. *Proceedings of the2018AAAI/ACMConferenceonAI,Ethics,andSociety*,67–73.

Flaugher, R. L. (1978). The many definitions of test bias. *American Psychologist*,*33*(7),671.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for imagerecognition.*Proceedings of the IEEE conference on computer vision andpatternrecognition*,770–778.

Huang, G., Liu, Z., van der Maaten, L., & Weinberger, K. Q. (2017). Denselyconnected convolutional networks. *Proceedings of the IEEE ConferenceonComputerVisionandPatternRecognition(CVPR)*.

Kaushal, A., Altman, R., & Langlotz, C. (2020). Health care ai systems are biased.*ScientificAmerican*.

Kim, B., Kim, H., Kim, K., Kim, S., & Kim, J. (2019). Learning not to learn:Training deep neural networks with biased data. *Proceedings of theIEEE/CVF Conference on Computer Vision and Pattern Recognition*,9012–9020.

Larrazabal, A. J., Nieto, N., Peterson, V., Milone, D. H., & Ferrante, E. (2020).Gender imbalance in medical imaging datasets produces biased classi-fiers forcomputer-aided diagnosis.*Proceedings oftheNationalAcademyofSciences*, *117*(23), 12592–12594.

Mehrabi, N.,Morstatter, F.,Saxena, N.,Lerman, K.,& Galstyan,A. (2019).A surveyonbiasandfairnessinmachinelearning.*arXivpreprintarXiv:1908.09635*.

Nelson, G. S. (2019). Bias in artificial intelligence. *North Carolina medical jour-nal*,*80*(4),220–222.

Olteanu, A., Castillo, C., Diaz, F., & Kıcıman, E. (2019). Social data: Biases,methodological pitfalls, and ethical boundaries. *Frontiersin BigData*, *2*,13.

Pavlovski, M.,Zhou, F.,Arsov, N.,Kocarev, L.,& Obradovic,Z. (2018). Generalization-awarestructured regressiontowards balancingbias andvariance. *IJCAI*,2616–2622.

Prates, M. O., Avelar, P. H., & Lamb, L. C. (2019). Assessing gender bias in machine translation: A case study with google translate. *Neural Com-puting andApplications*,1–19.

Serna, I., Peña, A., Morales, A., & Fierrez, J. (2020). Insidebias: Measuring bias in deep networks and application to face gender biometrics.*arXiv preprintarXiv:2004.06592*.

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks forlarge-scale imagerecognition.*arXivpreprintarXiv:1409.1556*.

Stanovsky, G., Smith, N. A., & Zettlemoyer, L. (2019). Evaluating gender biasinmachinetranslation.*arXivpreprintarXiv:1906.00591*.

Stegbauer,C., Bauer,E., Kartashova,E., &Rausch, A.(2009). *Wikipedia*. Springer.

Suresh,H.,&Guttag,J.V.(2019).Aframeworkforunderstandingunintendedconsequencesofmachine learning.*arXivpreprintarXiv:1901.10002*.

Tan, M., & Le, Q. (2019). Efficientnet: Rethinking model scaling for convolu-tional neural networks. *International Conference on Machine Learning*,6105–6114.

Wang, X., Peng, Y., Lu, L., Lu, Z., Bagheri, M., & Summers, R. M. (2017). Chestx-ray8: Hospital-scale chest x-ray database and benchmarks onweakly-supervisedclassification andlocalization ofcommon thoraxdis-eases. *Proceeding soft he IEEE conference on computer vision and pat-ternre cognition*, 2097–2106.

Zou, J., & Schiebinger, L. (2018). Ai can be sexistand racist—it's time to makeit fair.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Use of SMOTE Method in Histological Staging Problem of Hepatitis-C Disease

Recep Sinan ARSLAN [1], Emre ÖLMEZ [2,*], Orhan ER [3]

[1] *Kayseri University, Dept. of Computer Engineering, Turkey*
[2] *Yozgat Bozok University, Turkey*
[3] *Izmir Bakircay University, Dept. of Computer Engineering, Turkey*

* Corresponding Author: *Yozgat Bozok University*
Tel.: +90 354 217 89 91. E-Mail: emre.olmez@bozok.edu.tr

Publication Information

Keywords :

- Clinical decision support systems,
- Class imbalance,
- Classification,
- SMOTE

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Obtaining the dataset required to classify each stage in the histologically staging problem of Hepatitis C, a liver disease caused by the blood-borne Hepatitis C virus (HCV), is quite difficult as it is in other health problems. In this study, the class imbalance problem that occurs in a sample Hepatitis C disease data has been addressed, and the effect of the use of over-sampling methods on the classification results is shown comparatively. After the original version of the anonymous Hepatitis C disease data taken from an international database was tested with different artificial intelligence methods, the levels in the data sets were balanced and the tests are repeated. When the obtained results were compared, it was seen that a higher classification performance was reached with data balancing. SMOTE, BORDERLINE-SMOTE, ADASYN, SVMSMOTE and SMOTENC techniques have been used to balance the datasets. Classification tests were performed using 11 different methods such as RandomForest, Kneighbors and Logistic Regression, and the results were evaluated according to Accuracy, Precision, Recall and F1 Score metrics. In this study, the effects of the data balancing process on the classifier were examined, and as a result, it was seen that a serious improvement was obtained for the same problem in all metrics.

1. Introduction

Hepatitis C disease is an important health problem that approximately 70 million people around the world are struggling with. In Turkey, almost one out of every 100 people, that is 750 thousand are estimated to be hepatitis C patients. Although today there are treatments that provide complete cure against Hepatitis C, which is an important disease because of liver failure, research studies of different artificial intelligence solutions on the determination of the diagnosis and staging periods are continue and it is seen that they have not reached the desired levels yet [1]. Making wrong decisions in health problems can lead to a number of problems such as the administration of unnecessary and expensive treatments to the patients, avoidance of treatment to patients in need of it, or the application of cures that are not related to the disease. In such cases, clinical decision support systems serve to provide a second opinion to assist healthcare units in practice [2]. Diagnostic tools of lung disease support by decision support system [3-5], recommendation systems in diabetes [6-9] or many studies have been conducted on support systems in hepatitis types [10-12].

Although health data is widely available on the internet, it is often not possible to reach the complete, balanced and unrelated data required for the development of an intelligent support system. In these data distributed as open source, a number of problems may arise due to various reasons such as privacy concerns, incomplete sharing of data, and the inclusion of features that are not valid for a certain user class. If we classify the deficiencies in these datasets, it can be randomly divided into types such as missing some patient data, missing data on certain patients or missing data on a particular feature. Randomly missing patient data among these will reduce the overall dataset size. However, if this decrease does not affect the classification, it can be ignored. Similarly, deleting a certain feature completely will not cause a problem if the remaining properties are sufficient for classification. However, in the last case, the deletion of the data of patients in certain situations will cause bias in the model and non-objective results in classification. For this reason, it will be necessary to perform a preliminary process on the dataset before classification for cases that are not neglected [13].

Unbalanced datasets express the numerical difference in the number of data belonging to different classes. Specific to the data and classification method, clusters need to be rebalanced in order to observe the sample imbalance in classes. Balancing at the data level can also be affecting the dataset from start to finish. It can be done in the form of over-sampling and under-sampling on the basis of data. In the over-sampling process, data in clusters with a small number of samples are increased. Using this method, there is no loss in the original dataset. On the other hand, in under-sampling operation, the number of samples in clusters with more samples than other clusters are reduced. This can result in data loss. At this point, both methods have basic differences.

In this study, the classification levels of the dataset resulting from the the rebalancing of the datasets were determined using the Synthetic Minority Oversampling Techniques (SMOTE), which perform missing value assignments with k-nearest neighbor (KNN) algorithm. Thus, the improvement levels of data balancing methods in the classification process required for determining the stages in Hepatitis C disease have been shown. The effect of the usage levels of different SMOTE methods and the SMOTE process for different classification algorithms on the results are given comparatively.

2. Literature Review

Many studies have been conducted to find solutions to the unbalanced distribution of datasets clusters. In study [14], where simultaneous use of over-sampling and under-sampling methods is recommended to balance in clinical dataset, classification was made using cardio-vascular disease dataset. SMOTE and under-sampling methods are used in cluster architecture. In tests performed with 823 data and 26 features, an improvement of 19.61% and 16.71% was achieved in classification rate with fuzzy logic and regression, respectively.

In a study conducted to observe the effect of different data balancing algorithms on classifiers [15], it was studied with datasets including abdominal pain, hip pain, scrotal pain and asthma exacerbation data obtained from the emergency department. The results were evaluated according to the sensitivity. As a result, classification with Naive Bayes has better results than other algorithms and the performance increase was at the level of 50%.

In the study [16], the use of the SMOTE method was proposed to achieve performance increase for the detection of the deadly virus in the Covid-19 outbreak, and the Outliner-SMOTE technique was used. The results were compared by working with 5 different datasets and evaluated according to f1 score, sensitivity and precision metrics. Outliner-Smote technique provided more performance increase compared to SMOTE and ADASYN.

Based on the fact that early diagnosis is important in the control of malaria, a model that uses machine learning techniques in the diagnosis of malarias is proposed [17]. Using the patient information obtained from Pubmed, classification was made with DVM, RF, Adaboost and GB algorithms and the results were evaluated comparatively. Data imbalance has been corrected with the SMOTE technique. It was stated that the weight of the features in the model changed after the use of Smote, an improvement of 7.3% was achieved in the AUC value, and the increase varied for different classification algorithms.

3. Materials and Methods

3.1 Dataset Description

The Hepatitis-C disease dataset, consisting of 1385 infected patient's records, was collected by the University of California, Faculty of Computer Science researchers and shared anonymously with others over an international database (UCI Repository) [19,21]. When the data examined, 7070 patients, 51% of the dataset, are male, while 678 patients are female. It includes a total of 29 characteristics such as age, gender, fever, nausea/vomiting, headache, diarrhea, fatigue, general bone pane and jaundice. Output according to this data collected for classification purposes to estimate different levels of fibrosis:

- F0 : Fibrosis,
- F1 : Portal fibrosis,
- F2 : Several septa,
- F3 : Many septa
- F4 : Those who do not have cirrhosis

as representing.

3.2 Proposed Model

In order to observe the effects of SMOTE methods on clinical data, a model with a flow diagram was created in Figure-1. In the tests of this model, the Hepatitis-C dataset, on which the classification studies were conducted before, was used [18].

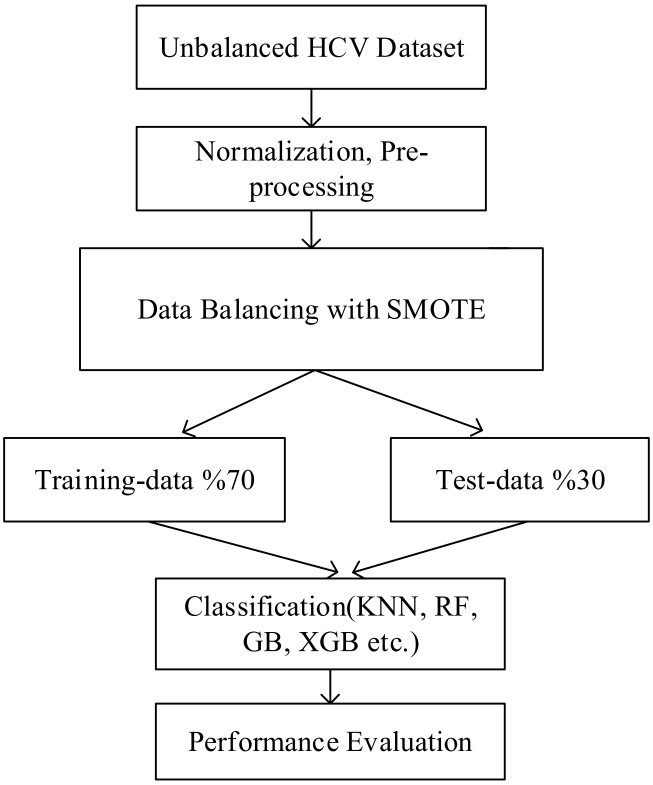


Figure 1 The proposed model for data balancing.

Normalization processes in the data and pre-processes for data editing were applied, before testing the methods in the dataset used in the proposed model. When the classification was made with the data obtain afterwards, it was seen that the classification performance was quite low. Therefore, when the data was analyzed, it led to the conclusion that there was a numerical imbalance between the clusters. While the number of samples belonging to some classes is high, in some classes is less. To find a solution to this, synthetic data were produced using SMOTE method and the clusters were balanced. After this balancing, the data were separated by random sampling method at the rate of 70%-30% for training and testing and tested with different classifiers. All tests were evaluated according to different performance metrics.

In the datasets, if the representation of the classes is not equal, this will affect the classification performance. To find a solution to this problem, balancing is done by reducing the size in classes with a large number of samples or by increasing the size in classes with a small number of samples. As the number of samples is reduced in the balancing approach with size reduction, an advantageous shortening will be achieved in the working time of the model. However, this may cause some valuable data to be lost. On the other hand, when the size is increased, data will not be lost, but there will be an increase in the possibility of overfitting. SMOTE is an over-sampling technique used to reduce this imbalance [21]. For synthetic sample production, the approach of including the closest neighbors in the cluster is performed with the KNN algorithm. First of all, the difference between the sample and the determined neighbor is calculated using the Minkowski distance. This difference value is multiplied by the randomly generated value between 0 and 1 and added to the value of the sample. The biggest advantage of this method is that it can model large and discrete decision regions.

4. Experimental Results

In this study, in order to determine the effect of SMOTE process on HCV health data, tests were carried out with different machine learning techniques. The results obtained are given in Figure-2, and the results obtained before any SMOTE process is performed with blue color. As can be seen in the figure, although it varies according to the classification method, an average of 35% accuracy was achieved without SMOTE.

After this process, the SMOTE process was re-applied 1, 2, 3, 4, 5,7 and 10 times, respectively, and the effect of these operations on the classification was examined. As a result, a significant performance increase was achieved in Kneighbour, RandomForest, DecisionTree, GradientBoosting, ExtraTree, XGB and SVC algorithms, while the same performance was not achieved in Logistic Regression, Gaussian, Linear Discriminant and Ada Boosting methods. These results show the importance of classifier specific to the problem in the use of SMOTE techniques. Therefore, this method does not show the same effect for every classifier.

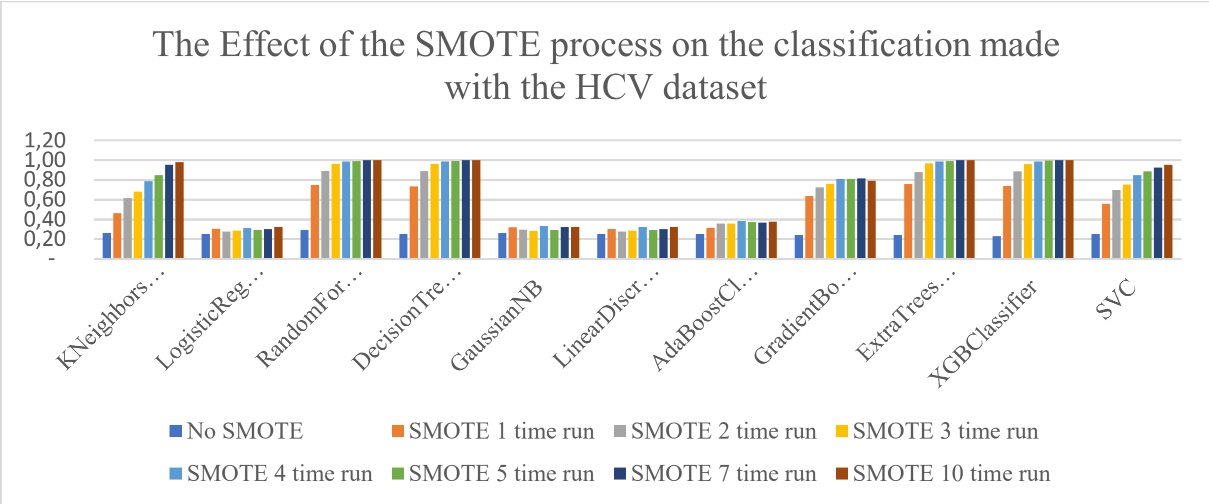


Figure 2 The Effect of the SMOTE process on the classification made with the HCV dataset.

Using the Kneighbors classification algorithm, which is the method with the highest performance increase, tests have been carried out to monitor the improvement in accuracy, sensitivity and F1 score metrics together with the ACC value, and the results obtained are given in Figure-3. When the results were examined, it was seen the SMOTE process provided a remarkable increase in all metrics. This shows that if there is an improvement in accuracy in the use of the SMOTE process on health data, it will also affect other metrics. In this case, it shows that there is not only an improvement in TP value, but also an increase in TN which is very important in clinical studies.

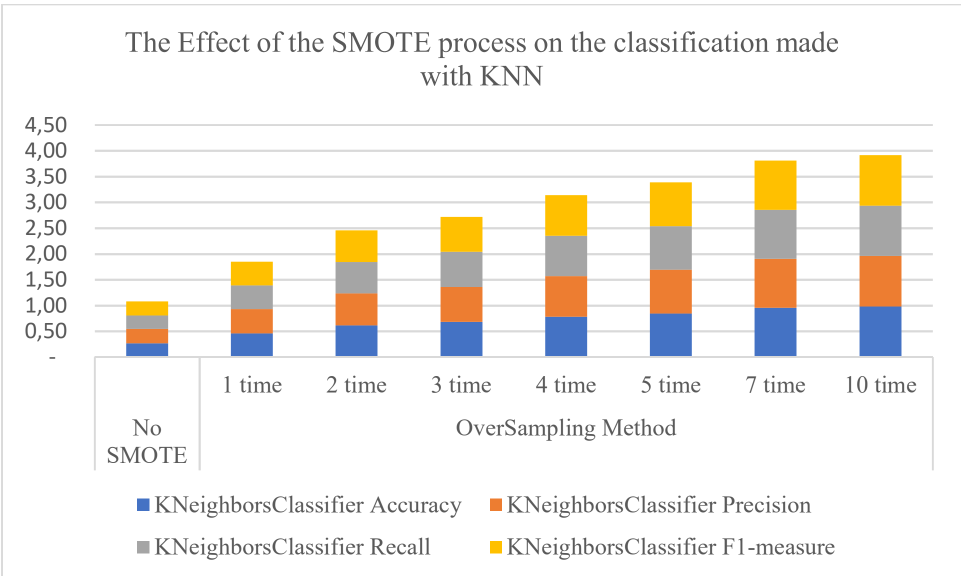


Figure 3 The Effect of the SMOTE process on the classification made with KNN.

There are many different SMOTE algorithms that can be used to balance clusters in Hepatitis-c data. In this study, some of them were selected and their performance contribution levels were tried to be shown. All tests were performed using the KNN classifier, with the best results previously obtained. Figure-4 shows the results related to this. When the graph was examined, it was seen that not all SMOTE techniques showed the same effect, and some even regressed in performance. For this reason, it should be decided correctly which SMOTE technique should be chosen for the problem in data balancing.

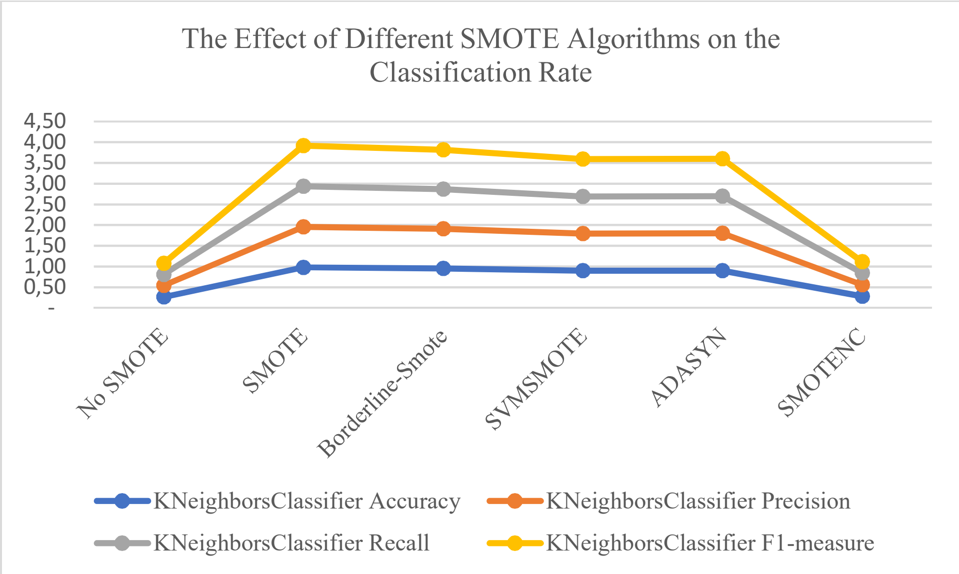


Figure 4 The Effect of Different SMOTE Algorithms on the Classification Rate.

5. Conclusion

In this study, in order to eliminate the imbalance between clusters in clinical data, the use of SMOTE technique, which is one of the synthetic data generation algorithms, and its effect on the results, was studied with different classifiers on Hepatitis C disease data from an international database (UCI-HCV). The data sets are balanced using the KNN algorithm, which works according to the principle of including the closest neighbor samples to the data set. An anonymous Hepatitis C data was used to examine the effect of these procedures on classification performance. As a result, it was concluded that it is important to solve the imbalance between data sets, and that a significant improvement in classification performance can be achieved with the correct choice of SMOTE technique.

References

1. Acıbadem Hastanesi, Online Web Site: https://www.acibadem.com.tr/ilgi-alani/hepatit-c/, Access Date: 13.03.2021.
2. S. Sreejith, H. Nehemiah, A. Kannan, “Clinical data classification using an enhanced SMOTE and chaotic evolutionary feature selection”, Computers in Biology and Medicine, 126, 2020, 1-14.
3. P.Han, S.H. Lee, K.Noro, M. Nakatsugawa, S. Sugiyama, J.Haller, T.R. McNutt, J.Lee, K.R.Voong, R.K. Hales, “Clinical Decision Support System Improves Early Identification of Lung Cancer Patients at High Risk for Significant Weight Loss During Radiotherapy”, International Journal of Radiation Oncology Biology Physics, 108(3), 2020, 124-125.
4. K.M.Atkins, D.S.Bitterman, P.Selesnick, C.Carpenter, R.A.Cormack, R.H.Mak,”Dosimetric Tradeoffs of Mean Heart Dose Reduction Predicted by Machine Learning-Guided Decision Support Software in Lung Cancer”, International Journal of Radiation Oncology Biology Physics, 105(1), 2019,256-257.
5. A. Dekker, S. Winod, L. Holloway, C. Oberije, A. George, G. Goozee, G.P.Delaney, P.Lambin, D. Thwaites,”Rapid learning in practice: a lung cancer survival decision support system in routine patient care data”, Radiotherapy and Oncology, 113(1), 2014, 47-53.
6. C.I.Ossai, N. Wickramasinghe, “Intelligent therapeutic decision support for 30 days readmission of diabetic patients with different comorbidities”, Journal of Biomedical Informatics, 107, 2020, 1-10.

7. S. Piri, D. Delen, T. Liu, H. M. Zolbanin, “A data approach to building a clinical decision support system for diabetic retinepathy: Developing and deploying a model ensemble”, Decision Support Systems, 101, 2017, 12-27.
8. F. Özdemir, A. Ari, M. H. Kilcik, D. Hanbay, İ. Şahin, “Prediction of neuropathy, neuropathic pain and kinesiophobia in patients with type 2 diabetes and design of computerized clinical decision support systems bu using artificial intelligence”, Medical Hypotheses, 143, 2020, 1-4.
9. İ. Özer, “Uzun Kısa Dönem Bellek Ağlarını Kullanarak Erken Aşama Diyabet Tahmini”, Mühendislik Bilimleri ve Araştırma Dergisi, 2, 2, 2020, 50-57.
10. A.B. Jessop, S.B. Bass, J. Brajuha, M. Alhajji, M. Burke, M. T. Gashat, C. Wellington, N. Ventriglia, J. Coleman, P. D’Avanzo, “Take Charge, Get Cured: Pilot testing a target mHealth treatment decision support tool for methodone patients with hepatitis C virus for acceptability and promise of efficacy”, Journal of Substance Abuse Treatment, 109, 2020, 23-33.
11. N. George, A. Liapakis, K. M. Korenblat, T. Li, D. Roth, J. Yee, K. J. Fowler, L. Howard, J. Liu, M. C. Politi, “ A patient decision support tool for hepatitis C virus and CKD Treatment”, Kidney Medicine, 1(4), 2019, 200-206.
12. F. Osmani, M. Ziaee, “Assessment of the risk factors for vitamin D3 deficiency in chronic hepatitis B patient using the decision tree learning algorithm in Birjand”, Informatics in Medicine Unlocked, 23, 2021, 1-6.
13. A. Rogier, T. Donders, G. Heijden, T. Stijnen, K. Moons, “Review: a gentle introduction to imputation of mission values”, Journal of Clinical Epidemiol., 59(10), 2006, 1087-1091.
14. M. Rahman, D. Davis, “Addressing the class imbalance problem in medical datasets”, International journal of machine learning and computing, 3, 2013, 1-6.
15. S. Wilk, J. Stefanowski, S. Wojciechowski, K. Farion, W. Michalowski, “Application of Preprocessing Methods to Imbalanced Clinical data: An Experimental Study”, Conference of Information Technologies in Biomedicine, 2016, 503-515.
16. V. Turlapati, M. Prusty, “Outliner-Smote: A refined oversampling technique for improved detection of COVID-19”, Intelligence-Based Medicine, 3, 2020, 1-10.
17. Y. Lee, J. Choi, E. Shin, “Machine learning model for predicting malaria using clinical information”, Computers in Biology and Medicine, 129, 2021, 1-7.
18. K. Ahammed, S. Satu, I. Khan, M. Whaidduzzaman, “Predicting Infectious State of Hepatitis C Virus Affested Patient’s Appliying Machine Learning Methods, IEEe Region 100 Symposium, 5-7 June 2020, Dhaka, Bangladesh.
19. M. Nasr, H. Bahnasy, M. Hamdy, S. Kamal, “A novel model based on non invasive methos for prediction of liver fibrosis”, 13th International Computer Engineering Conference, Cairo, Egypt, 17 December 2017, 1-6.
20. ICU Machine Learning Repository, Online Web Site: https://archive.ics.uci.edu/ml/datasets/Hepatitis+C+Virus+%28HCV%29+for+Egyptian+patients#, Access Date: 13.03.2021.
21. N. Chawla, K. Bowyer, L. Hall, W. Kegelmeyer, “SMOTE: Synthetic Minority Over-sampling Technique”, Journal of Artificial Intelligence Research, 16, 2002, 321-357.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Artificial Intelligence Approach For Odor Recognition Using Electroencephalogram

Evin ŞAHİN SADIK [1,*], Hamdi Melih SARAOĞLU [1], Sibel CANBAZ KABAY [2], Mustafa TOSUN [3], Gönül AKDAĞ [2]

[1] *Kütahya Dumlupinar University, Faculty of Engineering Dept. of Electrical Electronics Eng., Turkey*
[2] *Kütahya Health Sciences University, Faculty Of Medicine, Dept. Of Neurology Turkey*
[3] *Kütahya Dumlupınar University, Simav Faculty of Technology Dept. of Electrical Electronics Eng., Turkey*

* Corresponding Author: Kütahya Dumlupinar University, Dept. of Electrical Electronics Eng., Turkey
Tel.: +90 274 443 4233. E-Mail: evin.sahin@dpu.edu.tr

Publication Information

Keywords :
- EEG;
- Odor;
- Classification;
- Artificial Intelligence

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

The effects of odor are important not only because of its use in aromatherapy but also because it is a harbinger of neurodegenerative diseases and Covid-19. The idea that such diseases can be detected using artificial intelligence algorithms and Electroencephalogram (EEG) signals has been the motivation of the research and this experimental work was planned as a preliminary study. Within the scope of the study, four different scents (rosemary, lavender, mint and rose) were classified using EEG signals to determine the effects of different odors on brain signals. EEG signals were recorded while the volunteers without any neurological or psychological disease and without a sinonasal pathology sniffed these four essential odors. Four different entropy features were extracted from the EEG signals and the extracted features were evaluated using 3 different artificial intelligence algorithms. Four odors were classified with 96.59% accuracy by KNN, 95.96% by SVM, and 96.98% by CART, respectively.

1. Introduction

The brain and nervous system are highly complex systems. Understanding the behavior and dynamics of brain signals requires knowledge of several signal-processing techniques, from the linear and non-linear domains, and their correlation to the physiological [1]. The process by which olfactory information is perceived by receptors and processed in the brain is one of the most complex processes of the human brain, and many studies are conducted to make sense of these processes. Volatile chemicals diffused from their source are detected by olfactory receptors in the human nose. Each chemical bind to a specific set of receptors and these receptors send signals to the brain to detect the odor with high-level signal processing [2]. Decreased or lost sense of smell is considered a symptom of some neurodegenerative diseases [3,4] and is also associated with the recently spreading Covid-19 infection [5].

Looking at previous studies, it has been observed that the researchers investigated the relationship between olfactory perception and Electroencephalogram (EEG) from different perspectives. Owing to a crucial development in data science and artificial intelligence, in recent years, studies have been carried out about the classification and determination of the effects of odors on brain signals. In some of these studies were investigated how much the complexity of the odor affects the respiratory system [6]. Also, some studies that evaluated the effect of different levels of odor on EEG signals have been investigated [7,8]. In other studies, which were conducted to distinguish good and bad smells from EEG signals [9-11]. In another study, while evaluating the odors, subjective opinions were asked and the odors were scored as pleasant and unpleasant [2]. However, the olfactory perception of the human brain has not been fully analyzed yet. Therefore, novel studies are needed to understand the response of the human brain to odors, regardless of whether odors are perceived as good or bad.

In this study, thirty volunteers sniffed four odors (rosemary, rose, lavender, and peppermint) without separating them as good or bad, and the volunteers' EEG signals were recorded. Entropy features were extracted from the recorded signals and the signals were classified using commonly used artificial intelligence algorithms. After the introduction, in section two material and methods are explained. Findings were discussed in the 3 part of the study, and the results were evaluated in the last part of the study.

2. Material and Method

Within the scope of this study, thirty nonsmoking volunteers without any neurological, psychological or sinonasal pathology were included in the study. Ethics committee approval of the study was obtained from Kütahya Health Sciences University Clinical Research Ethics Committee. EEG signals were recorded with a 16-channel Nihon Kohden device with a sampling frequency of 500 Hz. The general block diagram of this study is given in Figure 1. As can be seen from the figure, the study consists of 4 fundamental steps. These are EEG data acquisition, signal preprocessing, feature extraction and artificial intelligence. The paradigm applied to the volunteer during the EEG Data Acquisition phase is as: Eyes opened (15 sec), eyes closed (15sec), eyes opened (15 sec), applying odor (5 sec) and after each odor, the smell of coffee was sniffed by the volunteers and the room was ventilated during the break time. This process was repeated twice for each odor which was rosemary, lavender, peppermint and rose, respectively and EEG signals were recorded.

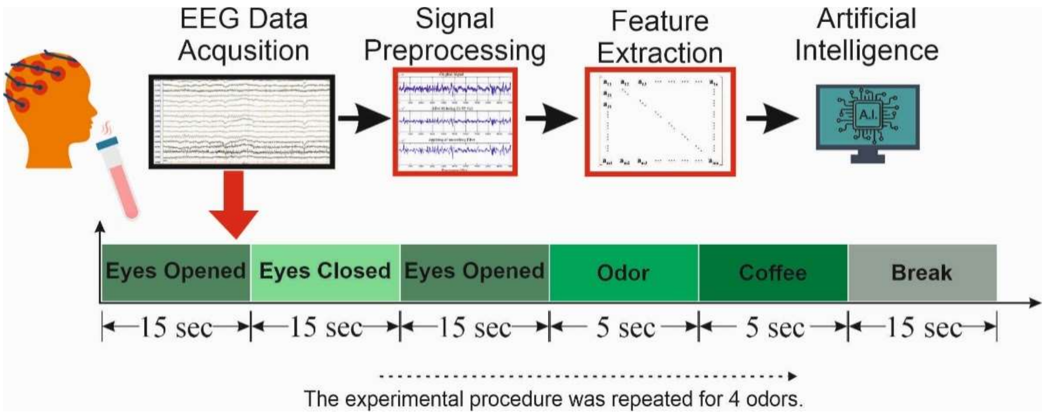


Figure 1. Block diagram of the experiment

A 50 Hz notch filter was applied to the recorded EEG signals in the preprocessing stage to remove line noise and Independent Component Analysis (ICA) [12] was applied to remove eye movement artifacts. In addition, each channel of EEG signal was augmented using the amplifying all-time data method [13,14]. In the feature extraction phase, the signal Butterworth band-pass filters are used to divide each channel of EEG signal into five frequency sub-bands: delta, theta, alpha and beta and gamma waves. The extracted features are Approximate Entropy [15], Permutation Entropy [16], Spectral Entropy [17], and Sample Entropy [18]. Twenty-four entropy features were extracted for each odor, being from the entire signal and each sub-band. The extracted features were separated 80% as training and 20% as testing and classified with 3 different artificial intelligence algorithms which are K-Nearest Neighbors (KNN) [19], Classification And Regression Trees (CART) [20] and Support Vector Machine (SVM) [21].

3. Results

The extracted entropy features were found to be distinctive for 4 odors. Training network validation results for three classification algorithms are shown in Figure 2. All results shown in Figure 2 were obtained using five-fold cross-validation. The data set is divided into three groups. 60% of the data set was used to train the network. 20% of the data were used as stopping criteria for the validation set, and 20% of the test data was used to calculate the final classification accuracy. Figure 2 shows that all three classification algorithms have high cross-validation accuracy scores (>90%). The KNN algorithm has the highest mean accuracy of 91.8% of the five-fold cross-validation scores with a standard deviation of 0.98%. Moreover, the CART and SVM algorithms have a mean accuracy of 90.2% and 90.3%, standard deviation of 0.79% and 0.59%, respectively.

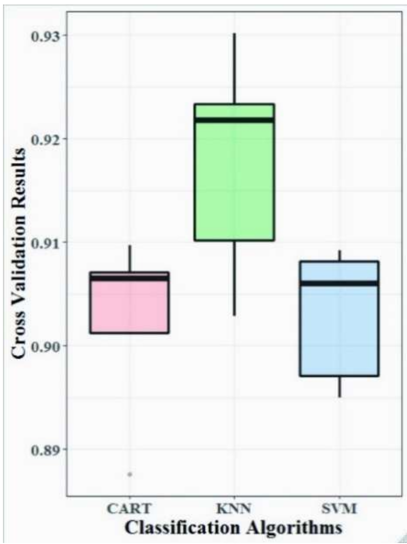


Figure 2. Cross validation results

The confusion matrix obtained using all entropy attributes and 4 odor classes is given in Table 2. Along diagonals for three classification algorithms shows correct classifications, all other entries indicate incorrect classifications. The confusion matrix values were used in computing the performance criteria of the classification which are accuracy, sensitivity, F1 score and precision.

Table 1. Confusion matrix for all classes.

	SVM				KNN				CART			
	Rosemary	Lavender	Peppermint	Rose	Rosemary	Lavender	Peppermint	Rose	Rosemary	Lavender	Peppermint	Rose
Rosemary	575	9	6	11	574	9	9	9	583	9	6	3
Lavender	26	572	9	6	15	586	3	9	9	580	18	6
Peppermint	2	4	589	7	0	0	596	6	3	3	596	0
Rose	9	7	0	549	9	9	3	544	9	6	9	541

Test results evaluation results for three classification algorithms are as given in Table 2. As can be seen from Table 2, an average sensitivity of 96,5%, a precision of 96,58%, an accuracy of 96,51% were obtained in this study with entropy features. These results show that the entropy features of odor can be successfully distinguished from EEG data in this study.

Table 2. Classification algorithms results

	KNN	SVM	CART
Accuracy	%96,59	%95,96	%96,98
Sensitivity	%96,75	%96,00	%96,75
F1 Score	%96,50	%96,00	%96,50
Precision	%96,75	%96,25	%96,75

4. Conclusion and Evaluation

This paper has investigated and compared three artificial intelligence algorithms to distinguish odors from EEG signals using entropy features. According to the experimental results, essential odors could be classified with high performance from EEG signals using multi-class artificial intelligence algorithms. Four odors were classified with 96.59% accuracy by KNN, 95.96% by SVM, and 96.98% by CART, respectively. With the results of this study, it is concluded that entropy features can be used distinctively in the classification of odors and it has been observed that the brain gives different responses to different odors during the olfactory activity, and these responses can be distinguished from EEG signals with entropy features.

ACKNOWLEDGEMENT

This study was supported by the Scientific Research Projects of Kütahya Dumlupınar University within the scope of the project numbered 2020/26. Also, it was conducted by researchers at Kütahya Dumlupınar University Neurotechnology Education Application and Research Center.

References

[1] N. Kannathal, M. L. Choo, U. R. Acharya, and P. K. Sadasivan, “Entropies for detection of epilepsy in EEG,” *Comput. Methods Programs Biomed.*, vol. 80, no. 3, pp. 187–194, 2005, doi: 10.1016/j.cmpb.2005.06.012.

[2] K. Ezzatdoost, H. Hojjati, and H. Aghajan, “Decoding olfactory stimuli in EEG data using nonlinear features: A pilot study,” *J. Neurosci. Methods*, vol. 341, p. 108780, 2020.

[3] G. Kjelvik *et al.*, “The Human Brain Representation of Odor Identification in Amnestic Mild Cognitive Impairment and Alzheimer’s Dementia of Mild Degree,” *Front. Neurol.*, vol. 11, no. January, pp. 1–12, 2021, doi: 10.3389/fneur.2020.607566.

[4] S. Rahayel, J. Frasnelli, and S. Joubert, “The effect of Alzheimer’s disease and Parkinson’s disease on olfaction: a meta-analysis,” *Behav. Brain Res.*, vol. 231, no. 1, pp. 60–74, 2012.

[5] Z. M. Soler, Z. M. Patel, J. H. Turner, and E. H. Holbrook, “A primer on viral-associated olfactory loss in the era of COVID-19,” *Int. Forum Allergy Rhinol.*, vol. 10, no. 7, pp. 814–820, 2020, doi: 10.1002/alr.22578.

[6] H. Namazi, A. Akrami, and V. V. Kulish, “The Analysis of the Influence of Odorant’s Complexity on Fractal Dynamics of Human Respiration,” *Sci. Rep.*, vol. 6, no. May, pp. 1–9, 2016, doi: 10.1038/srep26948.

[7] M. W. Ho, W. Ser, B. F. L. Sieow, M. O. Lwin, and K. F. K. Kwok, “A study of EEG signals modeling for different scent intensity levels,” in *2013 6th International IEEE/EMBS Conference on Neural Engineering (NER)*, 2013, pp. 1445–1448.

[8] M. Laha, L. Ghosh, S. Parui, S. Ghosh, and A. Konar, “Evaluation of Density Based Odor Classification by General Type-2 Fuzzy Set Induced Pattern Classifier,” *2018 Int. Conf. Wirel. Commun. Signal Process. Networking, WiSPNET 2018*, 2018, doi: 10.1109/WiSPNET.2018.8538634.

[9] E. Kroupi, A. Yazdani, J.-M. Vesin, and T. Ebrahimi, “EEG correlates of pleasant and unpleasant odor perception,” *ACM Trans. Multimed. Comput. Commun. Appl.*, vol. 11, no. 1s, pp. 1–17, 2014.

[10] M. A. Becerra *et al.*, “Odor pleasantness classification from electroencephalographic signals and emotional states,” in *Colombian Conference on Computing*, 2018, pp. 128–138.

[11] N. I. Abbasi, R. Bose, A. Bezerianos, N. V. Thakor, and A. Dragomir, "EEG-Based Classification of Olfactory Response to Pleasant Stimuli," *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS*, pp. 5160–5163, 2019, doi: 10.1109/EMBC.2019.8857673.

[12] R. Vigârio, J. Särelä, V. Jousmäki, M. Hämäläinen, and E. Oja, "Independent component approach to the analysis of EEG and MEG recordings," *IEEE Trans. Biomed. Eng.*, vol. 47, no. 5, pp. 589–593, 2000, doi: 10.1109/10.841330.

[13] E. Lashgari, D. Liang, and U. Maoz, "Data augmentation for deep-learning-based electroencephalography," *J. Neurosci. Methods*, vol. 346, no. July, p. 108885, 2020, doi: 10.1016/j.jneumeth.2020.108885.

[14] A. Sakai, Y. Minoda, and K. Morikawa, "Data augmentation methods for machine-learning-based classification of bio-signals," *BMEiCON 2017 - 10th Biomed. Eng. Int. Conf.*, vol. 2017-Janua, pp. 1–4, 2017, doi: 10.1109/BMEiCON.2017.8229109.

[15] S. M. Pincus, "Approximate entropy as a measure of system complexity," *Proc. Natl. Acad. Sci. U. S. A.*, vol. 88, no. 6, pp. 2297–2301, 1991, doi: 10.1073/pnas.88.6.2297.

[16] C. Bandt, "Ordinal time series analysis," *Ecol. Modell.*, vol. 182, no. 3–4, pp. 229–238, 2005, doi: 10.1016/j.ecolmodel.2004.04.003.

[17] I. A. Rezek and S. J. Roberts, "Stochastic complexity measures for physiological signal analysis," *IEEE Trans. Biomed. Eng.*, vol. 45, no. 9, pp. 1186–1191, 1998.

[18] J. S. Richman and J. R. Moorman, "Physiological time-series analysis using approximate entropy and sample entropy maturity in premature infants Physiological time-series analysis using approximate entropy and sample entropy," *Am. J. Physiol. Hear. Circ. Physiol.*, vol. 278, pp. H2039–H2049, 2000.

[19] M. Cover T and E. Hart P, "Nearest Neighbor Pattern Classification," *IEEE Trans. Inf. Theory*, pp. 1–12, 1967.

[20] L. Breiman, J. Friedman, C. J. Stone, and R. A. Olshen, *Classification and regression trees*. CRC press, 1984.

[21] C. Cortes and V. Vapnik, "Support-vector networks," *Mach. Learn.*, vol. 20, no. 3, pp. 273–297, 1995.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Exploring Comorbidities in ICU with Association Rule Learning

Zeliha ERGUL AYDIN [1,*], Zehra KAMISLI OZTURK [1]

[1] *Eskisehir Technical University, Dept. of Industrial Engineering, Turkey*

* Corresponding Author: *Eskisehir Technical University*, *Dept. of Industrial Engineering*, Turkey
Tel.: +90 (0222) 321 35 50. E-Mail: zergul@eskisehir.edu.tr

Publication Information

Keywords :

- Data mining,
- Association rule learning,
- Comorbidity

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

The length of stay, readmission, and mortality rate of intensive care unit patients are all affected by comorbidities. Discovering the comorbidities of disease is important for the treatment plan. This study aims to explore medical comorbidities in the intensive care unit patients' data with association rule learning. We applied the Apriori algorithm on 42175 ICU patients and their disease to explore medical comorbidities. We found nine rules with the specified threshold. Congestive heart failure, renal failure, and hypertension had the highest association with 8.5% support and 84.1% confidence. Our findings also showed that hypertension is the most common comorbidity in the intensive care unit.

1. Introduction

Comorbidity is defined as the presence of multiple disease in the same person [1]. Comorbidities increase the complexity of treatment, reduces the patient's quality of life, and also increase healthcare cost. Furthermore, comorbidities play a key role in intensive care unit (ICU) patients' length of stay, readmission, and mortality risk. With the increase in electronic health records availability, researchers who can access large-scale medical databases can find comorbidity more accurately. One of the most effective methods for discovering the relationship between diseases in large databases is Association Rule Learning.

Tai and Chui [2] applied association rule learning to Taiwan National Health Insurance Research Database for exploring the attention-deficit/hyperactivity disorder's comorbidities. Wang et al. [3] also used association rule mining to explore the comorbidities of psychological disorders. Held et al. [4] investigated the prevalence of multimorbidity and comorbidity in an older population with association rule learning. Lakshmi and Vadivu [5] proposed a weighted association rule learning algorithm for predicting comorbidities in protein-protein interaction data, Pathway data, and Gene Ontology annotation data. Although many studies focus on a specific disease or group of patients, there are a limited number of studies focusing on discovering comorbidities in intensive care units. Hyuna and Newton [6] explored comorbidities in ICU patients with a hospital-acquired pressure injury.

Sülekli [7] applied association rule learning to reveal the most common diagnoses and rules in patients who died in intensive care units. As far as we know, there is no study that explores comorbidities in the intensive care unit by considering all intensive care unit patients to Accordingly, we aim to explore medical comorbidities in all intensive care unit patients' data with association rule learning. For this, we use 42175 ICU patients and their disease diagnoses from the Medical Information Mart for Intensive Care (MIMIC-III) database [8] retrospectively and the Apriori algorithm. The rest of the article is laid out as follows. Section 2 briefly explains dataset characteristics and the Apriori algorithm used in this study. Section 3 presents the result of the Apriori Algorithm and discussions. Finally, Section 4 provides the conclusion and future works.

2. Material and Methods

Medical Information Mart for Intensive Care (MIMIC-III)[8] database includes data like demographic information, vital signs, laboratory tests, medical notes, diagnoses, medications, etc. Data of 46520 patients are stored in 26 different tables as a relational format. In the database, disease diagnoses were recorded according to ICD-9 (International Classification of Disease), which is a universal coding system. We used PostgreSQL to take patients' diagnoses from tables for finding comorbidities in ICU. When determining the diseases to be analyzed, we excluded the first digit of the ICD-9 codes 'E' and 'V' letters that related to injuries. After this procedure, 42175 patients remained in the data set. Apriori algorithm, one of the association rule learning algorithms, was used to extract the comorbidities in ICU.

Association rule learning is a rule-based data mining technique that finding the relationships between variables frequently used together in large databases. Apriori algorithm, the most commonly used association rule algorithm, was developed by Agrawal and Srikant in 1994 [9]. Relationships between variables are evaluated according to support and confidence value in this algorithm. In this study, the support value is calculated by Equation 1, and the confidence is calculated by Equation 2, where N is the number of patients, X and Y represent disease. The support is the frequency of the coexistence of disease set, and the confidence is the frequency disease Y appears in a disease set that contains disease X.

$$Support(X \rightarrow Y) = \mathrm{P}(\mathrm{X} \cap Y) = \frac{Frequency(X,Y)}{N} \qquad (1)$$

$$\text{Confidence } (\mathrm{X} \rightarrow \mathrm{Y}) = \mathrm{P}(\mathrm{Y}|\mathrm{X}) = \frac{Frequency(X,Y)}{Frequency(X)} \qquad (2)$$

4. Results and Discussions

Table 1 shows the results of the Apriori with 6% as a support threshold and 70% as a confidence threshold. We found nine association rules with the specified threshold information. Congestive heart failure, renal failure, and hypertension had the highest confidence with 8.5% support and 84.1% confidence. This also means that the probability that congestive heart failure, renal failure, and hypertension coexist is 0.085. Besides, when it is known that patients have congestive heart failure and renal failure, the probability of patients having hypertension is 0. 841. Renal failure and hypertension had the second highest confidence with 16.1% support and 83.8% confidence. These findings support that Osuji et al. [10] and Lee et al. [11], respectively. Hypertension, included in all nine rules, is the most common comorbidity in intensive care units.

Table 1. Results of the Apriori algorithm.

Rules	Support (%)	Confidence(%)
{'renal_failure', 'congestive_heart_failure'} -->{'hypertension'}	8.5	84.1
{'renal_failure'} -->{'hypertension'}	16.1	83.8
{'renal_failure', 'fluid_electrolyte'} -->{'hypertension'}	6.8	83.3
{'renal_failure', 'cardiac_arrhythmias'} -->{'hypertension'}	6.6	82.5
{'diabetes_complicated'} -->{'hypertension'}	6.8	76.3
{'diabetes_uncomplicated'} -->{'hypertension'}	17.9	73.1
{'diabetes_uncomplicated', 'cardiac_arrhythmias'} -->{'hypertension'}	6.2	72.9
{'peripheral_vascular'} -->{'hypertension'}	9.3	72.8
{'congestive_heart_failure', 'diabetes_uncomplicated'} -->{'hypertension'}	6.5	72.2

5. Conclusion

This paper reveals medical comorbidities in intensive care unit patients' data with the Apriori algorithm. This study's finding shows most common comorbidity in ICU is hypertension. In addition, the discovered association rules support existing studies. As future work, we plan to use these findings of comorbidity information in ICU length of stay and mortality prediction.

Acknowledgement

This study is supported by Eskisehir Technical University Scientific Research Projects Committee (ESTUBAP-20DRP025).

References

1. William, M. K.(2002),Comorbidity, Editor(s): Michel Hersen, William Sledge, Encyclopedia of Psychotherapy, Academic Press, 2, 475-479,https://doi.org/10.1016/B0-12-343010-0/00053-2.
2. Tai, Y.M., Chiu, H.W. (2009). Comorbidity study of ADHD: Applying association rule mining (ARM) to National Health Insurance Database of Taiwan, *International Journal of Medical* Informatics, *78 (12),* 75-83, https://doi.org/10.1016/j.ijmedinf.2009.09.005
3. Wang, C. H., Lee, T. Y., Hui, K. C., & Chung, M. H. (2019). Mental disorders and medical comorbidities: Association rule mining approach. *Perspectives in psychiatric care, 55(3),* 517–526. https://doi.org/10.1111/ppc.12362
4. Held,F.P.,Blyth, F., Gnjidic,D., Hirani, V., Naganathan,V.,Waite, L.M.,Seibel, M. J., Rollo, J., Handelsman, D. J., Cumming, R. G. &Le Couteur, D. G. (2016). Association Rules Analysis of Comorbidity and Multimorbidity: The Concord Health and Aging in Men Project, *The Journals of Gerontology: Series A, 71(5),* 625–631, https://doi.org/10.1093/gerona/glv181
5. Lakshmi, K.S., Vadivu, G. (2019). A novel approach for disease comorbidity prediction using weighted association rule mining. *J Ambient Intell Human Comput.* https://doi.org/10.1007/s12652-019-01217-1
6. Hyun, S., & Newton, C. (2019). Comorbidity Analysis on ICU Big Data. International Journal of Advanced Culture Technology, 7(2), 13–18. https://doi.org/10.17703/IJACT.2019.7.2.13
7. Sülekli, E. (2019). Yoğun Bakım Ünitelerinde Yatan Hastalara İlişkin Mortalite ve Yatış Süresine Etki Eden Faktörlerin Veri Madenciliği Yöntemleriyle İncelenmesi,Yoğun Bakım Ünitelerinde Yatan Hastalara İlişkin Mortalite ve Yatış Süresine Etki Eden Faktörlerin Veri Madenciliği Yöntemleriyle İncelenmesi (Master's thesis, Hacettpe University, Ankara, Turkey).

8. Johnson, A., Pollard, T., Shen, L. et al. MIMIC-III, a freely accessible critical care database. *Sci Data 3,* 160035 (2016). https://doi.org/10.1038/sdata.2016.35
9. Agrawal,R., Srikant R. (1994) .Fast algorithms for mining association rules,J.B. Bocca, M. Jarke, C. Zaniolo (Eds.), *Proceedings of the 20th international conference on very large data bases (VLDB'94),* Morgan Kaufmann, Los Altos, CA, 487-499.
10. Osuji, C. U., Nwaneli, C. U., Onwubere, B. J., Onwubuya, E. I., & Ahaneku, G. I. (2012). Renal function in patients with hypertension associated congestive cardiac failure seen in a tertiary hospital. *International journal of nephrology*, 769103. https://doi.org/10.1155/2012/769103
11. Lee, W. C., Lee, Y. T., Li, L. C., Ng, H. Y., Kuo, W. H., Lin, P. T., Liao, Y. C., Chiou, T. T., & Lee, C. T. (2018). The Number of Comorbidities Predicts Renal Outcomes in Patients with Stage 3⁻5 Chronic Kidney Disease. *Journal of clinical medicine, 7(12),* 493. https://doi.org/10.3390/jcm7120493

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

The Distracting Intervention of Virtual Reality in Healthcare: A Current Review

Arzu USLU [1,*], Selda ARSLAN [1]

[1] *Necmettin Erbakan University, Faculty of Nursing, Department of Internal Medicine Nursing, Konya, Turkey*

* Corresponding Author: Necmettin Erbakan University, Faculty of Nursing, Department of Internal Medicine Nursing, Konya, Turkey.

Tel.: +90 0332 320 40 49 E-Mail: arzu.uslu86@gmail.com

Publication Information

Keywords :

- Health
- Virtual reaility
- Distraction

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Virtual reality applications, which are products of artificial intelligence, have recently become desired and sought by everyone. Virtual reality applications make the individual feel that they are in the virtual environment by moving them away from the existing environment. Thus, by distracting attention to the virtual environment, it removes the individual from negative emotions, thoughts and feelings. Considering this feature, it is seen that today it is used a lot in terms of distraction patients' attention to another direction in the field of health. The purpose of this review is to evaluate the usage areas of virtual reality applications in randomized controlled studies published in the field of health. It is seen that it is used in the fields of virtual reality application; before dental surgery, peripheral intravenous catheterisation, intramuscular injection, postoperative nasal endoscopy and debridement, hemodialysis fistula cannulation, daily dressing change, endoscopic urological surgery, outpatient hysteroscopy, thermal pain and symptom management in breast cancer patients. In these studies, it has been reported that the virtual reality application distracts the patients' attention and reduces the pain, stress and anxiety of the patients, and increases their satisfaction and quality of life. In these studies, it was reported that virtual reality applications, which are a distracting method, are effective, have no side effects, are noninvasive and useful when compared to standard care or other interventions. For this reason, it is thought that it would be beneficial to use virtual reality applications by health professionals as a method of distracting attention.

1. Introduction

Virtual Reality (VR) technology is a product of Artificial Intelligence (AI). Virtual Reality allows the user to move virtual objects, access information, use their calculating ability, and feel like they are in a world-like environment with virtual sounds (Zheng, Chan, & Gibson, 1998). Virtual Reality is defined as a human-computer interface that makes one feel like one is in another world. With its three-dimensional display and motion-sensing technology, VR stimuli are distracting (Nwosu et al., 2021). All VR stimuli illicit real-world responses through a headset, a head-mounted device that provides VR for the wearer. The headset helps the wearer focus their attention on the image they watch and makes them feel like they are in another world. Therefore, the virtual environment with augmented reality results in distraction (Erdogan &

Ozdemir, 2021; Le May et al., 2021; Trost, France, Anam, & Shum, 2021). In fact, immersive VR is better at distracting the user than non-immersive VR (Malloy & Milling, 2010).

Distraction methods are cognitive behavioral therapy techniques that include approaches to cognitive skills. Distraction affects thoughts and feelings. Consequently, cognitive psychology improves behavioral methods and problem-solving skills (Özcan & Çelik, 2017). Based on the principle of "here and now," distraction enables the user to enter another environment from the one they are actually in (Malloy & Milling, 2010). Some distraction methods are listening to music or poetry, painting, watching TV, solving puzzles, daydreaming, performing relaxation techniques, watching movies, doing meditation or yoga, praying, and using VR technology (Özcan & Çelik, 2017; Trost et al., 2021). Research shows that VR can be used as a distraction method. Those studies show that VR helps users manage symptoms of depression (Trost et al., 2021), anxiety (Lahti, Suominen, Freeman, Lähteenoja, & Humphris, 2020; Mohammad & Ahmad, 2019), fatigue (Malloy & Milling, 2010) and pain (Basak, Duman, & Demirtas, 2020; Patterson et al., 2021; Trost et al., 2021). Therefore, VR technology can be used as a distraction method to manage symptoms and to maintain health (Le May et al., 2021; Trost et al., 2021). Virtual Reality is also used medically because it is an affordable and non-invasive technology with no side effects. It also motivates the user and makes them feel good (Lahti et al., 2020; Trost et al., 2021). This review looked into the areas and impacts of VR applications and distraction interventions in current studies in the field of health.

2. Current Examples of Virtual Reality's Distracting Intervention Practices in Healthcare

The review shows that the VR-based distraction method is used for dental surgery (Lahti et al., 2020), peripheral intravenous administration (Basak et al., 2020), intramuscular administration of benzathine penicillin injection (Basak, Demirtas, & Yorubulut, 2021), postoperative endoscopy and debridement application (Gray et al., 2021), cannula insertion into the hemodialysis fistula (Ghadimi Aghbolagh et al., 2020), daily dressing change in surgery patients with hemorrhoid (Ding et al., 2019), spinal endoscopic urological surgery under anesthesia (Moon et al., 2019), outpatient hysteroscopy (Deo et al., 2021), thermal pain (Patterson et al., 2021) and symptom management in patients with breast cancer (Mohammad & Ahmad, 2019).

The review shows that many studies involve VR-based distraction interventions in different areas. Lahti et al. (2020) reported that patients who received VR-based distraction experienced less anxiety than those who received standard care before dental surgery (Lahti et al., 2020). Basak, Duman, and Demirtas (2020) also looked into the impact of and patient satisfaction with VR-based distraction methods for the relief of pain associated with peripheral intravenous catheter insertion. They used standard care, optical illusion cards, and underwater 3D audio videos. They concluded that the distraction cards and VR-based distraction reduced pain levels and increased patient satisfaction (Basak et al., 2020). Basak, Demirtas, and Yorubulut (2020) found that 3D videos (VR-based distraction) and distraction cards helped patients experience less pain during intramuscular benzathine penicillin injection procedures and made them more satisfied with the intervention. The researchers also stated that the patients were more satisfied with the VR-based distraction than the distraction cards (Basak et al., 2021). Gray et al. (2021) conducted a randomized controlled trial on VR-based distraction to assess pain, anxiety, and satisfaction levels in outpatients undergoing outpatient postoperative nasal endoscopy and debridement. They concluded that the VR-based distraction method showed a safe analgesic and anxiolytic effect, with which most patients were satisfied (Gray et al., 2021). Ghadimi Aghbolagh, et al. (2020) determined that visual and auditory distractions reduced the severity of fistula cannulation pain in older patients undergoing hemodialysis. They also reported that visual distraction was better at reducing pain than auditory distraction (Ghadimi Aghbolagh et al., 2020). Ding et al. (2019) conducted a randomized controlled trial to determine the impact of immersive VR distraction on pain before, during, and after dressing in patients who underwent hemorrhoid surgery. They found that patients who received immersive VR distraction experienced less pain than controls. According to the researchers, although there was no significant difference in heart rate and oxygen saturation between the two groups, VR distraction was an effective method for reducing pain (Ding et al., 2019). Moon et al. (2019) determined that patients who received VR distraction were more satisfied with spinal anesthesia than sedation during endoscopic urological surgery. They also reported that the distraction group had a lower incidence of apnea and was more satisfied with spinal anesthesia because it did not have the side effects which sedation had (Moon et al., 2019). Another recent study reported that immersive VR reduced pain and anxiety in patients who underwent outpatient hysteroscopy and concluded that immersive VR was an effective distraction method (Deo et al., 2021). Patterson et al. (2021) conducted a randomized controlled trial and detected that VR- (Snow World) and hypnosis-based distraction effectively reduced thermal pain. They gave patients as much heat as they could tolerate (the highest temperature was 48 °C at least 30 seconds) with a thermostat with a safe temperature rise option. According to their results, hypnosis alone was less effective, but VR with hypnosis effectively reduced pain (Patterson et al., 2021). Mohammad and Ahmad (2019) found that VR-based distraction helped patients with breast cancer experience significantly less pain and anxiety. They also reported that immersive VR, as an adjuvant intervention, was more effective than morphine in relieving pain and anxiety and was much safer than pharmacological treatment (Mohammad & Ahmad, 2019).

Visual and auditory VR-based distractions used in all these current studies were the beach, waterfall, space, rowing (Lahti et al., 2020), underwater (Aqua) (Basak et al., 2021; Basak et al., 2020; Lahti et al., 2020; Moon et al., 2019), a VR game called SpaceBurgers (JunoVR) (Gray et al., 2021), animal images, natural and eye-catching visuals, and auditory videos, such as river, waterfall, and forest sounds, and bird songs (Ghadimi Aghbolagh et al., 2020), Snow World, which is an immersive VR software (Ding et al., 2019; Patterson et al., 2021), Forest of Serenity (Deo et al., 2021), sitting on the beach (Happy Place), and diving underwater (Ocean Rift) (Mohammad & Ahmad, 2019).

3. Conclusion and Evaluation

These current reviews show that VR-based distraction is an effective method that reduces anxiety, pain, and stress and increases patient satisfaction. Compared to standard care and/or other interventions, VR-based distraction is a helpful method that can be used in the medical field. Virtual Reality is a safe distraction method because it is noninvasive and has no side effects. We recommend that healthcare professionals incorporate VR technology into standard care.

References

Basak, T., Demirtas, A., & Yorubulut, S. M. (2021). Virtual reality and distraction cards to reduce pain during intramuscular benzathine penicillin injection procedure in adults: A randomized controlled trial. *Journal of Advanced Nursing*(00), 1-8.

Basak, T., Duman, S., & Demirtas, A. (2020). Distraction-based relief of pain associated with peripheral intravenous catheterisation in adults: a randomised controlled trial. *Journal of clinical nursing, 29*(5-6), 770-777.

Deo, N., Khan, K. S., Mak, J., Allotey, J., Gonzalez Carreras, F. J., Fusari, G., & Benn, J. (2021). Virtual reality for acute pain in outpatient hysteroscopy: a randomised controlled trial. *BJOG: An International Journal of Obstetrics & Gynaecology, 128*(1), 87-95.

Ding, J., He, Y., Chen, L., Zhu, B., Cai, Q., Chen, K., & Liu, G. (2019). Virtual reality distraction decreases pain during daily dressing changes following haemorrhoid surgery. *Journal of International Medical Research, 47*(9), 4380-4388.

Erdogan, B., & Ozdemir, A. A. (2021). The effect of three different methods on venipuncture pain and anxiety in children: Distraction cards, virtual reality, and Buzzy®(randomized controlled trial). *Journal of Pediatric Nursing*.

Ghadimi Aghbolagh, M., Bahrami, T., Rejeh, N., Heravi-Karimooi, M., Tadrisi, S. D., & Vaismoradi, M. (2020). Comparison of the Effects of Visual and Auditory Distractions on Fistula Cannulation Pain among Older Patients Undergoing Hemodialysis: A Randomized Controlled Clinical Trial.

Gray, M. L., Goldrich, D. Y., McKee, S., Schaberg, M., Del Signore, A., Govindaraj, S., & Iloreta, A. M. (2021). Virtual reality as distraction analgesia for office-based procedures: a randomized crossover-controlled trial. *Otolaryngology–Head and Neck Surgery, 164*(3), 580-588.

Lahti, S., Suominen, A., Freeman, R., Lähteenoja, T., & Humphris, G. (2020). Virtual Reality Relaxation to Decrease Dental Anxiety: Immediate Effect Randomized Clinical Trial. *JDR Clinical & Translational Research, 5*(4), 312-318.

Le May, S., Tsimicalis, A., Noel, M., Rainville, P., Khadra, C., Ballard, A., . . . Chougui, K. (2021). Immersive virtual reality vs. non-immersive distraction for pain management of children during bone pins and sutures removal: A randomized clinical trial protocol. *Journal of Advanced Nursing, 77*(1), 439-447.

Malloy, K. M., & Milling, L. S. (2010). The effectiveness of virtual reality distraction for pain reduction: a systematic review. *Clinical psychology review, 30*(8), 1011-1018.

Mohammad, E. B., & Ahmad, M. (2019). Virtual reality as a distraction technique for pain and anxiety among patients with breast cancer: A randomized control trial. *Palliative & supportive care, 17*(1), 29-34.

Moon, J. Y., Shin, J., Chung, J., Ji, S.-H., Ro, S., & Kim, W. H. (2019). Virtual reality distraction during endoscopic urologic surgery under spinal anesthesia: a randomized controlled trial. *Journal of clinical medicine, 8*(1), 2.

Nwosu, A. C., Mills, M., Roughneen, S., Stanley, S., Chapman, L., & Mason, S. R. (2021). Virtual reality in specialist palliative care: a feasibility study to enable clinical practice adoption. *BMJ supportive & palliative care*.

Özcan, Ö., & Çelik, G. (2017). Bilişsel davranışçı terapi. *Türkiye Klinikleri J. Child Psychiatry-Special Topics, 3*(2), 115-120.

Patterson, D. R., Hoffman, H. G., Chambers, G., Bennetts, D., Hunner, H. H., Wiechman, S. A., . . . Jensen, M. P. (2021). Hypnotic Enhancement of Virtual Reality Distraction Analgesia during Thermal Pain: A Randomized Trial. *International Journal of Clinical and Experimental Hypnosis*, 1-21.

Trost, Z., France, C., Anam, M., & Shum, C. (2021). Virtual reality approaches to pain: toward a state of the science. *Pain, 162*(2), 325-331.

Zheng, J., Chan, K., & Gibson, I. (1998). Virtual reality. *Ieee Potentials, 17*(2), 20-23.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || ISBN : 978-605-69730-2-4

More information available at aita.bakircay.edu.tr

Hypothetical Framework For Early Detection of Covid19 From Symptomatic Information by Using Deep Learning

Omar NAJAR [1, *]

[1] *Süleyman Demirel University, Faculty of Electrical and Electronic Engineering , Turkey*

* Corresponding Author: Süleyman Demirel University, Faculty of Electrical and Electronic Engineering, Turkey
Tel.: +90 552 5511697. E-Mail: eng.omarnj@gmail.com

Publication Information

Keywords :

- Covid19
- Pandemics,
- Symptoms
- Deep Learning
- Cross Validation.

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Epidemic diseases are an endless chain that affect people's lives. People suffer from mental illnesses before the physical illnesses in the virus period and beyond. Viruses like Coronavirus leave significant marks on the behavior of people in many aspects including, psychological and social behaviors. The world after Corona needs something to keep them feeling safe from any incoming epidemic diseases or the same epidemic with different shapes.

In this research paper, First, the impact of these diseases and their effects will be shown to prove that the society needs early prediction models to detect epidemic diseases. Then, a hypothetical dataset based on the symptoms of former patients who had covid19 or a normal flu will be applied by using deep learning in order to predict the type of virus. It also helps people to discover in earlier time and know in which level the disease is and it will provide for them recommendation to do if any necessary action is discovered. The model could make people have early discovering of the viruses in order to make them calm and know how to behave before the time passes.

1. Introduction

The endless chain of epidemic diseases was started from SARS in 2003 followed by Influenza (H1N1) in 2009 and then MERS in 2012 and Ebola in 2014 and then Zika Virus in 2016 and finally with Covid19 in 2019 [1,2]. This chain has made the world always worry about any incoming virus. The impact of these viruses was either death or people who suffer from mental illnesses. The pandemic reaches a life-threatening stage, increases anxiety levels and avoidance actions from one person to another which brings the social life to a standstill [3]. With the Covid19 which was discovered first in December 2019 and spread out around the world in just two months has made the world nearly stopped and affects not only people, politics, economics and all other fields.

With the occurrence of all these types of viruses, the seasonal or regular flu remains, which comes every year, and the patient can recover from it with ease. But with the Coronavirus, the matter becomes complicated because people get worried while they have a normal flu or a coronavirus which makes them sick with these confused thoughts. In addition, in the time of waiting for their PCR Test result, people suffer from mental illnesses and high levels of nervousness which might lead to other diseases. Epidemic diseases have negative social impacts on the patients and their relatives as well as high treatment costs and labour losses. Providing protective healthcare services is necessary to prevent pandemics which aim to take the important measures before the outbreak of the diseases are more advantageous approaches in the long term [4]. One of the approaches proposed in this research paper as a hypothetical framework to prove that we need a model depends mainly on the symptoms of the patients to predict the type of virus. This framework is hypothetical because it is built by using data that does not exist in the real world because the absence of data which depends mainly on the symptoms of the patients. To the best of our knowledge, the datasets available for researchers are collected by either using self-reported symptoms on twitter [5] or it depends on the laboratory dataset [6] which depends on different factors other than the actual symptoms of the coronavirus. Other datasets are based on the chest x-rays [7] or sound dataset such as cough. These efforts are made by the research community in seeking to prove the strength of Deep Learning in Medical applications, But still we need data that is well described for the patient's situation. Based on thousands of former patients who experienced corona or a normal flu, we can apply a deep learning model to predict for new patients their virus.

This framework builds a classification model by using 2-layer deep neural networks to predict for new patients their virus (normal flu or coronavirus) based on the information of former patients who experienced both viruses. Additionally, the model categorizes them into three different levels (Low, Mid , High) in case the model predicts coronavirus for them, this classification followed by certain criteria will be explained in section 2.4. The model then gives recommendations to tell how serious the situation of the patient is and let them have earlier actions.

The age of the patients and the chronic diseases will also be taken into consideration. Many people suffer from one or more of three popular chronic diseases including heart, blood pressure, and diabetes. The case of corona patients who are old and have one or two chronic diseases is different than the case for old people who do not have any chronic disease. In addition, the case of patients who are young and have difficulty breathing are different from the case of young or old patients who don't have difficulty breathing. A previous study done by [8] showed the state of art for chronic diseases and coronavirus.

Nowadays, hospitals don't receive all patients in the hospitals unless they have difficulty in breathing or other dangerous situations. Some of the patients just need to rest at home without seeing others. So a recommendation should be provided to patients after prediction. The model provides some recommendations to do in case you have low, mid, or high levels of coronavirus. As a result, the patients in turn can act in earlier time without any multiples in the virus.

.2. Methods and Material

2.1 RapidMiner Platform

RapidMiner is an end-to-end data science platform. It provides the ability to perform Data Preparation, Machine Learning, Model operations and more in this platform. For the ease of use, the framework is built by using deep learning, cross validation and other attribute generations by using RapidMiner Platform as shown in figure 1. in which the data was prepared, trained, tested, and predicted by the model. As a future work, RapidMiner offers a server that the model can serve on and let people identify their problems within seconds of time.

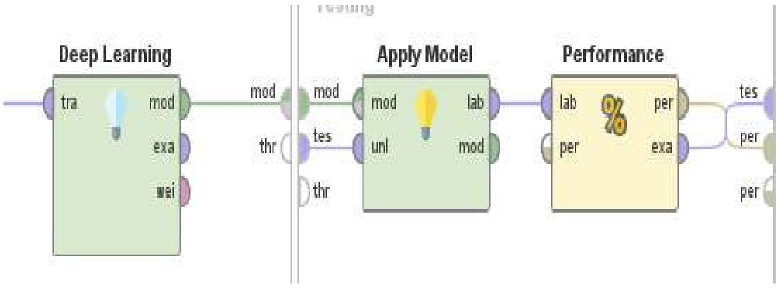


Figure 1. Deep Learning Operator in RapidMiner Platform.

2.2 Data Collection and Preparation

The dataset consists of 299 former patients. Each patient with his/her age, fever and other symptoms. Based on the centres of disease control and prevention, the main symptoms that the software will work on are the following: Chills, Cough, Shortness of breath or difficulty breathing, Fatigue, Muscle or body aches, Headache, New loss of taste or smell, Sore throat, Congestion or runny nose, Nausea or vomiting, and Diarrhea. Based on the same resource, the main symptoms of the normal flu are the following: Fever or feeling feverish chills, Cough, Sore throat, Runny or stuffy nose, Muscle or body aches, Headaches, Fatigue (tiredness) [9]. Basically, the model will work on one label attribute called the type of virus and other 13 attributes to make the prediction from. Also the dataset includes for each patient if he/she has a chronic disease such as heart, blood pressure, or diabetes since these chronic diseases increase the risk to human life. The training of the data was applied on the symptoms, age, and fever only. As a feature selection step, the patient id was excluded to not affect the training process.

2.3 Deep Neural Networks

The project was developed by using RapidMiner platform that takes the data into a 10 fold cross validation and applies a 2-layer deep neural network with 50 neurons in each layer on the data with rectifier activation function. The model performed 10 epochs on the dataset since it contains 299 examples with automatic loss function The model was able to predict for each patient their type of virus as a training process with intervals of confidence. After That, 10 unlabeled examples were applied on the same deep learning model to predict their type of virus.

In case of passing new patients who the type of virus is unknown, the model will predict for them either they have coronavirus or a normal flu with a confidence of each type. After that, the model will classify those who have a corona prediction into three levels low, mid, and high based on their age, fever and their chronic diseases. The model will provide recommendations based on the level of coronavirus telling them if they need to go to the doctor or they need to rest at home.

2.4 Classification Model Criteria

After the prediction, the system filtered the examples for only people who have coronavirus prediction and generated an attribute with name of (level of virus) to classify them. The criteria in classifying is as following:

1. If the patient has difficulty in breathing and has one or more chronic diseases, his level will be high.
2. If the patient is old with difficulty in breathing and has one or more chronic diseases, his level will be high.
3. If the patient is in the middle ages without difficulty in breathing but one or less than two chronic diseases , he/she will have a middle level of coronavirus.

4. If the patient is less than 40 years old without difficulty in breathing and without chronic diseases, he/she will have low levels of corona viruses.

Note that, this criteria is based on what the world encounters along this period since most of the deaths are old people who experience difficulty in breathing or have chronic diseases besides the coronavirus. All could be improved by the information that the health organizations have. The power of deep learning can be effectively involved in medical applications and be a good solution in detecting Covid19 for patients in early time.

3. Results

The model trains 299 patients and records a performance of 99.33% (+/- 2,11%) as shown in Table 1. In addition, a test dataset was used on 10 new patients to predict their type of virus with showing the interval of confidence for each type as shown in Table 2. Then, the data took 7 examples and classified them as low, mid, and high level and provided them recommendations. The result of this model could be improved in case the exact dataset is published and used by the hospitals and health organizations. In this hypothetical framework, we would like to show the power of Deep Learning in discovering these viruses in early time.

Table 1. The performance of the model for training/testing the dataset

	Ture: COVID	True: FLU	Class Precision
Pred. COVID	212	1	99.53%
Pred. FLU	1	85	98.85%
Class Recall	99.53 %	98.85%	
Accuracy	99.33 % +/- 2.11%		

Table 2. The predictions of new patients with confidence interval.

Row No.	Prediction	Confidence COVID	Confidence FLU
1	COVID	1.000	0
2	COVID	0.975	0.025
3	COVID	0.999	0.001
4	COVID	0.999	0.001
5	FLU	0.002	0.998
6	FLU	0.003	0.997
7	FLU	0.004	0.996
8	COVID	0.999	0.001
9	COVID	0.995	0.005
10	COVID	0.994	0.005

4. Discussion

The result of the 299 patients has a good insight for the framework and proved in a way that prediction covid19 from symptomatic information is possible. More data results in more accuracy, better prediction, and better confidence. Algorithmically, increasing the data will drive variance down without a trade-off in bias. Therefore, another experiment was applied with the use of 1000 former data patients on the same model. As shown in Table 3. the performance of the model increased by 0.7 %.

By dealing with a larger dataset that has thousands or millions of patients who experienced corona or a normal flu and we identify all the symptoms, the model can predict better. Also, we can assign each patient his chest x-ray in order to take everything into consideration. In that view, The power of deep learning will get to a level that could be as accurate as other tests like PCR tests since most people have similar symptoms especially if the infection moves from one person to another.

Table 3. Improved performance for 1000 former patient dataset.

	Ture: COVID	True: FLU	Class Precision
Pred. COVID	590	3	99.49%
Pred. FLU	3	404	99.26%
Class Recall	99.49 %	99.26%	
Accuracy	99.40 % +/- 0.52%		

The research community is in a real need for a dataset to be provided by official health organizations and hospitals to explain the exact status of the patients. Providing such data to the research community will help in different fields including the following:

1. Ability of knowing the most affected symptoms of each level of coronavirus.
2. Hospitals will be able to deal with high level patients and prepare rooms and their needs in earlier time.
3. Detecting distinct kinds of pattern in the dataset for identifying the underlying patterns
4. In case of experiencing new symptoms which might result in a different shape of the virus, previous actions could be made to avoid spreading the situation.

All of the above and more advantages could be obtained by providing the suitable dataset to include the real status of coronavirus patients and other viruses. Indeed, alternative models could be advised to do the job of prediction and other tasks. Logistic Regression is a good method for classification and prediction for new patients. The task of prediction and the power of Machine Learning and Deep Learning could provide efficient outcomes for future researches.

5. Conclusion and Evaluation

The role that deep learning plays in prediction has been the major tool for health departments to help in recognizing patterns which are unseen. This advantage should be applied on open datasets for researchers to study the real symptoms and draw conclusions to help people in the future to discover these diseases early. In this paper, we tried to prove that this data if it was real, it could help in discovering. By using former patient information we can maintain the type of virus by predictions based on deep learning algorithms.

References

1. Er AG, Ünal S. 2019 Coronavirus Salgını, Anlık Durum ve İlk İzlenimler, Flora, 2020;25:1-5. https://doi.org/10.5578/
2. lora.202001 8. Peeri NC, Shrestha N, Rahman MS, Zaki R, Tan Z, Bibi S, Baghbanzadeh M, Aghamohammadi N, Zhang W, Haque U. The SARS, MERS and Novel Coronavirus (COVID-19) Epidemics, The Newest and Biggest Global Health Threats: What Lessons Have We Learned?, International Journal of Epidemiology, 2020;1:1-10. https://doi.org/10.1093/ ije/dyaa033 PMid:32086938
3. Çırakoğlu OC. Domuz Gribi (H1N1) Salgınıyla İlişkili Algıların, Kaygı ve Kaçınma Düzeyi Değişkenleri Bağlamında İncelenmesi, Türk Psikoloji Dergisi, 2011;26(67). Available at: www.psikolog.org.tr/tr/yayin lar/dergiler/1031828/tpd1300443320110000m000096pdf
4. Oysul FG, Bakır B. Orta Doğu Solunum Sendromu-MERS", Türkiye Klinikleri, 2015;1(3):46-52. Available at: www.turkiyeklinikleri.com/article/tr-orta-dogu-solunumsendromu-mers74196.html
5. Abeed Sarker, Sahithi Lakamana, Whitney Hogg-Bremer, Angel Xie, Mohammed Ali Al-Garadi, Yuan-Chi Yang, Self-reported COVID-19 symptoms on Twitter: an analysis and a research resource, Journal of the American Medical Informatics Association, Volume 27, Issue 8, August 2020, Pages 1310–1315, https://doi.org/10.1093/jamia/ocaa116
6. T. B. Alakus and I. Turkoglu, "Comparison of deep learning approaches to predict COVID-19 infection", Chaos Solitons and Fractals, pp. 1-14, June 2020.
7. Ozturk T, Talo M, Yildirim EA, Baloglu UB, Yildirim O, Acharya UR. Automated detection of COVID-19 cases using deep neural networks with X-ray images. Computers in Biology and Medicine. 2020;121. Available:https://doi.org/10.1016/j.compbiomed.2020.103792.
8. Haybar H, Kazemnia K , Rahim F. Underlying Chronic Disease and COVID-19 Infection: A State-of-the-Art Review, Jundishapur J Chronic Dis Care. Online ahead of Print ; 9(2):e103452. doi: 10.5812/jjcdc.103452.
9. Symptoms of coronavirus, Centres for disease control and prevention. Dec. 22, 2020. Symptoms of Coronavirus | CDC

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

The Place of Artificial Intelligence in Women's Health

Sevgi ÖZKAN[1], Merve VİCİR[2]

[1]*Pamukkale University, Faculty of Health Sciences, Department of Nursing, Department of Obstetrics and Gynecology Nursing*
[2] *Pamukkale University, Institute of Health Sciences, Obstetrics and Gynecology Diseases Nursing*

* Corresponding Author: Pamukkale University, Institute of Health Sciences, Obstetrics and Gynecology Diseases Nursing, Turkey Tel: +0905303050610 E-mail: mvicir20@posta.pau.edu.tr

Publication Information

Keywords :

- Artificial Intelligence
- Women's Health

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

In this study, has been conducted by aiming compile artificial intelligence applications developed in gynecological diseases.

Artificial intelligence technology can reproduce derive algorithms that can be used for diagnosis and treatment of diseases and medical research. It provides real-time advice on health risks and predicts health problems by providing information from a large patient population. By this means, it provides advantages in many areas such as early diagnosis, decision-making and health protection. Artificial intelligence is used in many areas related to women's health. Artificial intelligence technologies are used in the presence of many different diseases and pathologies such as endometrial cancer prediction, human papilloma virus types affecting the risk of recurrence of cervical dysplasia, breast cancer diagnosis, and menopause. Besides, it has been suggested that technologies can play an important role in the personalization of infertility treatments, with live birth prediction, embryo implantation potentials, effect on endometriosis assisted reproductive technology and the like. Along with the positive results of the studies conducted in the field of women's health, it is predicted that women's health nursing will also be positively affected.

1. Introduction

When we look at the history books, it is seen that the first applications related to artificial intelligence (Al-article intelligent) occurred in 1960 and 1970. Alan Turing, one of the first theorists, questioned whether the computer would work like a human brain (Turıng 1950). It was used for the first time in the Second World War as a machine learning principle (Glandvin 1997). Artificial intelligence has entered our lives as structures that can think, analyze, learn and make decisions like human beings by interacting with informatics and computers. With its self-renewal and learning features, it is used in medicine mostly on the basis of diagnosis. Artificial intelligence technology can reproduce derive algorithms that can be used for diagnosis and treatment of diseases and medical research. By this means, it provides advantages in many areas such as early diagnosis, decision-making and health protection. (Amezcua-Prieto et.all 2020, Yoldemir 2020).

2. History of Artificial Intelligence in Health

With the emergence of artificial intelligence that it can be used to specifically solve or clarify complex biomedical problems, interest in its potential has grown exponentially, and as a result, it has begun to enter the field of health. In 1961, Warner et al. conducted a study on the establishment of an automatic diagnosis system by obtaining data from 1035 patients referred and analyzed for cardiac catheterization as a result of congenital heart disease (Warmer et al. 1961). Subsequently this first research on diagnosis, another study was carried out with a computer program developed at Stanford University in 1970, in addition to the diagnosis of the disease, to recommend antibiotics and to determine the causative bacteria and adjust the dose according to body weight. Along with GUIDON, derived from AI's intelligent computer-aided education program in late 1970, the program was developed and used to teach the diagnosis of infectious diseases to medical students (Clancey et. all 1979).. Other artificial intelligence systems were developed, advances in diagnosis were discussed and comparisons of different systems were made (Kulikowski et.al 1982). In future studies, studies have been conducted to compare the diagnostic capabilities of physicians with the capabilities of artificial intelligence. Later on studies have been conducted to compare the diagnostic capabilities of physicians with the capabilities of artificial intelligence. According to the results of these studies in which artificial intelligence systems were evaluated, it has been reported that the systems help the diagnosis of physicians with an objective approach and strengthen the diagnosis. (Adams et. all 1986, Dombal et. all 1972). These studies, which were carried out in the early stages of the history of artificial intelligence, shed light on many studies that are now implemented.

3. Artificial intelligence in women's health

In the light of many studies from the past to the present, artificial intelligence is an area that has received a lot of attention recently, with its ability to diagnose disease, analyze data and predictive data analysis. It is thought that it will continue to be a dynamic subject with the changing and developing age. Artificial intelligence is used in many areas related to women's health. Positive results have been obtained in many studies conducted for the diagnosis of gynecological cancer. Endometrial cancer is one of the gynecological cancer types that has increased over time and is common in many parts of the world. Although it is not a commonly used screening test, early diagnosis is very important. According to research done; In the light of the information obtained from hysteroscopic images, an artificial intelligence-based system has been developed. In this study, which included 177 patients, there were 60 normal endometrial images, uterine myoma, polyps, atypical endometrial hyperplasia and endometrial cancer images. As a result of the study, it is seen that the accuracy of diagnosis has increased from 80% to 90% and above. In the study, it is seen that this artificial intelligence-based system is a tool to facilitate the diagnosis of endometrial cancer (Takahashi et al. 2021). A different study has also been conducted to accurately detect endometrial lesions and endometrial lesion type with hysteroscopic images. In this study, the importance of artificial intelligence in personal diagnosis is emphasized due to its success in pre-maning period with higher sensitivity compared to gynecologists (Zhang et al. 2021).

Just as with endometrial cancer, ovarian cancer does not have a screening test, and its recurrence rate is high because it is diagnosed in the late stages. Early diagnosis leads to positive changes in many areas from the treatment process to the surgical process (Stewart et. all 2019). In an artificial intelligence study conducted for the diagnosis of ovarian cancer, information obtained from blood test results, patient's history, imaging tests and preoperative examination were obtained from 202 patients, and five different deep learning methods were used. As a result of the study, it was concluded that the pathological diagnosis of ovarian cancer may play a role in predicting from preoperative examinations (Akazawa et al. 2020).

Cervical cancer ranks second in terms of gynecological cancer mortality. Cervical intraepithelial neoplasia (CIN) is closely related in patients with HPV (human papilloma virus) and persistent infection. HPV screening periods have been increased in developed countries. Although with the increase in screening programs, there is no method other than periodic observation for women who are positive (Fan et al.2018). A study has been conducted using artificial intelligence technology to determine whether the HPV genotype could predict the persistence and recurrence risk of cervical dysplasia before treatment. As a result of the study, it has been revealed that some types of HPV may pose a risk in relapse and cancer cases. Therefore, it has been concluded that artificial intelligence technologies are an advantageous technology for personalized treatment and additional vaccination programs (Bogani et al. 2017). It is known that preasetic acid test and postacetic acid test are methods used for colposcopy images and CIN diagnosis. According to a study, it has been reported that by useing artificial intelligence technology with these images obtained, quite high estimates have emerged in terms of specificity, accuracy and sensitivity for the diagnosis of CIN (Peng et al. 2021). In a study conducted with deep learning methods developed for survival prediction of 797 uterine adenosarcoma patients, it was been reported that highly accurate predictions were made in personalized prognoses (Qu et al. 2021). A review dealing with the development of artificial intelligence in gynecological cancers, that this has been discuss accuracy of diagnosis and the prediction of early diagnosis. However, it is emphasized that there will be many moral problems such as ethics and health insurance in the future, since artificial intelligence cannot be fully humanized (Zhou et al. 2021).

Breast cancer screening has been shown to significantly reduce the mortality rate in women. The increasing use of screening exams has led to increased demands for fast and accurate diagnostic reporting. With the advancing screening tests, artificial intelligence technology has taken a very important way in the diagnosis of breast cancer (Tran et al.2021). For the last five years, digital mammography images have been used for the diagnosis of breast cancer, which is one of the common research areas in the field of gynecology, in systems developed by deep learning and neural networks in artificial intelligence technology. Commercial products have emerged in artificial intelligence technology developed for breast cancer diagnosis. In studies conducted with these developing technologies, experienced radiologists were been compared with artificial intelligence technologies, and it was concluded that their performances were equal. With these positive results, it is clear that artificial intelligence technology will play an important role in the diagnosis of breast cancer in the future (Sechopoulos et al. 2020).

With the menopause period, technologies that can calculate and evaluate the risk of osteoporosis have been used for osteoporosis, which affects women's health, using artificial intelligence technologies. In an artificial intelligence technology study, which was studied to identify patients at risk of bone fracture beforehand, it was observed that osteoporosis fractures were predetermined using different deep learning methods (Ferizi et al. 2019).

Assisted reproductive techniques (ART) have become an indispensable issue in the treatment of infertility. The decision-making phase in ART practices is clinician-centered, and the decision-making process is based on the experience of the physician and evidence-based practices. The reason for ART intervention is based on many factors. In vitro fertilization (IVF) is a popular method of eliminating complications such as endometriosis, poor egg quality, a genetic disease of the mother or father, ovulation problems, antibody problems that damage sperm or eggs, inability of sperm to penetrate or survive. IVF application is a very laborious process because of its high cost and uncertain outcome (Goyal et al. 2020). Recurrent reproductive failure (RRF) such as recurrent pregnancy loss and recurrent implantation failure is characterized by complex etiologies and is particularly associated with various maternal factors. Currently, it is believed that RRF is closely related to the maternal environment, which is influenced by complex immune factors.

Without the use of automated tools, it is often difficult to evaluate the interaction and synergistic effects of various immune factors on pregnancy outcome. For such reasons, artificial intelligence technology has been begun to be investigated in the field of assisted reproductive techniques. According to a study conducted; the study, in which 561 samples were used, was divided into two groups. 90% of them were been used for training and the remainder for testing. Different data panels have been created to predict pregnancy outcomes in four different pregnancy nodes, including biochemical pregnancy, clinical pregnancy, ongoing pregnancy and live birth. Parameters used for diagnosis; hormone levels, autoantibodies, peripheral immunology, endometrial immunology and embryo parameters. All these data contain 64 different variables. According to the results of the study; It was concluded that it could serve as a basis for helping more precise and personalized diagnosis and treatment planning in patients with RRF, thus this been provided a light for clinicians to treat patients more accurately (Huang et al.2021). According to another study, parallel results were obtained and positive results were obtained in terms of diagnosis, treatment and live birth prediction of artificial intelligence technology in IVF treatment (Goyal et al. 2020). Artificial intelligence technology has also been used in assisted reproductive techniques in line with these positive results related to gynecology and fertility. Although there is no development for cost reduction yet, it is thought that the studies in this area will result in the future (Letterie 2021).

Besides, in a study evaluating perinatal outcome estimates using artificial intelligence technologies with amniotic fluid taken from asymptomatic pregnant women with short cervical length; Six different deep learning machine techniques have been compared and evaluated. In this study with limited patient population, it was concluded that some deep learning methods were better than others, and in general, artificial intelligence technology correctly predicted perinatal outcomes (Bahado-Singh et al. 2019). Furthermore With the artificial intelligence technology developed for fetal heart rate scans, it has been concluded that it can accurately predict fetal asphyxia (Zhao et al. 2019).

4. Result

With the results of this screening we have done, researches conducted in many areas affecting women's health will increase the accuracy of artificial intelligence technology diagnoses; at the same time, it was concluded that it would help to provide personalized treatment for cancer, osteoperosis, breast cancer, and assisted reproductive tests.

References

1. Turıng A.M. (1950) Computıng Machınery And Intellıgence, Mınd A Quarterly Revıew Of Psychology And Phılosophy. Pages 433–460, Https://Doi.Org/10.1093/Mind/Lıx.236.433
2. Gladvin L.A. (1997) Alan Turıng Enıgma and the Breakıng of German Machıne Cıphers in World War . Pages; 203-217
3. Büyükgözü S., Dereli E. (2020) Dijital Sağlık Uygulamalarında Yapay Zeka, ResearchGate. Pages; 1-7
4. Amezcua-Prieto C., Fernandez-Luna J.M., Huete-Guadix J.F., Bueno-Cavanillas A., Khan K.S. (2020) Artificial intelligence and automation of systematic reviews in women's health Copyright © 2020 Wolters Kluwer Health, Inc. All rights reserved. Pages; 334-341. DOI:10.1097/GCO.0000000000000643
5. Yoldemir T. (2020) Artificial intelligence and women's health, Climacteric,23:1, 1-2, DOI: 10.1080/13697137.2019.1682804
6. Warner H.R., Toronto A.F., Veasey G., Stephenson R. (1961) A Mathematical Approach to Medical Diagnosis Downloaded From: http://jama.jamanetwork.com/ by a New York University User on 05/29/2015 Pages:177-183
7. Clancey W. J. Buchanan B.G. (1979) INTELLIGENT COMPUTER-AIDED INSTRUCTION FOR MEDICAL DIAGNOSIS 1979 IEEE Pages; 175-183

8. Kulikowski CA , Weiss SM . (1982) Representation of expert knowledge for consulta- tion: the CASNET and EXPERT Projects". Artificial intelligence in medicine. Szolovits P, editor. Boulder, CO: Westview Press
9. Adams I.D., Chan M., Clıfford P.C., Cooke W.M., Dallos V., Dombel F.T.D., Edwards M.H., Hancock D.M., Hewett D.J., Mcıntyre N., Somervılle P.G., Spıegelhalter D.J., Wellwood J., Wılson D.H. (1986) Computer aided diagnosis of acute abdominal pain: a multicentre study BRITISH MEDICAL JOURNAL VOLUME 293 27 SEPTEMBER 1986
10. Dombal F.T., Leaper D.J. Stanıland J.R., Mccann A.P., Horrocks J.C (1972) Computer-Aided Diagnosis Of Acute Abdominal Pain British Medical Journal, 1972, 2, 9-13
11. Takahashi Y, Sone K, Noda K, Yoshida K, Toyohara Y, Kato K, et al. (2021) Automated system for diagnosing endometrial cancer by adopting deep-learning technology in hysteroscopy. PLoS ONE 16(3): e0248526. https://doi.org/10.1371/journal.pone.0248526
12. Zhang Y., Wang Z., Zhang J., Wang C., Wang Y., Chen H., Shan L., Huo J., Gu J., Ma X. (2021) Deep learning model for classifying endometrial lesions *(2021) 19:10* https://doi.org/10.1186/s12967-020-02660-x
13. Stewart C., Ralyea C., Lockwood S. (2019) Ovarian Cancer: An Integrated Review. Seminarsin Oncology Nursing. Pages; 151-156 https://doi.org/10.1016/j.soncn.2019.02.001
14. Akazawa M., Hashımoto K. (2020) Artificial Intelligence in Ovarian Cancer Diagnosis ANTICANCER RESEARCH *40*: 4795-4800 (2020) doi:10.21873/anticanres.14482
15. Fan Y., Meng Y., Yang S., Wang L., Zhi W., Lazare C., Cao C., Wu P (2018) Screening of Cervical Cancer with Self-Collected Cervical Samples and Next-Generation Sequencing. Hindawi Disease Markers Volume 2018, Article ID 4826547, 4 pages https://doi.org/10.1155/2018/4826547
16. Bagoni G., Ditto A., Martinelli F., Signorelli M., Chiappa V., Maggiore U.L.R., Taverna F., Lombardo C.,Borghi C., Scaffa C., Lorusso D., Raspagliesi F. (2017) Artificial intelligence estimates the impact of human papillomavirus types in influencing the risk of cervical dysplasia recurrence: progress toward a more personalized Approach. European Journal of Cancer Prevention 2018, 00:000–000 DOI: 10.1097/CEJ.0000000000000432
17. Peng G., Dong H., Liang T., Li L., Li J. (2021) Diagnosis of cervical precancerous lesions based on multimodal feature changes Computers in Biology and Medicine Volume 130, March 2021, 104209 https://doi.org/10.1016/j.compbiomed.2021.104209
18. Zhou J., Zeng Z.Y., Li L. (2021) Progress of Artificial Intelligence in Gynecological Malignant Tumors. Cancer Management and Research Pages; 12823-12840. http://doi.org/10.2147/CMAR.S279990
19. Tran W. T., Sadeghi-Naini A., Lu F., Gandhi S., Meti N., Brackstone M., Rakovitch E., Curpen B. (2021) Computational Radiology in Breast Cancer Screening and Diagnosis Using Artificial Intelligence. Can Assoc Radiol J 2021 Feb;72(1):98-108. doi:10.1177/0846537120949974.
20. Sechopoulos I., Teuwen J., Mann R. (2020) Artificial intelligence for breast cancer detection in mammography and digital breast tomosynthesis: State of the art. *Seminars in Cancer Biology*, https://doi.org/10.1016/j.semcancer.2020.06.002
21. Ferizi U., Besser H., Hysi P., Jacobs J., Rajapakse C.S., Chen C., Saha P.K., Honig S., Chang G. (2019) Artificial Intelligence Applied to Osteoporosis: A Performance Comparison of Machine Learning Algorithms in Predicting Fragility Fractures From MRI Data. J Magn Reson Imaging 2019 Apr;49(4):1029-1038. doi: 10.1002/jmri.26280.
22. Goyal A. Kuchana M., Ayyagari K.P.R. (2020) Machine learning predicts live-birth occurrence before in-vitro fertilization treatment. Scientific Reports | (2020) 10:20925 | https://doi.org/10.1038/s41598-020-76928-z
23. Huang C., Xiang Z., Zhang Y., Tan D.S., Y.p C.K., Liu Z., Li Y., Yu S., Diao L., Wong L.Y., Ling W.L., Zeng Y., Tu W. (2021) Using Deep Learning in a Monocentric Study to Characterize Maternal Immune Environment for Predicting Pregnancy Outcomes in the Recurrent Reproductive Failure Patients. Frontiers in Immunology doi: 10.3389/fimmu.2021.642167

24. Letterie G. (2021) Three ways of knowing: the integration of clinical expertise, evidence-based medicine, and artificial intelligence in assisted reproductive Technologies. Journal of Assisted Reproduction and Genetics https://doi.org/10.1007/s10815-021-02159-4
25. Bahado-Singh R.O., Sonek J., Mckenna D., Cool D., Aydas B., Turkoglu O., Bjorndahl T., Mandal R., Wishart D., Friedman P., Graham S.F., Yilmaz A. (2019) Artificial intelligence and amniotic fluid multiomics: prediction of perinatal outcome in asymptomatic women with short cervix. Ultrasound Obstet Gynecol 2019 Jul;54(1):110-118. doi: 10.1002/uog.20168
26. Zhao Z., Deng Y., Zhang Y., Zhang Y., Zhang X., Shao L. (2019) DeepFHR: intelligent prediction of fetal Acidemia using fetal heart rate signals based on convolutional neural network. BMC Medical Informatics and Decision Making (2019) 19:286 https://doi.org/10.1186/s12911-019-1007-5

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || ISBN : 978-605-69730-2-4

More information available at aita.bakircay.edu.tr

A New Approach in Drug Management: Smart Drug Managament in Geriatric Care

Rabiye Sezen TEK [1,*], Hatice TEL AYDIN [2]

[1] *Sivas Cumhuriyet Universty, Health Sciences Institutei Turkey*
[2] *Sivas Cumhuriyet Universty, Faculty of Health Sciences, Turkey*

*Corresponding Author: Sivas Cumhuriyet Universty, Health Sciences Institutei Turkey.
Tel.: +90 507361353 E-Mail: rabiyetek@outlook.com

Publication Information

Keywords :
- Artificial intelligence,
- Smart medicine system,
- Drug compliance,
- Elderly,
- Nursing.

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

The world population is getting older, there is an increase in the prevalence of chronic health problems with aging population. Appoximately 90 percent of the elderly have at least one chronic health problem. Due to this condition, multiple medicine usage is common in the elderly people. Elderly individuals and their caregivers who need long-term medication due to decreased physical functions, memory and cognitive function problems may have difficulties in administering drug therapies. Difficulties in the pharmaceutical industry prolongs the treatment process of diseases, it causes permanent damage and can even cause death. This situation causes elderly people to become dependent on healthcare services. As well as, the cost of healthcare increases the current complex burden.

The use of artificial intelligence solutions in the field of health, which targets difficulties experienced by individuals pharma management, is increasing day by day. Nowadays, many prototypes of the smart medicine systems used for this purpose have been developed that can be used both at home and in hospitals. The prototypes include: Weekly Electronic Pills Dispenser, Pill Dispenser with Alarm Via Smart Phone, An Automatic Dose Dispenser for Microtablets, Advanced Medication Dispenser, SINICA Smart Medicine Dispenser, e-pill MedTime Station and A Highly Scalable with Remote Manegeability Smart Medicine Dispenser. The use of the smart medicine systems has some positive results such as increased compliance with drug treatment, reduction in wrong and missing dose errors, and improvement in time management for caregivers. Using smart medicine systems in the field of geriatrics, there are results showing that it supports their adherence to drug treatment and being more effective in disease management. There are also study results showing that these practices can reduce the burden on the health system by making elderly people less dependent on health and care services as a whole. In this article, the results of this study are presented by considering the use of smart medicine systems in geatric care in the health outcomes, health care costs and quality of health services of elderly individuals with using smart drug systems, basic features and approaches using smart drug systems are presented based on the current research results.

1. Introduction

According to the US census bureau, the number of people aged 60 and over which is 962 million, is expected to increase globally to 2.1 billion in 2050 and to 3.1 billion in 2100 (U.S Census Bureau, 2014). For the first time being in 2030 USA indicates that, there will be more elderly people than the child population. This great increase in the elderly population growth around the world is called the Silver Tsunami (De, Stoddart and George 2017). For old people to stay healthy/sustain their health they need more healthcare and social services. However, this increase in a system where resources are not sufficient illustrates important pressure factor on the services offered (Healty Itanalytics, 2021; WHO, 2011). The prediction of increase in elderly population, with significant cost increase and inefficiency in health system, will result in a serious threat to the health systems of the countries (De, Stoddart and George 2017).

Today along with elders having reached to a longer life expectancy, many elders try to continue their lives by having one or more than one health problems. Diabetes mellitus, hypertension, neurodegenerative, respiratory, gastrointestinal system diseases, arthritis, cognitive, mental disorders, sensory disorders are among the most important health problems of elderly individuals (OECD, 2011; Lang, Macdonald, Mark, 2015). Due to the diseases which are chronical, it is required to take medication for a long time or more than a single drug for these health problems (Shruthi et al. 2016). It has been shown that elderly individuals who have one or more than one chronic disease are using an average of 1-5 drugs per day (Rochon, 2019) which shows approximately 30% of the total medicine payments are made by elderly individuals in North America (Rochon, 2019).

Medication treatment is one of the most prevalent interventions in the care of elderly individuals (Berhals, Santos, and Fengler, 2017). However, it has been shown that the compliance of elderly individuals about their medication regimen has been worryingly weak in many studies (Fang, Meader, & Bjering, 2016; Shruthi et al. 2016). Failure to comply with drug treatment can be by not starting the recommended treatment at all, not implementing the treatment as recommended or cessation of treatment early (Vrijens et al 2012). The level of compliance with drug treatment has been indicated that it decreases along with age (Shruthi et al. 2016). Along with this, the chronicity of nature of health problems, complex medication plan, using a large number of drugs (Tsai et al.2012; Shruthi et al.2016), high treatment cost, side effects of drug, drug interactions, forgetfulness and social support inadequacy are among the factors that reduce the compliance of elderly individuals to drug treatment (Tsai et al. 2012).

Elderly individuals' low levels of compliance with drug treatment; hospitalization, increase in cost of illness, mortality and disability (Sokol et al. 2005; Shruthi et al. 2016), aggravation of the disease (Shruth et al. 2016) result in unwanted circumstances. It is thought that these results have harsh consequences on the well-being of individuals and on the cost of healthcare services (Turjaama, Kapanan, and Kangesniemi, 2020). Hence, by supporting elderly people's medication compliance it is needed to be developed effective drug management processes.

In their systematic compilation by Verlo et al. (2017); it has been observed that in the leadership and the intervention of the nurses' compliance of elderly people with drug treatment has shown considerable benefits. Today, the increase of usage of artificial intelligence technology in the field of health has led to rapid improvements in smart drug systems. Helping to encourage to elderly people's compliance to medical treatment, has been done with the goal of taking their medication independently, the usage of smart medicine systems increased (Rantanen, Parkkari, & Leikola, 2017; Zanjal & Talmale, 2016).

Smart drug systems help elderly patients to take the right amount of medication at the right time which includes wireless sensor network technology, robotics or applications that can be used to remind them (Minaam and Abdelfettah, 2018). There are smart medicine systems that are both used in home environment and hospital and in nursing homes (Kassem, Antoun, Hamad, and El-Mourcary, 2019). There are different models of smart drug systems in the world. These devices are comprised of an alarm system that inform the users without having any kind of database to record the data of the patients or having a remote access.

The main purpose of the drug systems is to keep elderly patients' medications without the possibility of underdose and helping them to take regularly, avoid accidental over/underdose help protect them (Kassem, Antoun, Hamad, and El-Mourcary, 2019).

Automatic drug dispensing systems, where medicine counting machines are used in pharmacies reaches to 1970's (Oswald & Caldwell, 2007). Nowadays, in many countries, hospitals automatic dispensing containers in pharmacies, automatic mobile medicine trolleys, barcoded medicine application systems, robotic collectors and like personal smart medicine dispensers, etc. technologies are used in drug distribution and management (Oswald and Caldwell, 2007; Agrawal, 2009; Kassem, Antoun, Hamad, and El-Mourcary, 2019).

Some of the current smart medicine systems are as follows:

Weekly Electronic Pills Dispenser with Circular Containers; it is a smart medicine system which 7 days a week, 4 different drugs per day can be placed in departments. The interface of the system consists of a two-line Liquid Crystal Display (LCD) with some navigation buttons that allow the user to edit the time intervals in which to take the pills. One part of the container turns on an alarm sound and opens up when the medication is due. A short message (SMS) is also added to warn people who forget to take their medication on time (Fărcaş, Ciocan, Palaghiţă, and Fizeşan, 2015).

Pill Dispenser with Alarm Via Smart Phone; the system consists of three medication cup compartments. When it is time to take the medicine, one of the containers opens, vibration motors push the drugs out of the container and when the desired number of pills is delivered, the infrared (IR) sensors that detect the number of pills stops working. The interface of the dispenser forms an LCD with several buttons used to set the time and date. When it is time to take medication, a notification is sent to the patient on his smartphone and a reminder is made (Othman & Ek, 2016).

Automatic Dose Dispenser For Micro Tablets; it has been developed for individuals using mini-tablets with a diameter of 2–3 mm or less. Device has cassette that holds micro tablets and has a screen for viewing and setting the dose contains. Micro tablets are electronically dispensed from attached cassette by automatic dispensing device counted as. The individual dose is set and the dispenser releases the correct number of microtablets. It is a battery-operated handheld device which is easy to use (Ranjith & Mahalaxmi, 2015).

Advanced Medication Dispenser; it has alarm for warning, system motors controlling the medication in the container, radio frequency identification (RFID) and there is a two-button LCD module. When the time comes of taking medication, a message is displayed on the LCD screen and the alarm starts to sound, the user should introduce itself by using an RFID tag to take the pill and stop the alarm. If the user exceeds the alarm threshold, the buzzer stops and the pill status replaced as missed. Pill states can be viewed remotely through its server with a user-authenticated web (Alexan, Osan, & Oniga, 2013).

SINICA Smart Medicine Dispenser; MSS (medication shedule specification) based on programming knowledge. MSS, radio frequency identification (RFID) is formed by a pharmacist together with tagged containers. A set of sockets in the base of the dispenser, an indicator light around each socket, an alarm, an LED display, a Push-To Dispense (PTD) button, a dispensing container, and an RFID reader. Pharmacist, places medicine containers to empty sockets with user card and MSS. The dispenser, shortly before each dose time, uses alarms to remind the user to take the drug(s). The user takes their medication by pressing the PTD button (Tsai, Chen, Yu, Shih, and Liu, 2011).

A Highly Scalable with Remote Manegeability Smart Medicine Dispenser; are available systems that can be used in multi-user environments such as, in hospitals and nursing homes. This smart medicine dispenser allows one medicine dispenser to have users more than one to use it is more than once. In a system which is continuously watched centrally by the pharmacy, medicines for each patient are stored in a medicine cartridge, and the cartridges are placed in the dispenser tray. As a user of this system, the personal password and password of the nurses' fingerprint is defined, the system is entered with the username and fingerprint. Medication of patients is taken from the cartridges and administered to the patient by the nurse. It is stated that instead of having used by the last medicine dispenser's it increases the cost efficiency and provides drug safety when used by the medical personnel and system administrators instead of users (Park and Pak, 2012).

E-hap MedTime STATION Automatic Pill Dispenser; is a product that provides distribution up to its portion stores in advance where drug containers labeled peripherally positioned with 6 alarms per day(until 28 doses of medicines). There is a safety/lock mechanism to prevent it from taking medication doses. By this way too much overdose is prevented. The user opens the lid the release lever to drop the medication into the medication cup and therefore one of the compartments of the circumferential container is opened and alarm is automatically closed (Epill, 2017).

Automated Pill Dispenser Project; an automated medicine dispenser aims to test the hypothesis of use. With automatic distribution devices, it is aimed to increasing the quality of people's life, being independent at home for longer periods, receive little more help. Target groups memory and mental health problems, physical difficulties consist of people with long-term medical problems. Feedback by patients and caregivers on the automated medicine dispensers has been extremely positive. The data collected during the project shows that cost per person over a six-month period in healthcare expenditures shows a significant saving of £ 1700 has been achieved. It has been found that pharmaceutical dispensers have been reliable, and it takes a few days to get used to it, little problems have been reported generally about how the device works and by people who need a reminder of what to do when alarms go off (Bowsher, 2012).

It has been reported that the use of smart drug systems is effective in preventing medication errors and that medication errors are detected faster and easier than the manual system with the use of these systems (Baril et al., 2014; Beobide Tellería et al., 2017; Cousein et al., 2014; Sinnemaki et al., 2017). In the study of Baril et al. (2013), in a nursing home providing care for 800 elderly people, four smart drug system used throughout the week, while 91 medication errors in manual distribution system in the smart drug system has been determined, when the drug error decreased to 57, patients in drug treatment that has been found that patients adapt to changes faster. In a study conducted using smart medicine systems in nursing homes and a nursing home with elderly patients; Using an automated drug delivery system has been reported to reduce from 52.93% to 14.08% by drug administration errors/ ccidents (errors such as not administering the drug, errors related to drug dosage, errors such as incorrect patient drug administration) (Baril et al., 2014). In the study of Beobide Tellería et al. (2017) comparing manual and automatic drug delivery systems in nursing homes over a period of two years; they found that drug delivery errors were reduced by 91% in the smart drug system. Cousein et al., (2014), Stuck et al., (2017) reported that smart drug systems increase drug safety and reduce the use of wrong drugs in elderly individuals.

It has also been reported that using smart drug systems has positive results, such as increasing the compliance of healthcare professionals to the time of administration of drugs, reducing the time they spend for preparing treatment and control processes (Baril et al., 2014). It has been determined that using smart pharma systems saves 15% in the day shift and 16% in the evening shift (Baril et al., 2014). Nurses using smart medicine systems reported that using technology enabled them to focus more on the other needs of the elderly (Baril et al., 2014). Nurses using smart pharmaceutical systems allows older people to focus more on their other needs (Barl et al., 2014). 98% of the elderly individuals' electronic drug delivery systems reported that it is easy to use the devices and they are satisfied with the devices (Hayes et al.,2006; Sather et al., 2007). Along with this, 3% of the elderly have experienced problems about the devices such as opening the partitions, and also that the equipment is too big to be moved, and in this case, they reported that they had to go home to get their medication (Hayes et al., 2006). In a study examining how the system of smart medicine affects the drug compliance of elderly people; they stated that 93% of individuals are compatible with this smart medicine system, in fact this the rate is 78%, 12% of the elderly without interrupting/missing their medication, but the actual rate is 5% and the it has been reported that much better results have been obtained better than the elderly responses (Hayes et al., 2006). In a study in which three elderly individuals living at home and using a personalized automatic dose drug delivery system were watched for three months; it was reported that the elderly who missed/did not take four or five doses of medication per week before using the system started to miss one or two doses and the elderly included in the study took 99% of the drug doses properly (Sather et al., 2007).

2. Conclusion and Evaluation

In this study, several prototypes of smart drug systems, basic usage features, users on drug compliance, drug administration safety and treatment efficacy relevant information has been reviewed, with some research results dealing with the effects. More than one chronical medication management in elderly people with the disease can be made easier for both themselves and their medicine caregivers. It can be seen that intelligent medicine systems can prevent medication errors, increase the drug compliance of the elderly and save time for the caregivers. With the intelligent medicine systems the efficiency of the treatment can be increased and undesirable consequences can be avoided, older individuals become more independent and burden of the health system can be reduced, it may be more possible to provide cost-effective healthcare services to elderly people.

References

1. Agrawal A. (2009). “Medication Errors: Prevention Using İnformation Technology Systems”, British Journal of Clinical Pharmacology, 67 (6): 681-686.
2. Alexan A., Osan A., Oniga S. “Advanced Medication Dispenser,” Carpathian Journal of Electronic and Computer Engineering, vol. 6, no. 2, pp. 26-31, 2013
3. Baril C., Gascon V., St-Pierre L., *vd.* Technology and medication errors: impact in nursing homes Int J Health Care Qual Assur, 27 (2013), pp. 244-258
4. Baril C., Gascon V., Brouillette C. Impact of technological innovation on a nursing home performance and on the medication-use process safety J Med Syst, 38 (2014)
5. Beobide-TelleríaI., Ferro-Uriguen A., Miró-Isasi B. *vd.* The impact of automation on the safety of drug dispensing in nursing homes. Farm Hosp, 42 (2017), pp. 141-146
6. Bierhals C., Santos N., Fengler F., *vd.* Needs of family caregivers in home care for older adults. Rev Lat Am Enfermagem, 25 (2017)
7. Bowsher M.,“The Automated Pill Dispenser project – the right pills at the right time delivering the right outcomes,". End project evaluation report. West Midlands [Walsall]: Improvement and Efficiency West Midlands, March 2012, 53p.
8. Cousein E., Mareville J., Lerooy A., vd. Effect of automated drug distribution systems on medication error rates in a short-stay geriatric unit. J Eval Clin Pract, 20 (2014), pp. 678-684
9. De P., Stoddart K. and George T. Using Artificial Intelligence to Reduce Long-Term Care Costs and Improve Patient Outcomes. Healthcare Financial Managament Association. Sep 30, 2017 (https://www.hfma.org/)
10. Epill.com. (2017). e-pill MedTime STATION Automatic Pill Dispenser. https://www.epill.com/epillstation.html

11. Fang K.Y., Maeder A.J., Bjering H. Current trends in electronic medication reminders for self care. Stud Health Technol Inform, 231 (2016), pp. 31-41

12. Fărcaş C., Ciocan I., Palaghiţă N., and Fizeşan R. "Weekly electronic pills dispenser with circular containers," 2015 IEEE 21st International Symposium for Design and Technology in Electronic Packaging (SIITME), pp. 125-129, 2015.

13. Hayes TL., Hunt HM., Adami A. et al. An electronic pillbox for continuous monitoring of medication adherence, (2006), 10.1109/IEMBS.2006.260367.

14. https://healthitanalytics.com/ Using AI, Data Analytics to Enhance Person-Centered Care for Seniors

15. Kassem A ., Antoun W., Hamad M., and El Moucary C. "Smart Medicine Dispenser (SMD)" the 4th IEEE Middle East Conference on Biomedical Engineering, MECBME 2018, pp. 20–23, 2018.

16. Lang A., Macdonald M., Marck P. et al. Seniors managing multiple medications: using mixed methods to view the home care safety lens. BMC Health Serv Res, 15 (2015), 10.1186/s12913- 015-1193-5

17. Minaam D.S.A., Abdelfattah M. Smart drugs: improving healthcare using smart pill box for medicine reminder and monitoring system. Science, 3 (2018), pp. 443-456

18. National Institutes of Health/World Health Organization. Global health and aging. NIH publication no 11-7737. 2011. http://www.who.int/ageing/publications/global_health.pdf.

19. OECD. Health reform: Meeting the challenge of ageing and multiple morbidities. 2011. http://www.oecd ilibrary.org/docserver/download/8111171e.pdf?expires=1493716006&id=id&accname=ocid49027884&checksum=255577E73173C96A9607DFAA81932937

20. Oswald, S. ve Caldwell, R. (2007). "Dispensing Error Rate After İmplementation of an Automated Pharmacy Carousel System", American Journal of Health-System Pharmacy, 64 (13):1427-1431.

21. Othman N.B. and Ek O.P. "Pill dispenser with alarm via smart phone notification," 2016 IEEE 5th Global Conference on Consumer Electronics, pp. 1-2, 2016.

22. Pak J.G., and Park K.H. "Construction of a Smart Medication Dispenser with High Degree of Scalability and Remote Manageability," Journal of Biomedicine and Biotechnology, vol. 2012, Article ID 381493, 10 pages, 2012. doi:10.1155/2012/381493

23. Ranjith K. and Mahalaxmi R. "Pharmaceutical mini tablets," International Journal of PharmTech Research. 7. 507-515, 2015

24. Rantanen P., Parkkari T., Leikola S. *vd.* An in-home advanced robotic system to manage elderly home-care patients' medications: a pilot safety and usability study. Clin Ther, 39 (2017), pp. 1054-1061

25. Rochon PA. Drug prescribing for older adults.(2019)

https://www.uptodate.com/contents/drug-prescribing-for-older-adults

26. Sather B.C., Forbes J.J., Starck D.J. and Rovers J.P. Effect of a personal automated dose-dispensing system on adherence: A case series. January 2007 Journal of the American Pharmacists Association: JAPhA 47(1):82-5 DOI:10.1331/1544-3191.47.1.82.Sather SourcePubMed

27. Shruthi R., Jyothi R., Pundarikaksha H.P., Nagesh G.N., Tushar T.J. A study of medication compliance in geriatric patients with chronic ıllnesses at a tertiary care hospital. J Clin Diagn Res. 2016; 10(12): FC40–FC43. doi: 10.7860/JCDR/2016/21908.9088.

28. Sinnemäki J., Airaksinen M., Valaste M. *vd.* Impact of the automated dose dispensing with medication review on geriatric primary care patients drug use in Finland: a nationwide cohort study with matched controls. Scand J Prim Health Care, 35 (2017), pp. 379-386

29. Sokol MC., McGuigan KA. Verbrugge RR., Epstein RS. Impact of medication adherence on hospitalization risk and healthcare cost. Med care, 2005;43(6):521-530.

30. Stuck R.E., Chong A.W.,Mitzner T.L. *vd.* Medication management apps: usable by older adults? Proc Hum Factors Ergon Soc Annu Meet, 61 (2017), pp. 1141-1144

31. Tsai P.H., Chen T.Y., Yu C.R., Shih C.S. and Liu J.W.S "Smart Medication Dispenser: Design, Architecture and Implementation," in IEEE Systems Journal, vol. 5, no. 1, pp. 99- 110, March 2011.

32. Tsai K., Chen J., Wen C. Medication adherence among geriatric outpatients prescribed multiple medications. The American Journal of Geriatric Pharmacotherapy. 2012;10(1):61–68.

33. Turjamaa R., Kapanen S., Kangasniemi M. How smart medication systems are used to support older people's drug regimens: A systematic literature review. Geriatr Nurs. Nov-Dec 2020;41(6):677-684. doi: 10.1016/j.gerinurse.2020.02.005. Epub 2020 Mar 17.

34. U.S. Census Bureau (https://www.census.gov/newsroom/press-releases/2014/cb14-84.html)

35. Verloo H., Chiolero A., Kiszio B., Kampel T., Santschi V. Nurse interventions to improve medication adherence among discharged older adults: a systematic review. *Age and Ageing*, 2017; 46(5):747–754. https://doi.org/10.1093/ageing/afx076

36. Vrijens B., De Gaeest S., Hughes DA, et al. A new taxonomy for describing and defining adherence to medications. Br J Clin Pharmacol, 2012;73(5):691-705.

37. Zanjal S.V., Talmale G.R. Medicine reminder and monitoring system for secure health using IOT. Procedia Comput Sci, 78 (2016), pp. 471-476.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4
More information available at **aita.bakircay.edu.tr**

Evaluation of Entrepreneurship Level of Nursing Students

Havva ÖZTÜRK[1], Çiğdem TORUN KILIÇ[1, *], Aysun BAYRAM[1]

[1] *Department of Nursing, Faculty of Health Science, Karadeniz Technical University, Trabzon, Turkey.*

* Corresponding Author: Department of Nursing, Faculty of Health Science, Karadeniz Technical University, Trabzon, Turkey.
Tel.: +90 538 951 0317. E-Mail: cigdemtorunkilic@gmail.com

Publication Information

Keywords :

- Nursing,
- Nursing students,
- Entrepreneurship

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Aim: To determine the entrepreneurship levels of nursing students and to compare their entrepreneurship levels according to some factors.
Method: The population of this descriptive and cross-sectional study consisted of 738 students studying in the nursing department of a university in the Black Sea Region, and the sample consisted of 220 students studying in the first and fourth grades.
Results: Student nurses are 20.45±1.76 years old, 83% are girls and 56% are senior students. 61% of their mothers are primary school graduates and 43% of their fathers are high school graduates. 59% ot students chose the nursing because of the opportunity to have a job, and 5% of students received training on entrepreneurship. The mean score of the Students' Entrepreneurship Tendency Scale totally is 3.09±0.51, sub-dimension of taking risk score is 2.82±0.73, sub-dimension of adapting to innovations score is 3.85±0.66 and sub-dimension of perceived educational support score is 2.58±0.91. It is statistically significant that male (t=2.248), employee (t=2.014) and entrepreneurship-related education (t=2.235) and students whose mothers are high school graduates (χ^2KW=10.864) are higher in overall total entrepreneurship score mean ($p<0.05$).
Conclusion: The nursing students' entrepreneurship levels are medium level. To increasing the level of entrepreneurship providing students with training on the subject, supporting their creativity and risk-taking levels.

1. Introduction

The rapidly growing scientific advances and technological innovations had a significant impact on the healthcare industry as in all sectors. Besides, the changes in disease forms and increasing prevalence, shifting expectations of the society, cost-effective service approaches, and new circumstances and needs emerging in the healthcare system have made changes and innovations in healthcare institutions inevitable (Şahin et al, 2021). As a result, the concept of entrepreneurship emerges as a rising value of today's world (Küçük, 2014) considering that entrepreneurship in the general sense is the process of taking risks, catching up with innovations, taking advantage of opportunities and actualising all of these in the new era (Bahar et al., 2019).

Nurses should therefore possess the entrepreneurial trait to be able to keep up with the changes in the field of health and to be effective in this process of transformation. In other words, nurses should develop new strategies and be entrepreneurs in order to respond to the changing demands for nursing practices (Şahin et al, 2021). Developing entrepreneurship skills is therefore seen as one of the goals of nursing education. Entrepreneurship in nursing, a health discipline consisting of science and art, improves nurses' ability to develop creative and innovative methods in patient care as well as their ability to cope with uncertainties and complexities related to work (Boore & Porter, 2011; Klavuz & Aydın, 2020; Shırey et al., 2007). Concordantly, the International Council of Nurses (ICN, 2004) states that nurse entrepreneurs should have the personal traits of being strong, self-confident, risk-taking, creative, goal-oriented, reliable, patient, visionary, initiative-taking, disciplined and planned. ICN defines entrepreneur nurses as those involved in the provision of direct nursing services such as providing occupational health consultancy, developing health improvement projects and healthcare products, personnel management, nursing care, elderly care and counselling (ICN, 2004). For this reason, students studying in nursing departments and inclined towards entrepreneurship should be encouraged to participate in entrepreneurship activities. The content of nursing education should be able to identify and develop students' entrepreneurial characteristics (Dolu et al., 2016; Şahin et al., 2021). It has been reported that teaching techniques that support the creative thoughts of nursing students will contribute to the development of entrepreneurship in nursing. The nursing curriculum should therefore be arranged accordingly and environments, where students can express themselves better, should be developed (Uludağ & Uzun, 2018).

A scan of the literature for studies on nursing students' entrepreneurship tendencies and levels yielded a limited number of studies investigating their entrepreneurship traits and tendencies. Therefore, this study was conducted with the aim of determining the entrepreneurship levels of nursing students in the faculty of health sciences of a university in the Eastern Black Sea Region.

2. Materials and Methods

2.1. Type of Study

This is a descriptive study as it was conducted to determine the entrepreneurship levels of students studying in the first and fourth years of the nursing department of a university.

2.2. Study Population and Sample

The population of the study consisted of 738 students studying in the first, second, third and fourth years of the Faculty of Health Sciences of a university in the Eastern Black Sea Region, while the sample included 220 students who were studying in the first and fourth years and volunteered to participate in the study. Sample selection was not used and it was aimed to reach all students studying in the first and last years.

2.3. Data Collection Tools

The data were collected by hand between 25 November and 2 December 2019 using the Personal Information Form containing the demographic information of the student nurses, the Information Form for Determining Entrepreneurship Characteristics and the Entrepreneurial Inclination Scale.

Personal Information Form: It consists of 10 questions about the age and gender of the nursing students, the high school they graduated from, the year they were studying, whether they were working in an income-generating job, the reason for choosing nursing, educational level of parents, their current place of residence, and their education on entrepreneurship.

Information Form for Determining Entrepreneurship Characteristics: The 30-item form developed by Hmielseki and Corbett in 2006 was translated into Turkish by Karabulut (2009). It is a questionnaire rather than a scale and is evaluated as yes or no. Eleven items of this form were used.

Entrepreneurial Inclination Scale: The form developed by Ulutürk, Akman, and Bektaş (2015) to determine the entrepreneurship level of university students consists of 11 items. It includes three subdimensions: ‘Risk-taking propensity’ (items 1-4), ‘Being open to innovations (items 5-8),’ and ‘perceived educational support’ (items 9-11). Prepared in five-point Likert style, the scale is evaluated as strongly disagree (1), disagree (2), neutral (3), agree (4) or strongly agree (5). According to Ulutürk Akman and Bektaş (2015), the Cronbach alpha value of the scale was 0.793 in total, 0.855 in the risk-taking propensity subdimension, 0.721 in the being open to innovations subdimension, and 0.854 in the perceived educational support subdimension.

2.4. Data Evaluation

Students’ demographics and their views on entrepreneurship levels were tested with number, percentage and average. ANOVA, t-test, Kruskal Wallis, Mann Whitney U and Spearman Correlation analysis were used to compare some demographic characteristics and entrepreneurship levels of the students. Normality of the distribution was evaluated with the Kolmogorov and Smirnov test, and regression analysis was used to determine the factors affecting entrepreneurship levels.

2.5. Limitation of the Study

The study is limited to the opinions of the nursing department students studying at the Faculty of Health Sciences of a university located in the Eastern Black Sea Region.

2.6. Ethical Aspects of the Study

Prior to the data collection phase, written permission was obtained from the institution where the research was to be conducted on 13 November 2019. The nursing students participating in the study were interviewed and were explained the subject and purpose of the study. Volunteering participants were accepted to the study by making clear that names and signatures were not requested from the students and that any information they would provide would remain confidential.

3. Results

The average age of the student nurses participating in the study was 20.45. 82.7% of the students were female and 55.9% were fourth-year students. 73.6% of them were living in a dormitory and 3.6% were working in an income-generating job. 60.5% of their mothers were primary school graduates and 43.2% of their fathers were high school/university graduates. 58.6% chose nursing because of the opportunity to find a job, and 4.5% received training on entrepreneurship.

79.1% of the students stated that they were creative when working with limited resources and 72.3% of them told that they identified opportunities for new products/services. 71.4% reported that they found new uses for old methods or tools, 58.2% liked to take risks, and 50% stated that they were inventing new things and were creative.

The mean score of the Entrepreneurial Inclination Scale of all students participating in the study was 3.09±0.51 in total, 2.82±0.73 for risk-taking propensity, 3.85±0.66 for being open to innovations, and 2.58±0.91 for perceived educational support subdimensions.

Male students' entrepreneurship mean score was statistically significantly higher in overall total compared to female students ($t=2.248$; $p=0.026$). Besides, the working students compared to the non-working students ($t=2.014$; $p=0.045$) and the students who received education ($t=2.235$; $p=0.026$) compared to those who had not received education about entrepreneurship had statistically significantly higher mean entrepreneurship scores (Table 1).

Table 1. Comparison of Students' Entrepreneurship Inclination Scale Scores by Some Demographic Characteristics

Demographic characteristics	n	%	Entrepreneurial Inclination Mean±SD
Gender			
Female	182	82.7	3.05±0.48
Male	38	17.3	3.25±0.59
t-test; p value			t=2.248; p=0.026
Working Status			
Working	8	3.6	3.44±0.53
Not working	212	96.4	3.07±0.50
t-test; p value			t=2.014; p=0.045
Receiving entrepreneurship education			
Yes	10	4.5	3.43±0.42
No	210	95.5	3.07±0.51
t-test; p value			t=2.235; p=0.026
Total	220	100	

In the subdimensions, the male students' perceived educational support scores were statistically significantly higher than the female students ($U=2637.0$; $p=0.02$). Fourth-year students were also more open to innovations compared to first-year students ($U=5005.0$; $p=0.039$) and first-year students had higher scores in perceived educational support (U=4543.0; p=0.002) subdimensions compared to fourth-year students, both of which were statistically significant. Also, working students' scores in the risk-taking subdimension were statistically significantly higher than those who were not working (U=344.0; p=0.004) (Table 2).

There was a statistically significant relation between the reasons for nursing students to choose the profession and the perceived educational support subdimensions of the scale (χ^2KW=11.199; p=0.004); compared with the students who chose nursing for job opportunities, students whose choice was guided by their interest in the profession (p=0.009) and their university admission exam score (p=0.009) had higher perceived educational support scores (Table 2).

There was a statistically significant relation between the educational status of the students' mothers and the scale total (χ^2KW=10.864; p=0.004) and being open to innovations (χ^2KW=8.073; p=0.018) and perceived educational support (χ^2KW=10.0.31; p=0.007) subdimensions, where students whose mothers had high school education had higher perceived educational support scores (p=0.014, p=0.002, respectively) and scale total scores (p=0.001) than students whose mothers were primary and secondary school graduates (Table 2).

There was no statistically significant relationship between the students' ages, grades, the high school they graduated from, the reasons for choosing nursing, where they resided, and their fathers' educational status and entrepreneurial tendencies scale scores (p> 0.05).

Table 2. Comparison of Nursing Students' Total and Subdimension Scores from the Entrepreneurial Inclination Scale by Some Demographic Characteristics (n=220)

Characteristics	n	RP	BOI	PES	TOTAL
Gender		**Med(min-max)**	**Med(min-max)**	**Med(min-max)**	**Mean±SD**
Female	182	2.75 (1-5)	4 (1-5)	2.58 (1-5)	3.25 ± 0.59
Male	38	2.82 (1.25-5)	3.85 (2-5)	3 (1-5)	3.05 ± 0.48
t / MW-U		U = 2847.00	U = 3418.50	U= 2637.00	t =2.24
p value		0.085	0.911	**0.020**	**0.026**
Classes		**Med(min-max)**	**Med(min-max)**	**Med(min-max)**	**Mean±SD**
1st Class	97	2.75 (1-5)	3.75 (2-5)	3 (1-5)	3.09 ± 0.52
4th Class	123	2.75 (1-5)	4 (1-5)	2.33 (1-5)	3.08 ± 0.50
t / MW-U		U= 5265.50	U= 5005.00	U= 4543.50	t= 0.242
p value		0.133	**0.039**	**0.002**	0.809
Working status		**Med(min-max)**	**Med(min-max)**	**Med(min-max)**	**Mean±SD**
Yes	8	3.37 (2.75-4.25)	4.37 (3.25-5)	2.5 (1.33-4.33)	3.44 ± 0.53
No	212	2.75 (1-5)	4 (1-5)	2.66 (1-5)	3.07 ± O.50
t / MW-U		U=344.00	U=529.00	U=836.00	t =2.014
p value		**0.004**	0.69	0.945	**0.045**
Reason to choose nursing		**Med(min-max)**	**Med(min-max)**	**Med(min-max)**	**Med(min-max)**
Job opportunities (1)	129	2.75 (1-5)	3.85 (1-5)	2.33 (1-5)	3 (1-5)

Interest in Nursing (2)	76	2.78 (1-4.25)	4 (1.5-5)	3 (1-5)	3.16 (2-4.42)
University entrance score (3)	15	2.75 (2.25-4)	4 (2.75-4.5)	3 (1.67-4)	3.16 (2.56-3.92)
χ^2KW		KW= 0.343	KW=0.743	KW=11.199	KW=6.694
p value		0.842	0.690	**0.004**	**0.035**
Advanced test (MW-U)				2>1; 3>1 p<0.05	2>1 p<0.05
Maternal education status		**Med(min-max)**	**Med(min-max)**	**Med(min-max)**	**Med(min-max)**
Primary school (4)	133	2.75 (1-5)	3.85 (1-5)	2.58 (1-5)	3.02 (1-5)
Middle school (5)	40	3 (2-4)	4 (1.5-5)	2.33 (1-5)	3.09 (2-4.11)
High School (6)	47	2.75 (1-4.5)	4 (3.25-5)	3 (1-5)	3.25 (2-4.36)
KW		KW = 3.652	KW = 8.073	KW = 10.031	KW = 10.864
p value		0.161	0.18	**0.007**	**0.004**
Advanced test (MW-U)				6>4;6>5 p<0.05	6>4 p<0.05
Receiving entrepreneurship education		**Med(min-max)**	**Med(min-max)**	**Med(min-max)**	**Mean±SD**
Yes	10	3.37 (2.5-4.25)	4.25 (2.75-5)	2.45 (2-4.33)	3.43 ± 0.42
No	210	2.75 (1-5)	4 (1-5)	2.66 (1-5)	3.07 ± 0.511
t / MW-U		U = 563.00	U = 773.500	U = 971.500	t=2.235
p value		**0.013**	0.156	0.686	**0.026**

***RP:** Risk-taking propensity, **BOI:** Being open to innovation,**PES:** Perceived educational support

When the effects of students' entrepreneurship trait on entrepreneurial inclinations scale scores were evaluated, nursing students' traits of finding new uses for old methods/tools (= 0.225), liking to take risks (= 0.196) and inventing new things/being creative (β=0.169) significantly positively affected the scores of the entrepreneurship inclination scale with this developed model (p <0.01). This model was highly significant (F=12.594; p <0.001), but independent variables explained 14% of the total variance (R2=0.137) (Table 3).

Table 3. The effect of students' entrepreneurship traits on their entrepreneurial inclination scores

Independent variables	Beta	Standard error	Standardized Beta (%95 CI)	t	p
Constant	2.702	.071	2.561-2.842	37.910	**.000**
I invent new things / I'm creative.	.173	.066	.169 (.043-.303)	2.621	**.009**
I find new uses for old methods or tools.	.255	.073	.225 (.111-.398)	3.506	**.001**
I like to take risks.	.204	.066	.196 (.074-.333)	3.091	**.002**

4. Discussion

Current developments and changes in the field of medicine and technology make it necessary to train nurses with high entrepreneurial levels in nursing education as in every field. With this study, it was aimed to create awareness about this topic by determining the entrepreneurial traits of nursing students and the factors affecting them.

In our study, the majority of the students were female and lived in a student dormitory. More than half of them were in the fourth year, and the vast majority of them were not working, and more than half chose the nursing profession as a means for finding a job. According to previous studies, nursing students preferred nursing departments due to quick job opportunities after graduation (Özdelikara et al., 2016; Zencir & Eşer, 2016; Türk et al., 2018), consistent with our results. This may be due to the high possibility of finding employment even if the students found the nursing profession unattractive and the salary is not too high. Çiçek ve Ünlü's (2019) study also supports this view. The authors stated that the generation Z attaches importance to career development and shows improvement with technology and therefore students preferred more attractive professions over nursing (Çiçek & Ünlü, 2019).

As for the students' entrepreneurship traits, most of them stated that they were creative when they had to work with limited resources and identified opportunities for new products/services and found new areas of use for old methods or tools. However, half of the students stated that they liked to take risks and they were inventing new things and were creative. Some studies came to conclusions that support our research findings (Eminoğlu, 2016; Karabulut et al., 2009). According to the results of the research, the students' entrepreneurship traits displayed a positive outlook in the desired direction.

The students' entrepreneurship tendencies scale scores were average for the overall scale and in all subdimensions, and their mean scores from the subdimensions of risk-taking and perceived educational support were slightly lower. Bodur (2018) also found average entrepreneurship levels for nursing students but unlike our study, some other studies demonstrated high entrepreneurship levels for nursing students (Atasoy & Akbaş, 2020; Bahar et al., 2019; Dolu et al., 2016). These studies indicated that students have entrepreneurship potential. It is very important to know the characteristics of students with entrepreneurial trait, to reveal which variables are affected by these characteristics, and to create suitable environments for the development of entrepreneurship in order to support entrepreneurial youth. The reason for the students' lower risk-taking and perceived educational support scores despite the higher scores from being open to innovations in our study may be because students focus on their lessons rather than projects and activities that require entrepreneurship or professional organizational work. The schools they are studying at not offering these opportunities to the students may also be another reason. Yet, training, symposiums, competitions and congresses on entrepreneurship, creativity and innovation, idea generation are organized in nursing colleges. Supporting students to participate in scientific activities and informing them about entrepreneurship can also encourage them to take risks. In addition, introducing courses such as applied entrepreneurship and nursing care technology as elective courses in nursing undergraduate education may increase students' perceived educational support.

On the other hand, male students, students who work in an income-generating job and receive entrepreneurship-related education had higher overall entrepreneurship score averages. Previous studies with results that are in line with our findings are also reported that male students (Atasoy & Akbaş, 2020; Gömül et al., 2017; Klavuz & Aydın, 2020), those working in an income-generating job (Bahar et al., 2019; Eminoğlu, 2016; Keleş et al., 2016; Keleş et al., 2012) and those receiving training on entrepreneurship (Eminoğlu, 2016; Şahin et al., 2021) had higher entrepreneurship levels. The finding that male students seemed more entrepreneurial than female students can be attributed to the effect of the cultural structure. Today, female nursing students can also engage in entrepreneurial activities by using their skills in the healthcare industry. They should be encouraged for entrepreneurship by being supported materially and spiritually without gender discrimination. It can also be said that the positive experiences and knowledge gained by working in a job motivate students for the business world and increase their entrepreneurship level. Entrepreneurship, currently a focus of interest in Turkey, also appears to have become more prevalent, especially among the younger population, with contributions of entrepreneurship education and innovation congresses in nursing held at universities.

According to the subdimensions of the entrepreneurial inclinations scale, first-year students and male students perceived more educational support, while fourth-year students were more open to innovations, and students working in an income-generating job were more likely to take risks. Previous studies that reported similar results have also shown that working students had higher risk-taking levels (Eminoğlu, 2016; Dolu et al, 2016). We believe that the high tendency of 4th-year students to be open to innovations is because they feel they have to enter business life as their studentship is about to come to an end or because they have received entrepreneurship training until they reach the 4th year and thus realised their potential through this training.

The perceived educational support scores of the students who chose nursing because of the opportunity to find a job were higher than the students who chose nursing because of their interest and university admission exam score. Unlike our study, a study found higher perceived educational support scores for students who chose nursing because they were interested in the profession (Eminoğlu, 2016). In addition, students whose mothers had high school education were more open to innovations, perceived more educational support and had higher entrepreneurship levels compared to students whose mothers had primary and secondary education. Other studies with different results from this study concluded that participants whose fathers had at least high school education had more risk-taking tendency (Çelikoğlu, 2015) although there was no significant difference between maternal education level and entrepreneurship level (Çelikoğlu, 2015; Dolu et al., 2016). The high level of parent education may have been effective in supporting the students more and in raising them to have the entrepreneurship trait.

It was observed that the students who had the traits of finding new uses for old methods/tools, taking risks and inventing new things/being creative had higher entrepreneurship levels. Eminoğlu (2016) reported that students who had these traits had higher scores in the subdimensions of risk taking and being open to innovations, supporting our findings. In order to keep up with and implement innovations, identify changing needs and initiate changes, nurses and nursing students need to have certain traits such as being innovative, risk-taking, perceiving problems and being opportunity-oriented and entrepreneur. Innovative and entrepreneurial nursing students can contribute to the nursing profession in the future as practitioners that produce care technologies in the health care system, design products that improve the quality of nursing care, obtain patents, and produce innovative projects. Innovative and entrepreneurial nursing students can shape their professional and individual futures by following scientific and technological advances (Bodur, 2018).

5. Conclusion and Suggestions

In order to be a good entrepreneurial nurse, it is essential to have traits such as the habit of following medical and technological developments, taking risks, predicting the future and being open to innovations. However, in this study, the entrepreneurship levels of the students were average although students who were male, working and those who had received entrepreneurship education had higher levels of entrepreneurship. The students who had the traits of finding new uses for old methods/tools, taking risks and inventing new things/being creative also had higher levels of entrepreneurship.

Based on these results, motivational support can be provided by offering training and consultancy services to support the entrepreneurship tendencies of students. To boost entrepreneurship throughout the country, it is necessary to spread the entrepreneurship culture and education and to develop entrepreneurial personalities. In addition, making the currently elective entrepreneurship courses compulsory in some nursing departments, enriching their content and making the course practical may be beneficial to support students with an entrepreneurial spirit. Besides, considering the changes and progresses in the profession, nursing students can strengthen their entrepreneurial qualities specific to nursing by taking courses from business and management departments at the university in order to prepare for the future. Small projects and funds and informative training provided by the university to support the entrepreneurship levels of students can strengthen their entrepreneurship traits and increase how frequently they use this trait.

References

1. Atasoy, I., & Aktaş, A. B. (2020). Hemşirelik Öğrencilerinin Girişimcilik Algısına Cinsiyet ve Diğer Faktörlerin Etkisi. JAREN 2020;6(1):80-8. doi:10.5222/jaren.2020.89421
2. Bahar, A., Kocaçal Güler, E., Arslan, M., İnem, A. B., & Çimen, Z. S. (2019). Hemşirelik öğrencilerinde girişimcilik düzeyi ve etkileyen faktörlerin belirlenmesi.
3. Bodur, G. (2018). Hemşirelik öğrencilerinin bireysel yenilikçilik (inovasyon) düzeyleri ile girişimcilik eğilimleri arasındaki ilişki. *Sağlık Bilimleri ve Meslekleri Dergisi*, *5*(2), 139-148.
4. Boore J, Porter S. (2011). Education for entrepreneurship in nursing. Nurs Educ Today. 2011;(31):184-191.
5. Cuningham J.B., Lischeron J. . (1991). Defining entrepreneurship. journal of Small Business Menagement. vol. 29.
6. Çelikoğlu O. Eğitimde girişimcilik ve inovatif öğretim liderleri yetiştirmek. Akademik Sosyal Araştırmalar Dergisi. 2015;20:247-59. [CrossRef]
7. Çiçek H, Ünlü G. Z (2019). Kuşağının kariyer beklentileri: lise öğrencileri üzerinde bir uygulama. *Selçuk Üniversitesi Sosyal Bilimler Meslek Yüksekokulu Dergisi*, *22*(2), 447-458.
8. Dolu, İ. Ç., Temucin, E. D., & Ökan, H. A. (2016). Hemşirelik öğrencilerinin girişimcilik düzeyleri ile bazı ilişkili faktörlerin değerlendirilmesi.
9. Eminoğlu, A. (2016). Hemşirelik öğrencilerinin girişimcilik özellikleri ve eğilimleri. Yüksek Lisans Tezi. Gaziantep Üniversitesi, Sağlık Bilimleri Enstitüsü, Gaziantep.
10. Erol, Ö., Yacan, L., Hayta, R., Şahin, İ., & Yağcı, M. (2018). Hemşirelik Öğrencilerinin Yenilikçilik Özellikleri ve Etkileyen Faktörler. *Hemşirelikte Eğitim ve Araştırma*, *15*(3), 142-146.

11. Gümül F, Çalık A, Kurt H. (2017). Meslek yüksekokulu öğrencilerinin girişimcilik eğilimlerini incelemeye yönelik bir araştırma. Afyon Kocatepe Üniversitesi Sosyal Bilimler Dergisi. 9(2):91-107.
12. Karabulut A.T. (2009). Üniversite Öğrencilerinin Girişimcilik Özelliklerini Ve Eğilimlerini Belirleme. Marmara Üniversitesi İ.İ.B.F Dergisi. 2009; Cilt 26. Sayı 1. 331-356.
13. Keleş HN, Özkan TK, Doğaner M, Altunoğlu AE. (2012). Önlisans Öğrencilerinin Girişimcilik Düzeylerini Belirlemeye Yönelik Bir Araştırma. Uluslararası İktisadi ve İdari İncelemeler Dergisi 2012;9:107-18.
14. Kılavuz, F., & Aydın, A. K. (2020). Hemşirelik Öğrencilerinin Bireysel Girişimcilik Algıları ve Yaşam Boyu Öğrenme Eğilimleri Arasındaki İlişkinin Belirlenmesi. *Hacettepe Üniversitesi Hemşirelik Fakültesi Dergisi*, *7*(3), 240-248.
15. Konuk Şener D. (2012). Hemşirelikte Yeni ve Önemli Bir Kavram: Girişimcilik. İ.Ü.F.N. Hem. Derg. Cilt 20 - Sayı 2: 140-145.
16. Küçük O. (2019). Girişimcilik ve Küçük Işletme Yönetimi. 7. baskı, Ankara: Seçkin Yayıncılık, s. 26-30.
17. Internatıonal Councıl of nurses (ICN). Guidelines on The Nurse Entre/Intrapreneur Providing Nursing Service. Geneva, 2004.
18. Özdelikara, A. (2016). Hemşirelik öğrencilerinin öğrenimlerine ilişkin doyum düzeyi ve etkileyen faktörler. *Dokuz Eylül Üniversitesi Hemşirelik Fakültesi Elektronik Dergisi*, *9*(1): 2-8.
19. Shırey M.R et al. (2007). An evidence-based understanding of entrepreneurship in nursing, CNA. 2007;21(5):234-240.
20. Şahin, E., Yıldız, Öğüt., & Aydın, H. T. (2021). Hemşirelik öğrencilerinin girişimcilik ve bireysel yenilikçilik eğilimlerinin belirlenmesi. *Health Sciences Student Journal*.
21. Türk G, Adana F, Erol F, Akyol RÇ, Taşkıran N. (2018). Hemşirelik öğrencilerinin meslek seçme nedenleri ile bakım davranışları algısı. *Gümüşhane Üniversitesi Sağlık Bilimleri Dergisi*, *7*(3): 1-10.
22. Uludağ, E., & Sevda, Uzun (2018). Hemşirelik Eğitiminde Öğrencilerin Yaratıcı Düşünce Becerilerinin İncelenmesi (Gümüşhane İli Örneği). *Gümüşhane Üniversitesi Sağlık Bilimleri Dergisi*, *7*(3), 63-70.
23. Ulutürk Akman S, Bektaş H. (2015). Üniversite Öğrencilerinin Girişimci Özelliklerinin İncelenmesi. Marmara Üniversitesi İ.İ.B. Dergisi, 2015; Cilt 37, Sayı I, ss. 217-232.
24. Zencir G, Eşer İ. (2016). Hemşirelik öğrencilerinin hemşirelik mesleğine yönelik tutumları ile hemşirelik tercihi arasındaki ilişki: Türkiye Örneği. *Dokuz Eylül Üniversitesi Hemşirelik Fakültesi Elektronik Dergisi*, *9*(2): 30-37.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Virtual Reality and Augmented Reality Applications in Pediatric Dentistry

Meltem EKİNCİ [1,*], Can ÖZÜKOÇ [1]

[1] *Istanbul Medipol University, Faculty of Dentistry, Dept. of Pediatric Dentistry, Turkey*

* Corresponding Author: Istanbul Medipol University, Faculty of Dentistry, Turkey
Tel.: +90 212 4401010. E-Mail: meltemekinc@medipol.edu.tr

Publication Information

Keywords :
- Augmented reality,
- Pediatric dentistry,
- Virtual reality

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Introduction: In the 2000s, a human computer interface was created with virtual reality devices that were sold commercially and users started to establish a dynamic relationship with the computer in a virtual environment. Virtual reality, or VR in short, distracts the user by disconnecting them from the outside world. The advantage of VR is that it can carry all auditory, visual and kinesthetic stimuli. For this reason, it seems appropriate to use it for the purpose of providing cooperation and distraction in pediatric dentistry.

Method: As a result of scanning the Pubmed and Google Scholar databases, the information obtained from the articles published in 2000 and after was systematically evaluated.

Results: By using 3D video game supported by virtual reality glasses, it was determined that the fear of dentists and pain, which is frequently seen in school-age children, was reduced and augmented reality applications were effective in patient motivation and education.

Conclusion: In studies conducted, it has been shown that devices in the form of glasses that can be worn on the head, 3-dimensional, wide field of view and can be controlled manually, are more successful in creating virtual surroundings, reduce the stress level and increase the pain threshold and provide analgesia. Similarly, in pediatric dentistry, with virtual reality and augmented reality applications, it has been shown that the stress level decreases and the response to painful stimuli decreases.

1. Introduction

Behavior caused by fear creates difficulties during dental treatments, and affects the quality of the treatment that the patient will receive [1,2,3]. The reason for the fear of dentists is that they think that the patient will feel pain during treatment [4,5,6].

The methods applied in order to reduce the stress that occurs during dental treatments in pediatric patients are examined in 2 main categories. In the first category, behavior orientation techniques such as tell-show-apply, distraction, positive reinforcement, non-verbal communication can be counted. The second category includes pharmacological methods (7,8).

Distraction is seen as a safe and inexpensive method for short-term dental treatments (7). When previous studies are examined, it seems to be the most preferred technique in short-term invasive treatments (9,10) By letting children listen to music, watch television during treatment, with the help of various objects or decorations in the room, and distract the patient by talking about a non-medical issue. technique has been applied (11). However, the ideal distraction practice should include auditory, visual and tactile stimuli at an optimal level and prevent harmful stimuli (11,12). In another study, in addition to the aforementioned features, active feeling is considered among the ideal features (13).

2. Results

As a result of the scanning of Pubmed and Google Scholar databases, the information obtained from the articles published in 2000 and after was systematically evaluated.

By using 3D video game supported by virtual reality glasses, it was determined that the fear of dentists and pain, which is frequently seen in school-age children, was reduced and augmented reality applications were effective in patient motivation and education.

3. Discussion

In the 2000s, a human computer interface was created with virtual reality devices that were sold commercially, and users started to establish a dynamic relationship with the computer in a virtual environment. Virtual reality, or VR in short, distracts the user by disconnecting them from the outside world.

Augmented Reality is an overlay of computer-generated content in the real world. The important note here is that the augmented content does not recognize physical objects in the real world. In other words, AR content and real world content cannot respond to each other.

Augmented Reality (AR) elements are a live, direct or indirect view of a physical, real-world environment complemented by computer-generated sensory input such as audio, video, graphics, or GPS data. Because AR is above our own world, it provides as much freedom in your normal life as it is given to you. AR uses your current reality and adds to it using some kind of device. Mobile and tablets are now the most popular environments for AR, applications place digital content around via the camera.

The advantage of VR and AR is that it can carry all auditory, visual and kinesthetic stimuli (11). However, in studies conducted, it has been shown that devices in the form of glasses that can be worn on the head, 3-dimensional, with a wide field of view and that can be controlled manually, are more successful in creating virtual surroundings, reduce the stress level and provide analgesia by increasing the pain threshold (11).

In a study comparing distraction techniques, it was found that video techniques were more effective than voice programs in reducing stress (14). It has been determined that kinesthetic stimulus does not occur when watching videos using VR only (11).

While VR glasses supported with video games to create the sense of kinesthetic stimulus and active sensation are used today because they reduce the pain that occurs in burn treatments, the game named SnowWorld, which was developed for use in burn treatment, is used by the American army (15). Similarly, many 3D games are used in burn treatment, cancer pain, chronic pain, blood draw, intravenous catheter applications with VR glasses (16). It has been reported that it decreases the frequency of contractions in patients with cerebral palsy and has a positive effect in children with autism, attention deficit and fetal alcohol syndrome (17).

Although there were not many studies in dentistry, patients were watched videos using LCD glasses, and in one study, a decrease in systolic blood pressure, a decrease in anxiety and pain was found (18). In another study, while the snow world game was applied to a patient with 3D glasses, the other patient was watched with 3D glasses, and the patient who played games with 3D glasses stated that he felt less pain, but it was observed to be more positive during treatment (19). In a study conducted by watching videos in children aged 4-6, it was stated that better results were obtained when the programs liked by children were preferred (20).

4. Conclusion

In studies conducted, it has been shown that devices in the form of glasses that can be worn on the head, 3-dimensional, with a wide field of view and that can be controlled manually, are more successful in creating virtual surroundings, reduce the stress level and provide analgesia by increasing the pain threshold. Similarly, in pediatric dentistry, with virtual reality and augmented reality applications, it has been shown that the stress level decreases and the response to painful stimuli decreases.

References

1. RM, Corah NL, Ayer WA. Sources of dentists' stress. JADA 1984;109(1):48-51.
2. Corah NL, O'Shea RM, Ayer WA. Dentists' management of patient's fear and anxiety. JADA 1985;110(5):734-6.
3. Milgrom P, Coldwell SE, Getz T, Weinstein P, Ramsey DS. Four dimensions of fear of dental injections. JADA 1997;28:756-62.
4. McNeil DW, Au AR, Zvolensky MJ, McKee DR, Klineberg IJ, Ho CC. Fear of pain in orofacial pain patients. Pain 2001 Jan;89(2-3):245-52.
5. de Jongh A, Muris P, ter Horst G, Duyx MP. Acquisition and maintenance of dental anxiety: the role of conditioning experiences and cognitive factors. Behav Res Ther 1995 Feb;33(2):205-10.
6. Townend, E, Dimigen, G., Fung, D. A clinical study of child dental anxiety. Behav Res Ther 2000;38:31-46.
7. Prabhaker AR, Marwah N, Raju OS. A comparison between audio and audiovisual distraction techniques in managing anxious pediatric dental patients. J Indian Soc Pedod Prev Dent 2007;25:177-82.
8. Ram D, Peretz B. Administering Local anaesthesia to paediatric dental patients –current status and prospects for the future. Int J Paediatr Dent 2002;12:80-9.
9. Sinha M, Christopher NC, Fenn R, Reeves L. Evaluation of non-pharmacologic methods of pain and anxiety management for laceration repair in the pediatric emergency department. Pediatrics 2006;117:1162-8.
10. Wang ZX, Sun LH, Chen AP. The efficacy of non pharmacological methods of pain management in school age children receiving venipuncture in a pediatric department: a randomized controlled trial of audiovisual distraction and routine psychological intervention. Swiss Med Wkly 2008;138:579-84.
11. Wismeijer A, Vingerhoets AD. The use of virtual reality and audiovisual eyeglasses system as adjunct analgesic techniques: a review of the literature. Ann Behav Med 2005;30:268-78.
12. Slifer KJ, Tucker CL, Dahlquist LM. Helping children and caregivers cope with repeated invasive procedures: how are we doing? J Clin Psychol 2002;9:131-52.
13. Leventhal H. I know distraction works even though it doesn't. Health Psychology. 1992;11:208–9.

14. Seyrek SN, Corah NL, Pace LF. Comparison of three distraction techniques in reducing stress in dental patients. J Am Dent Assoc 1984;108:327-9.
15. Hoffman HG, Patterson DR, Carrougher GJ, Sharar S: The effectiveness of virtual reality based pain control with multiple treatments. Clinical Journal of Pain. 2001;17:229–35
16. Malloy KM, Milling LS. The effectiveness of virtual reality distraction for pain reduction: A systematic rewiew. Clinical Psychology Rewiew. 2010;30:1011-8.
17. Parsons TD, Rizzo AA, Rogers S, York P. Virtual reality in paediatric rehabilitation: A review. Developmental Neurorehabilitation, August 2009;12(4): 224–38.
18. Frere CL, Crout R, Yorty J, McNeil DW. Effects of audiovisual distraction during dental prophylaxis. Journal of the American Dental Association. 2001;132:1031-8.
19. Hoffman HG, García-Palacios A, Patterson DR. The effectiveness of virtual reality for dental pain control: A case study. CyberPsychology & Behavior. 2001;4:527–5.
20. Aminabadi NA, Erfanparast L, Sohrabi A, Oskouei SG, Naghili A. The Impact of Virtual Reality Distraction on Pain and Anxiety during Dental Treatment in 4-6 Year-Old Children: a Randomized Controlled Clinical Trial. JODDD (Autumn 2012).

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || ISBN : 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Machine Learning Based Polyneuropathy Diagnosis Using Electromyogram Data

Nimet TANIK [1, *], Adnan KAVAK [2]

[1] *Kocaeli University, Faculty of Engineering, Dept. of Computer Engineering, Turkey*
[2] *Kocaeli University, Faculty of Engineering, Dept. of Computer Engineering, Turkey*

* Corresponding Author: Kocaeli University, Faculty of Engineering, Turkey
Tel.: +90 532 612 7338. E-Mail: nimetkara77@gmail.com

Publication Information

Keywords :

- EMG
- Polinöropati
- NaiveBayes
- K-NN algoritması
- SVM

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Information technologies, which are used at the decision support point for the most efficient treatment applications with early and accurate diagnosis, support to provide speed, time, accuracy and quality health care for healthcare servers and patients. Again, in this field, we can create a more efficient application area in medicine by developing models that use different algorithms and information technologies. The aim of this study is to implement machine learning methods to determine the risk of polyneuropathy based on structured electronic medical records collected in medical information systems databases. A total of 22,000 actual data sets belonging to 1,000 people (720 healthy, 280 polyneuropathies) were used for polyneuropathy detection based on EMG analysis, and the featured data was reconfigured to match commonly used Machine Learning algorithms. In this study, EMG (Electromiyogram) data was passed through the data preprocessing, data grouping and attribute extraction stages before being classified. At this stage, it is aimed to maximize efficiency by getting support from professional healthcare providers. In the next stage, data is classified with Decision Tree, Naive Bayes, K-NN algorithm, Support Vector Machine (SVM) Algorithm and Random Forest classification algorithms. In the case of multiple attribute vectors, Naive Bayes and K-NN algorithm classifiers classified EMG data with higher accuracy than other classifiers, with total accuracy at 78% for the upper and lower extremities.The resulting results were shared with health care providers and the efficiency was confirmed to be satisfactory. It has been determined that predictive models will find more applications in the field of health, providing health care and providing undeniable benefits in terms of the field.

1. Introduction

While developing information technologies have the opportunity to be applied in all areas of life, they also play critical roles in providing speed, time, accuracy and quality health care for health service providers and patients in the field of health that is closely related to humanity. Information technologies used at the point of decision support for the most efficient treatment applications with early and accurate diagnosis are emerging with more and more products every day [1].

We see that machine learning is the subject of research studies such as health diagnosis, personal care support, drug discovery, medical image analysis and the development of robotic health assistants [2,3,4,5,6]. Especially in the scope of humanity's always encounter with different types of diseases and early diagnosis and treatment, the benefits of Artificial Intelligence and Machine learning techniques have become more popular for healthcare providers. By continuing to use machine learning algorithms in health areas, doctors' workloads will be reduced and better quality health services will be provided to patients.

In this study, polyneuropathy disease, which greatly reduces the quality of life, was tried to be detected using machine learning techniques. For this purpose, a data set consisting of 1000 people was obtained from the public hospital, 720 of whom were healthy and 280 of whom had polyneuropathy. In this data set, there are 22 subdata in each data group determined by specialist physicians using electromyography (EMG). With this proposed system, it should be supported with an appropriate interface program in order to achieve faster and more accurate results in health institutions.

2. Polyneuropathy Disease

Polyneuropathy is a condition of damage to multiple peripheral (circumference) nerves, also known as peripheral neuropathy. Nerves other than the brain and spinal cord are classified as peripheral nerves. In polyneuropathy, multiple peripheral nerves are affected at the same time. In addition to the responsible nerves for our senses and mobility, autonomous nerves can also be damaged. In polyneuropathy, it is often seen that a large number of nerves are held simultaneously, so it is symmetrical. The causes of polyneuropathy, which is often seen more prominently in the legs, can only be determined in 65-70% of the cases, despite very detailed examinations. Diabetes is the most common cause of peripheral neuropathy. Neuropathy occurs due to high blood sugar and excessively released insulin effects, accumulation of metabolic byprotects on the nerves, lack of oxygen, blood disorder of the nerves. In diabetes, not only the nervous system, but also the kidneys and the eye are affected by diseases. Approximately half of all diabetic patients develop neuropathy. According to the results of the latest TURDEP study, the incidence of diabetes in our country is 14%. In other words, 14 out of every 100 people have diabetes. This means that half of these patients will develop neuropathy disease, indicating that we are facing a very serious situation. [14]

Another cause of polyneuropathy disease is the lack of vitamin B1, B6, B12, E, and Folic acid as a result of malnutrition or poor quality nutrition, which can cause serious damage to the sensory nerves, especially in people.

In general, the most common symptoms due to polyneuropathy are; tingling and sarcasm sensation, numbness, not feeling pain, difficulty using arms, legs, hands or feet, sleep problems due to night pain, hypersensit sensitivity to touch, feeling pain such as burning, stabbing and freezing, inability to detect temperature changes, visible changes in skin, hair and nails, muscle weakness and muscle cruising, fall attacks and lack of coordination, skin and nail infections, leg and foot ulcers, excessive sweating, inability to tolerate heat are the most common symptoms due to polyneuropathy [14].

Electromyography (EMG) has been widely used by researchers and clinicians over the past two decades for the correct diagnosis of polyneuropathy, a neuromascular disease. EMG electrodes are placed on the median, ulnar and radial nerves, peroneal, tibial, femoral and sural nerve points in EMG extraction (upper extremity). By giving an electric current with the electrode placed on the skin, the nerves are stimulated and the activity emitted in the nerve is recorded through another electrode. The meaning of the resulting numerical values is made by the relevant clinician.

The EMG data set used in this study was created with the data of real patients who visited to Balikesir State Hospital with suspected polyneuropathy disease. When creating EMG data, two messages are divided into nerve groups: motor nerve and sensory nerve.

Table 1. EMG sub and upper extremite motor and sensory nerve transmission normal speeds

		MOTOR NERVE MESSAGE VALUES			SENSORY NERVE MESSAGE VALUES		
		LATANS (msn)	AMPLITUD (mV)	SPEED (m/sn)	LATANS (msn)	AMPLITUD (mV)	SPEED(m/sn)
UPPER EXTREMITE	MEDIANUS	<=4,2	>=4	>=50	<=3,5	>=15	>=40
	ULNARIS	<=3,4	>=4	>=50	<=3,1	>=15	>=40
	RADIALIS	<=2,9	>=2	>=50	<=2,9	>=10	>=40
SUB-EXTREMITE	PERONEAL	<=6,5	>=2	>=40	<=4,4	>=6	>=40
	TIBIAL	<=5,8	>=4	>=40	<=4,4	>=5	>=40
	FEMORAL	<=6	>=4,1	>=40	<=2,8	>=10	>=40

In this study, machine learning methods are applied to determine the risk of polyneuropathy based on electronic medical records (EMG data), and the attribute vectors used in the diagnosis of polyneuropathy are classified using decision tree, naive bayes, K-NN algorithm, Support Vector Machine (SVM) Algorithm and Random Forest algorithms respectively.

3. Machine Learning

Machine Learning (ML) is the statistical and algorithmic models used to carry out specific tasks without implementing explicit instructions. ML is a subset of artificial intelligence that relies on reasoning and patterns [15]. Applying mathematical model, ML algorithms used sample data (referred to as the "training data") to predict specific tasks without carrying out explicitly programming [16].

Classification is the division of data into several groups that are predefined. This entails assigning old data forecasts to previously unseen data records based on a trained construct model [17]. Examples of the use of classification algorithms include: determining if a credit card transaction is fraudulent or not, judging whether the mortgage default probability is fair or bad, diagnosing whether a patient has a certain condition [18]. The most well-known algorithms used in the literature and chosen for use in this research are as follows. There are several distinct algorithms for classification.

3.1. Naive Bayes Classifier

The Naive Bayes classification is intended to determine the class (i.e. the form of data given to the system) with a set of calculations defined in accordance with the probability principles [19]. The 'Naive' part of the algorithm comes from the fact that it is presumed that the attributes (features) are independent of each other in the dataset. This implies that all of the other attributes are not contingent on the presence of an attribute in the dataset. The framework includes a certain amount of training data under the Naive Bayes classification. There must be a class category for the data provided for learning [20]. The new test data submitted to the system are run according to the pre-obtained probability values with the probability processes carried out on the training data and the test data submitted are used to assess the category [21,22].

The Bayes Theorem is defined as follows:

$$P(C/X) = \frac{P(X/C)*P(C)}{P(X)} \qquad (3.1)$$

In (3.1), P(C) is the posterior probability of attribute X given to class C. P(X) is the probability that class C attributes are given. The previous probability of class C is P(C), and the prior probability of the attributes is P(X).

The Naive Bayes classification can be summarized as follows:

- The dataset is translated into a frequency table.
- The most probable class would be considered as the class estimate [20,21].
- The likelihood of each variable is determined for probability classification. In calculating the likelihood of each class, the Naive Bayes equation is used.

3.2. Decision Trees

Decision Tree algorithms for supervised learning are among the most common algorithms. It can be used in order to solve problems of classification and regression. However it is often used in classification, since planning and tests are easy and the results are easier to explain and more effective [23].

Decision-tree classification is conducted in two stages. For a tree to be built, the first move is. In the second step, classification rules are obtained from this tree structure. According to the algorithm used, the tree structure can differ. Different tree structures may offer various outcomes for classification. There are a number of algorithms based on decision trees that are developed. According to root, node, and branching parameters, these algorithms are divided into different categories. ID3, C4.5, CART, and C5 [24] are widely recognized algorithms.

3.3. K-NN algorithm

K-NN is one of the simplest and most widely used classification algorithms. It is used to solve both classification problems and regression problems. [26]. K-NN is an algorithm for nonparametric learning, also called lazy'. The notion of "lazy" means that schooling should not have a preparation period. It does not benefit from the outcomes of testing, but instead it "memorizes" the training dataset. In the entire dataset, it finds the closest neighbors [27]. When it is used for a forecast to be made. The distance of the latest data to be included in the sample dataset shall be calculated on the basis of the available data and the area of K in the vicinity shall be investigated. Three kinds of distance functions are widely used for distance measurements; Euclidean distance, distance from Manhattan, and distance from Minkowski.

3.4 Support Vector Machine (SVM)

SVM is a supervised learning algorithm based on supervised learning theory which is used to classify and regress. The SVM is a linearly divisible two-class learning operation, [25]. The goal of the SVM is to find a hyper plane with a maximum margin capable of separating the two groups. In the training data of a classifier, an excellent classification performance and high precision of estimation for data from the same distribution as the training data can be generalized. In two classes, support vector machines are broken down into linear and nonlinear vector support machines.

3.5 Random Forest

Random forest, like its name implies, consists of a large number of individual decision trees that operate as an ensemble. Each individual tree in the random forest output a class prediction and the class with the most votes becomes our model's prediction.

4. Material and Method

In this study, it will be explained which algorithms are used to extract, make sense and classify features from EMG data. The flowchart for the study is given in Figure 1.

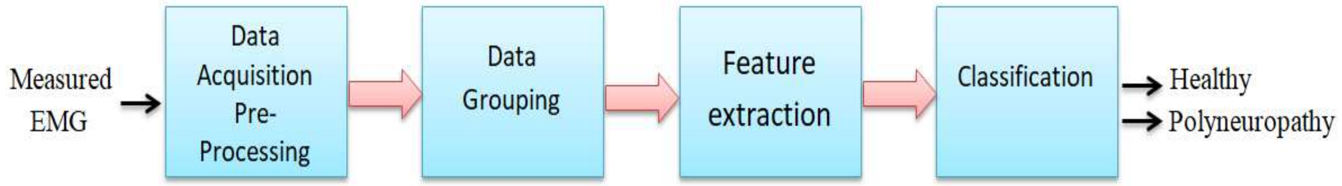


Figure 1. Flowchart Used in Classification of EMG Data

4.1. Data Acquisition and Preprocessing

EMG data used in this study are up-to-date data and are taken from Balikesir State Hospital EMG unit. The study data belong to 720 healthy people and 280 polyneuropathy patients, and there are also 22 subdata in each data group.

4.2.Data Grouping

The data is grouped according to certain criteria or differential characteristics. The resulting table is shared with health care providers and it is thought to examine the data as two sets of data as upper extremities and lower extremities.

4.3. Extracting Attributes

Feature extraction in EMG data is an important step in extracting useful information hidden from EMG data and removing unwanted portions and attempts from within the data. When we look at many studies on the classification of EMG data, it is seen that unnecessary property vectors are used. The successful classification of EMG data depends on the correct selection of the property vector. The choice of properties that are appropriate for the data is directly related to the high accuracy of the classifier [7,8]. During the data analysis phase, the focus is on the data groups that add the highest value to the study.

4.4. Classification

In this study, a total of 22000 data belonging to 1000 people (720 healthy, 280 polyneuropathy patients) were classified for EMG analysis. The featured data is reconfigured to match machine learning algorithms commonly used in data mining. All models are evaluated using a test data set. Common criteria are used in machine learning models to evaluate classification results.

Performance tests on above EMG data are run and compared using WEKA (Waikato Environment for Knowledge Analysis) software using Decision Tree, Naive Bayes ,K-NN, Support Vector Machine (SVM) and Random Forest classification algorithms [9,10,11,12].

4. Results

Results have been examined according to two data sets as upper extremities and lower extremities. The success rate of the data set with the K-NN algorithm using the upper extremity data set with the machine learning algorithms examined is 78%. Naive Bayes algorithm achieves a success rate of 77%. Support Vector Machine (SVM) Algorithm has a 71% success rate. With the Decision Tree algorithm, the success rate is found to be 77%. With the Random Forest algorithm, the success rate is found to be 72%.

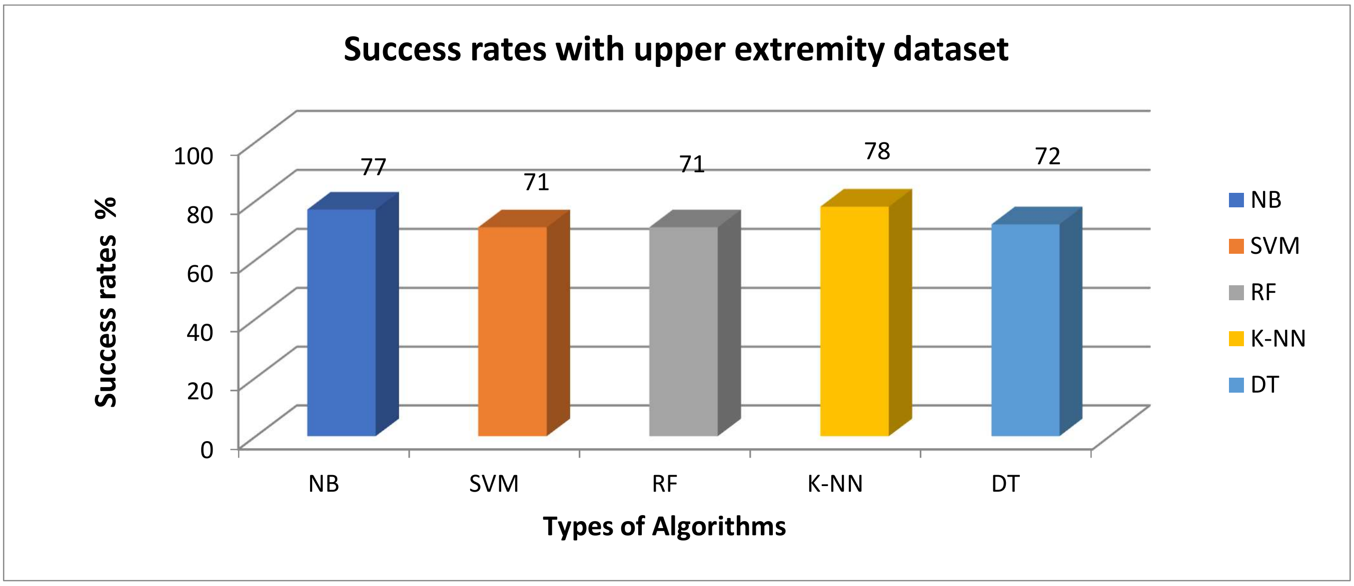


Figure 2. Machine learning success rates with the upper extremity data set

With the lower extremity data set we used as the second data set, a success rate of 78% is achieved with the Naive Bayes algorithm. Support Vector Machine (SVM) Algorithm has 74% success rate. The success rate is found to be 72% with the Decision Tree algorithm. With the Random Forest algorithm, the success rate is found to be 71%. With the K-NN algorithm, the success rate of the data set is 78%.

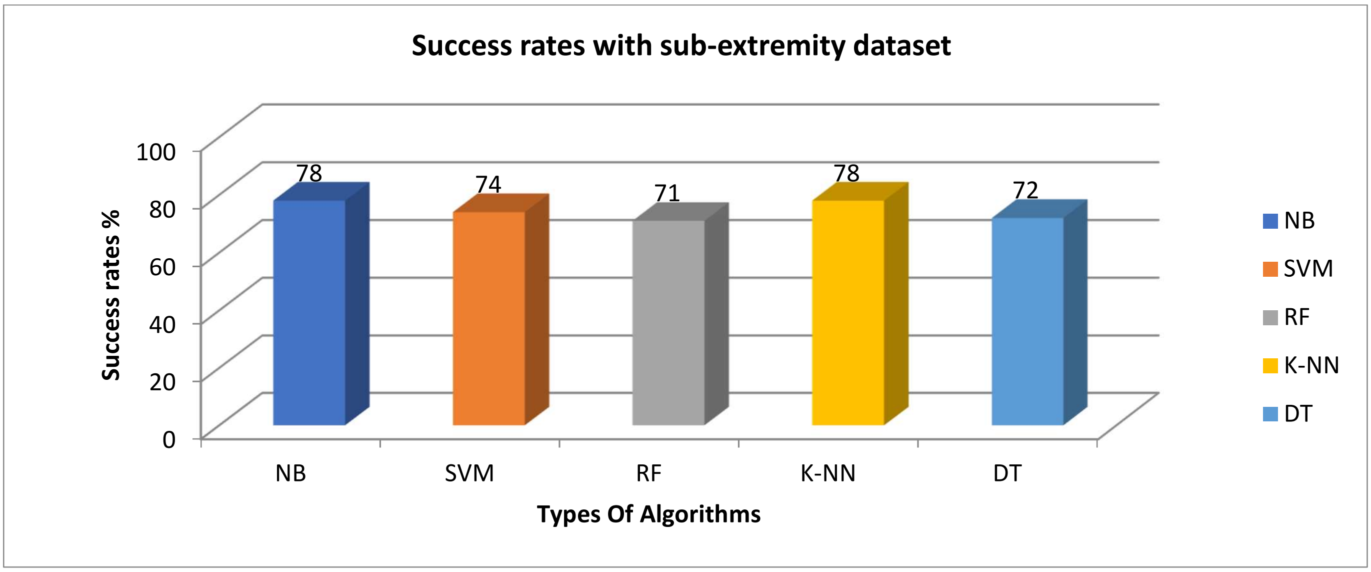


Figure 3. Machine learning success rates with sub-extremity dataset

5. Conclusion

In this study, the diagnosis of polyneuropathy disease, which greatly reduces the quality of life, was tried to be estimated by using a total of 22000 EMG data taken from Balıkesir State Hospital. The attribute vectors used in the diagnosis of polyneuropathy were classified using decision tree, naive bayes, K-NN, Support Vector Machine (SVM) and Random Forest algorithms. It has been found that K-NN algorithm outperforms with success rate of 78% on detecting polyneuropathy disease based on upper extremity and sub-extremity EMG data sets.

In our future studies, it is considered to develop a web-based application platform by defining more data sets into the system to achieve more accurate results using machine learning techniques. Thus, it is planned to reduce the workloads of our physicians by predicting the diagnosis of polyneuropathy disease as a result of transferring the data to the platform after EMG is shot.

References

[1] V. Basmajian, C.J. De Luca, Muscles Alive: Their Functions Revealedby Electromyography, 5th edition, William & Wilkins, Baltimore, 1985.
[2] Foster KR, Koprowski R, Skufca JD. Machine learning, medical diagnosis, and biomedical engineering research-commentary. Biomedical Engineering Online, 13(1), 94, 2014.
[3] Bhardwaj R, Nambiar AR, Dutta D. Study of machine learning in healthcare, In 2017 IEEE 41st Annual Computer Software and Applications Conference (COMPSAC) (Vol. 2, pp. 236-241). IEEE.
[4] Duch W, Swaminathan K, Meller J. Artificial intelligence approaches for rational drug design and discovery. Current Pharmaceutical Design, 13(14), 1497-1508, 2007.
[5] Shiraishi J, Li Q, Appelbaum D, Doi K,2011. Computer aided diagnosis and artificial intelligence in clinical imaging. In Seminars in Nuclear Medicine (Vol. 41, No. 6, pp. 449-462). WB Saunders.
[6] Taylor RH, Menciassi A, Fichtinger G, Fiorini P, Dario P. Medical robotics and computer integrated surgery. In Springer Handbook of Robotics (pp.16571684). Springer, 2016.
[7] Kavakiotis I, Tsave O, Salifoglou A, Maglaveras N, Vlahavas I, Chouvarda I.Machine learning and data mining methods in diabetes research. Comput Struct Biotechnol J.
2017;15:104–16.
[8] Zou Q, Qu K, Luo Y, Yin D, Ju Y, Tang H. Predicting diabetes mellitus with machine learning techniques. Front Genet. 2018; 9:515.

[9] Zhang X. Support vector machines. In: Encyclopedia of machine learning and data mining. Boston, MA: Springer US; 2017. p. 1214–20.
[10] Fürnkranz J. Decision tree. In:Encyclopediaof machine learning and data mining. Boston: Springer US; 2017. p. 330–5.
[11] Bashir S, Qamar U, Khan FH. IntelliHealth:a medical decision support application using a novel weighted multi-layer classifier ensemble framework. J Biomed Inform.
2016; 59:185–200.
[12] Ozcift A, Gulten A. Classifier ensemble construction with rotation forest to improve medical diagnosis performance of machine learning algorithms. Comput Methods Programs Biomed. 2011;104(3):443–51.
[13] Bozkurt MR. EMG İşaretlerinin Modern Yöntemlerle Önişlemesi ve Sınıflandırılması, Sakarya Üni. , Fen Bilimleri Ens., Doktora Tezi, Sakarya, 2007.
[14] Uludağ B. Nöropatiler ve Diyabetik Nöropatiler nedir? Neden olur?, İzmir, 2016
[15] Othman NA, Aydin I. A face recognition method in the Internet of Things for security applications in smart homes and cities. In: Proc. - 2018 6th Int. Istanbul Smart Grids Cities Congr. Fair, ICSG 2018, pp. 20–24, 2018, doi: 10.1109/SGCF.2018.8408934.
[16] Alhalaseh K, Migdadi H, Y RALH, “Home automation application using eeg sensor 1,” pp. 36–38, 2018.
[17] Ahmed O, Brifcani A. Gene Expression Classification Based on Deep Learning. In: 4th Sci. Int. Conf. Najaf, SICN 2019, pp. 145–149, 2019, doi: 10.1109/SICN47020.2019.9019357.
[18] Xie J et al., “A survey of machine learning techniques applied to software defined networking (SDN): Research issues and challenges,” IEEE Commun. Surv. Tutorials, vol. 21, no. 1, pp. 393–430, 2019, doi: 10.1109/COMST.2018.2866942.
[19] Wibawa AP et al., “Naïve Bayes Classifier for Journal Quartile Classification,” Int. J. Recent Contrib. from Eng. Sci. IT, vol. 7, no. 2, p. 91, 2019, doi: 10.3991/ijes.v7i2.10659.
[20] Fasidi F, Adebayo O. Rule-based Naïve Bayes Classifier for Heart Disease Risk Prediction and Int. J. Clin. Med. Informatics Rev., vol. 2, no. 2, pp. 51–59, 2019. 56
[21] Mukherjee A, Mondal S, Chaki N, Khatua S. Naive bayes and decision tree classifier for streaming data using hbase, vol. 897. Springer Singapore, 2019.
[22] Hassan MM, Jones E, Buck CE. A simple Bayesian approach to tree-ring dating. Archaeometry, vol. 61, no. 4, pp. 991–1010, 2019, doi: 10.1111/arcm.12466
[23] X. Hu, C. Rudin, and M. Seltzer, “Optimal Sparse Decision Trees,” no. NeurIPS, pp. 1–9, 2019.
[24] Mienye ID, Sun Y, Wang Z. Prediction performance of improved decision tree-based algorithms: A review. In: Procedia Manufacturing, 2019, vol. 35, pp. 698–703, doi: 10.1016/j.promfg.2019.06.011.
[25] L. L. Li, X. Zhao, M. L. Tseng, and R. R. Tan, “Short-term wind power forecasting based on support vector machine with improved dragonfly algorithm,” J. Clean. Prod., vol. 242, p. 118447, 2020, doi: 10.1016/j.jclepro.2019.118447.
[26] Demolli H, Dokuz AS, Ecemis A, Gokcek M. “Wind power forecasting based on daily wind speed data using machine learning algorithms,” Energy Convers. Manag., vol. 198, no. March, p. 111823, 2019, doi: 10.1016/j.enconman.2019.111823.
[27] Muppalaneni NB, Ma M, Gurumoorthy S, Soft Computing and Medical Bioinformatics. p. 139, 2019, doi: 10.1007/978-981-13-0059-2.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Use of Machine Learning in Diabetic Foot Management: A Systematic Literature Review

Merve GÜNBAŞ [1,*], Dilek BÜYÜKKAYA BESEN [2]

[1] *Dokuz Eylul University Institute of Health Sciences, Internal Medicine Nursing Doctorate Program İzmir, Turkey*
[2] *Dokuz Eylul University Faculty of Nursing, Department of Internal Medicine Nursing, İzmir, Turkey*

* Corresponding Author: Dokuz Eylul University Faculty of Nursing, Turkey
Tel.: +90 0534 2639113. E-Mail: mervegunbas94@gmail.com

Publication Information

Keywords :

- Artificial intelligence
- Machine learning
- Diabetes
- Diabetic foot

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Introduction-Purpose: Machine learning is a sub-branch of artificial intelligence that provides solutions to many problems such as image, picture and voice recognition by learning from examples instead of using coded information. Diabetes is a disease with severe acute and chronic complications and requires constant medical care. The probability of developing diabetic foot ulcer in advanced stages is 15-20%. More than 1 million patients each year face amputation due to early diagnosis of diabetic foot ulcers and lack of proper care. The purpose of this review is to examine the literature on machine learning methods used in diabetic foot management.
Material-Method: The literature on machine learning methods used in diabetic foot management was examined using PubMed, Cochrane Library and Google Scholar search engines and the keywords "artificial intelligence", "diabetes foot", "machine learning". Research articles, meta-analyzes, randomized controlled studies, and systematic reviews were reviewed in the literature between 2016 and 2021. 41 studies out of 1647 studies meeting the research criteria were examined in detail.
Results: As a result of the literature reviews, machine learning algorithms (color and thermal image segmentation process, segmentation and classification process, machine learning algorithms, etc.) are used for diabetic foot risk assessment, early diagnosis, classification, treatment and care processes. has been determined.
Discussion-Conclusion: It is thought that nurses' follow-up of artificial intelligence applications, contributing to their development and being a pioneer in their integration into applications will contribute to patient care and disease management.

1. Introduction

Diabetes Mellitus, generally known as diabetes, is a life-threatening chronic disease with serious complications such as cardiovascular, renal problems, hyperglycemia, blindness and lower extremity amputation [1]. Diabetes Mellitus is a common, chronic disease affecting 9.3%

of the world population (463 million) between the age group 20-79, according to 2019 data. This number is expected to increase to 600 million by the end of 2035 [2]. Diabetic foot ulcer occurs with the addition of infection and excess pressure on ischemia caused by neuropathy and peripheral vascular diseases. It is a serious picture that develops at a rate of 15-20% during the life of diabetes patients and amputation is seen in 7-10% of the cases. Every year, more than 1 million patients experience amputation due to the correct diagnosis of diabetic foot ulcers and lack of treatment [3]. According to the data of the Ministry of Health in 2015, approximately 12,000 amputations occur annually in our country, and most of these are amputations due to diabetes [7]. With the rapid spread of information and technologies and the development of healthcare services, new applications have been developed in diabetic foot management and monitoring. Machine learning is a sub-branch of artificial intelligence based on mathematical data called 'education data' based on sample data to make predictions or decisions without an open program to realize an event [4]. Thanks to machine learning, advancement in biosensors is used to detect diseases earlier and at a higher rate accurately and remotely and to eliminate all preventable hospitalizations [5].

The purpose of this review is to examine the literature on machine learning methods used in diabetic foot management.

2. Materials and Methods

The literature on machine learning methods used in diabetic foot management was examined using PubMed, Cochrane and Google Scholar search engines and the keywords "artificial intelligence", "diabetes foot", "machine learning". Research articles, meta-analyzes, randomized controlled studies, and systematic reviews were reviewed in the literature between 2016 and 2021. A total of 1647 studies were reached and 17 studies that fit the research criteria were examined in detail.

Research Inclusion Criteria

- Studies that talk about machine learning and artificial intelligence that serve the purpose of the study.
- Works with full text access
- Randomized controlled and research articles are included.

Research Exclusion Criteria

- Studies that do not fit the purpose of the study
- Studies where artificial intelligence and machine learning methods are not used
- Same studies in different search engines
- Studies that do not mention diabetic foot and machine learning in the text content
- Reviews
- Studies with Inaccessible Full Text
- Book Chapters are not included.

3. Result

The results of the studies in which machine learning methods used in diabetic foot management between 2016-2021 were used for the purpose of systematic literature review of this study are given in Table 1. When the studies are examined, thermography method, decision support systems, convolutional neural networks, databases such as DFUNet -WoundVue-ND Square-RCNN, support vector machines methods were used. Thanks to these methods, the risk of developing diabetic foot and amputation was determined, diabetic foot ulcers were diagnosed faster, instantaneous temperature changes, pressure amount, ulcer stage, wound depth and size were determined, prognosis was followed, and the type of infection that caused the ulcer was determined faster.

It was stated in only one of the studies that the risk of infection may develop. Wang et al. It was reported that the area of the diabetic foot ulcer was determined faster thanks to the image capture box they created in their study. However, it has been reported that this box has disadvantages such as contact with the feet of different people and not being properly cleaned [6].

Table 1. Studies on Machine Learning Methods Used in Diabetic Foot Management

First Author-Year-Country	Hood	Method	Goal	Sampling	Intervention	Research Result
Cruz Vega et.al (2020) [9] İsrail	Deep Learning Classifica tion for Diabetic Foot Therm ograms	Developing a new method of deep learning	Classifying diabetic foot thermographies and analyzing the use of artificial intelligence and deep learning highlights its advantages and disadvantages.	110 patients with a diagnosis of DM	It offers a variety of techniques such as data enhancement, rotation, translation, contrast enhancement, different color, spacing, and random scaling through deep learning. In this study, images were obtained with 90-180-270 ° rotation angles. In total, 5-level thermography grades were achieved.	Thanks to the research, instant temperature changes in the soles of the feet will be detected and it has been reported that the progression of diabetic foot ulcers is prevented.
Goyal et.al (2020) [10] Mancheste r, UK	Recognition of ischaemia and infection in diabetic foot ulcers: Dataset and techniques	DFUNET system development	A data set was created to determine the presence of infection and ischemia in diabetic foot ulcers	A database was created with 292 foot images	Bottom patches were created for the definition of each abnormal area from 105 healthy foot skins. A total of 1679 skin patches, 641 normal and 1038 abnormal, were produced. The differences in color and tissue properties between healthy and ulcerated tissue were determined by machine learning.	In this study, a new DFUNet system that separates ulcerated skin from healthy skin using traditional machine learning algorithms has been developed. This study has been reported to be a system that will facilitate the detection and treatment of diabetic foot ulcers.

Schäfer et.al (2021) [11] Denmark	Toward Machine-Learning-Based Decision Support in Diabetes Care: A Risk Stratification Study on Diabetic Foot Ulcer and Amputation	Risk Determination with Decision Support Method	Determining the risk of diabetic foot ulcer and amputation development of patients	Risk stratification was made with the data of 246,705 patients retrospectively.	Socioeconomic levels and past medical information of the patients were examined. Risk groups are determined.	Conditions such as low socioeconomic income, cardiovascular problems, peripheral artery, neuropathy, and chronic kidney functions have been reported to be among important risk factors.
Nurlisa Yusuf et.al (2015) [12] Malaysia	In-vitro diagnosis of single and poly microbial species targeted for diabetic foot infection using e-nose technology	Neural networks	It was made to quickly determine the bacterial species that cause diabetic foot infection.		The Cyranose320 has been produced as an effective device that "electronically" imitates the human olfactory system. It was prepared to detect and differentiate intricate odors based on a sensor array concept. Bacterial tissue was removed by debriding the diabetic ulcerated area. Bacteria were placed in the device after 24 hours of incubation. In the advanced stages, it is aimed to make a diagnosis by sniffing the feet of the patients.	As a result, it was determined that each type of bacteria emits a different odor. It has been stated that it is one step closer to testing directly on the patient.
Guilherme Pena et.al (2019) [13] Australia	Evaluation of a Novel Three-Dimensional Wound Measurement Device for Assessment of Diabetic Foot Ulcers	Three-dimensional image acquisition with the WoundVue system	It aims to evaluate the reliability and practicality of WoundVue® camera technology in the evaluation of diabetic foot ulcers.	57 diabetic foot wounds have been used	It consists of two infrared cameras and an infrared projector, and a three-dimensional (3D) view of the wound structure is obtained.	A 95% confidence interval was determined between measurements obtained using WoundVue from different angles to evaluate wounds of different sizes and shapes. It has been reported to be an ideal tool for monitoring diabetic foot wounds over time.

Renaid B Kim et.al (2020) [14] USA	Utilization of smartphone and tablet camera photographs to predict healing of diabetes-related foot ulcers	Deep Learning and Support Vector Machine	To create a machine learning model that can predict the healing of diabetes-related foot ulcers using both clinical features extracted from electronic health records and image features extracted from photographs.	381 ulcer images were obtained from 155 patients with smartphone and tablet photographs.	Between 2014-2017, information and images were collected in ResNet-50, and ulcer photos were obtained with deep learning. Recovery status predicted with support vector machine	It has been reported that photographs taken with smartphones and tablets will also predict the prognosis of diabetic foot ulcers
Ana Cláudia Barbosa Honório Ferreira et.al (2020) [15] Brazil	Competitive neural layer-based method to identify people with high risk for diabetic foot	Neuron layer-based method	Automatically identify patients with diabetes mellitus (DM) at high risk of developing diabetic feet through an unsupervised machine learning technique	A new database containing 54 known risk factors from 250 patients diagnosed with diabetes mellitus has been created. A competitive neuron layer-based method was used to automatically divide the training data into two risk groups.	As a result of sociodemographic and foot care data, 54 variables were obtained. Patients are divided into low and high risk classes to determine the risk class.	It has been reported that unsupervised learning can be used to screen patients with diabetes mellitus, pointing to high-risk individuals who require priority follow-up in the prevention of diabetic foot with 90% accuracy.

Lei Wang et.al (2019) [16] United States	Boundary determination of foot ulcer images by applying the associative hierarchical random field framework	Determining the wound boundary using the conditional random area method	The purpose of the system is to accurately determine the wound boundary in images obtained under image acquisition conditions where lighting, range and viewing angles can vary within reasonable ranges and to ensure that appropriate care is applied to patients.	Fifteen patients with diabetic foot ulcers were followed over a 2-year period.	100 foot ulcer images were obtained. Images were viewed at different ranges, illumination and vision levels	It shows that chronic wounds can be accurately positioned in an image and the wound margin can be determined without requiring tightly controlled range and lighting conditions. It has been determined that it is suitable for use in clinics.
Natalia Arteaga-Marrero et. al (2021) [17] Spain	Segmentation Approaches for Diabetic Foot Disorders	Deep Learning (Using Segmentation)	Adding this practice to standard diabetic care protocols, ensuring early recognition of foot ulcers.	74 images were obtained from 37 healthy individuals.	Multimodal images consisting of light, infrared and depth images were obtained. The segmentation methods discovered were based on both visual light and infrared images, and optimization was performed using the spatial information provided by the depth images. A basis for manual segmentation was created by two independent researchers	It has been reported that the method applied is reliable
Leik et.al (2017)	Area Determination of Diabetic Foot Ulcer Images Using Two-Stage SVM-Based Classification	Image capture box created using support vector machines	Creating a database with the image capture box, determining the wound boundaries and ensuring early treatment initiation	15 patients were followed and 100 images were obtained within 2 years.	An image capture box providing controlled illumination and range, and support vector machines were used to define foot ulcer images and wound borders	Although it is a promising method, a large data set has not been identified. Image capture box has been reported to pose a risk of infection.
Beatrice Kuang et.a l [18] (2021)	Assessment of a smartphone-based application for diabetic foot ulcer measurement	Accuracy evaluation with 2D and 3D imaging	Evaluation of the accuracy of the ND square mobile phone application	115 diabetic foot wounds evaluated	Two different phones were used to determine the accuracy of the measurements of 35 wounds	It has been reported that the ND Kare application is a fast and easily accessible application that can be integrated into diabetic wound care.

Fady S. Botros et.al (2016) [19] Egypt	Prediction of diabetic foot ulceration using spatial and temporal dynamic plantar pressure	Plantar pressure recording with Medilogic Foot Pressure Measuring System and Support vector machines	Design, implementation and testing of a method for predicting diabetic foot ulcer based on dynamic pressure distribution.	56 diabetic patients with peripheral neuropathy and 24 individuals without diabetes, 84 individuals in total were included in the study.	Dynamic plantar pressure distribution is recorded for both feet with Medilogic foot pressure measurement system. In order to cover the entire plantar surface, suitable soles were used for each subject. Equipped with socks to prevent slipping. They were allowed to walk at their desired speed for 15 m. The foot base is divided into 11 different regions, 30 different features have been determined.	As a result of the measurement, pressure difference was detected between the subjects with and without diabetes. It has been reported that pressure determination is made rapidly thanks to the method.
SASIKUMAR B. et.al (2020) [20] İndia	Diabetes prediction using sensors by analysing skin temperature	Thermo Electric Generator (TEG) system	It is to predict diabetes risk by determining the temperature change in an individual's foot.	It consists of 100 records collected over a period of time	The TEG sensor absorbs heat from the foot and converts it into an electrical source. The TEG sensor is placed on the right and left feet, the fast signals are collected, the recorded signals are calculated using the discrete islet and the diabetes value is calculated with the algorithm with spectrum analysis.	As a result, it has been reported that diabetic patients have higher temperature values than non-diabetic patients.
Can Cui et.al [21] (2019)	Diabetic Wound Segmentation using Convolutional Neural Networks	Deep Learning Network (Convolutional Neural Networks)	Determination of the segmentation of the ulcer area with deep learning methods	The dataset consists of 445 images in total.	The data set consists of a total of 445 images. 4500 patches were created from 445 images taken with a high resolution camera, patch pair, wound area, wound boundary were determined.	It has been reported that thanks to automatic wound segmentation, it enables the detection of conditions affecting the prognosis such as wound area measurement and wound diagnosis.

Muhammad Adam et.al [22] (2018) Singapore	Automated detection of diabetic foot with and without neuropathy using double density-dual tree-complex wavelet transform on foot thermograms	Thermography	Determine qualitatively and visually documented superficial temperature changes using infrared thermography (IRT) and evaluate the diabetic foot	51 healthy individuals and 66 diabetic patients (33 with neuropathy and 33 without neuropathy)	Partial plantar foot thermographs are decomposed into coefficients using dual density-binary tree-complex wavelet transform. Various entropy and tissue features are extracted from the decomposed images of the left, right, and bilateral feet. These features are reduced using a variety of dimension reduction techniques. 93.16% accuracy was achieved	It has been reported that it is a fast and reliable system to verify manually determined diabetic feet in clinics with the automatic diabetic foot detection system.
Qiong Liu (2020) [23] China	The Classification of Diabetic Foot Based on Faster R-CNN	Convolutional Neural Network	Identification of the diabetic foot using a faster R-CNN model	1019 Diabetic Foot Picture	The R-CNN model was created by 6 categories of experts between 0-5, which completely fit the Wagner classification. A convolutional neural network is used with the advantages of automatic feature extraction, strong generalization capability and high recognition accuracy.	It shows that the accuracy of the method has been increased to 95.24% on the original basis. It has been reported to provide effective solutions for current clinically assisted primary screening of diabetic foot severity.
Chujia Lin et.al (2019) [24] China	The amputation and survival of patients with diabetic foot based on establishment of prediction model	Foresight Model	To establish predictive models and examine amputation and survival of patients with diabetic feet	200 patients with diabetic foot inpatient	Amputation and survival status of diabetic foot patients were followed up by phone. Relevant indicators were scanned by cluster analysis. The predictive model was built based on proportional hazard regression analysis, back propagation neural network (BPNN) and BPNN based on genetic algorithm optimization, respectively, and the reliability of the three prediction models (PM) was evaluated and compared.	Risk factors for amputation were severe ulcer disease, glycosylated hemoglobin, and low density lipoprotein cholesterol. Risk factors for death have been reported to be cerebrovascular disease, severe ulcer disease and peripheral artery disease.

4. Conclusion and Recommendations

Determining the stage of diabetic foot ulcer through machine learning, performing risk analysis, determining the agent, determining instantaneous temperature changes with thermography methods, performing accurate and fast staging with segmentation analysis and starting fast treatment, determining the infection with the databases created, making the prognosis prediction with deep learning methods. There are many benefits. By using artificial intelligence and machine learning methods, it was ensured that diabetic foot ulcers that caused high costs were prevented and severe infection cases leading to amputation were detected earlier. In the studies conducted, both the cost of care in the health system has decreased, the workload of health professionals has been reduced, and positive results have been obtained regarding the prognosis of the disease. In future studies, it is recommended to enlarge the existing databases with more images and to use more machine learning methods in the management of diabetic foot ulcers in our country.

References

[1] Cuschieri S, Grech S. COVID-19 and diabetes: The why, the what and the how. J Diabetes Complications. 2020;107637

[2] Saeedi P, Petersohn I, Salpea P, et al. Global and regional diabetes prevalence estimates for 2019 and projections for 2030 and 2045: Results from the International Diabetes Federation Diabetes Atlas, 9th edition. Diabetes Res Clin Pract. 2019;157:107843.

[3] Kalpakçı P, Sezer RE, Yılmaz S, Öztürk H, Erturhan S. Cumhuriyet üniversitesi hastanesinde 2007-2012 döneminde diyabetik ayağa bağlı operasyon olan hastaların özellikleri ile yaş ve cinsiyetin diyabetik ayak operasyonlarını tahmin ettirici etkisi. Türk Aile Hek Derg 2014; 18(2): 54-57.

[4] Zhang XD. (2020) Machine Learning. In: A Matrix Algebra Approach to Artificial Intelligence. Springer, Singapore. https://doi.org/10.1007/978-981-15-2770-8_6

[5] Pepito, JA., & Locsin, R. (2018). Can nurses remain relevant in a technologically advanced future International Journal of Nursing Sciences, 6,106-110. doi:10.1016/j.ijnss.2018.09.013

[6] Wang L, Pedersen PC, Agu E, Strong D, Tulu B. Boundary determination of foot ulcer images by applying the associative hierarchical random field framework. J Med Imaging (Bellingham). 2019 Apr;6(2):024002. doi: 10.1117/1.JMI.6.2.024002. Epub 2019 Apr 21. PMID: 31037245; PMCID: PMC6475526.

[7] Saltoğlu, N., Kılıçoğlu, Ö., Baktıroğlu, S., Oşar-Siva, Z., Aktaş, Ş., Altındaş, M., ... & Eraksoy, H. (2015). Diyabetik ayak yarası ve infeksiyonunun tanısı, tedavisi ve önlenmesi: ulusal uzlaşı raporu.

[8] IDF - International Diabetes Federation 2019 Atlası, 9 th, Edition

[9] Cruz-Vega, I., Hernandez-Contreras, D., Peregrina-Barreto, H., Rangel-Magdaleno, J. D. J., & Ramirez-Cortes, J. M. (2020). Deep learning classification for diabetic foot thermograms. Sensors, 20(6), 1762.

[10] M. Goyal, N. D. Reeves, A. K. Davison, S. Rajbhandari, J. Spragg and M. H. Yap, "DFUNet: Convolutional Neural Networks for Diabetic Foot Ulcer Classification," in IEEE Transactions on Emerging Topics in Computational Intelligence, vol. 4, no. 5, pp. 728-739, Oct. 2020, doi: 10.1109/TETCI.2018.2866254.

[11] Schäfer Z, Mathisen A, Svendsen K, Engberg S, Rolighed Thomsen T, Kirketerp-Møller K. Toward Machine-Learning-Based Decision Support in Diabetes Care: A Risk Stratification Study on Diabetic Foot Ulcer and Amputation. Front Med (Lausanne). 2021 Feb 18;7:601602. doi: 10.3389/fmed.2020.601602. PMID: 33681236; PMCID: PMC7931152.

[12] Yusuf N, Zakaria A, Omar MI, Shakaff AY, Masnan MJ, Kamarudin LM, Abdul Rahim N, Zakaria NZ, Abdullah AA, Othman A, Yasin MS. In-vitro diagnosis of single and poly microbial species targeted for diabetic foot infection using e-nose technology. BMC Bioinformatics. 2015 May 14;16(1):158. doi: 10.1186/s12859-015-0601-5. PMID: 25971258; PMCID: PMC4430918.

[13] Pena G, Kuang B, Szpak Z, Cowled P, Dawson J, Fitridge R. Evaluation of a Novel Three-Dimensional Wound Measurement Device for Assessment of Diabetic Foot Ulcers. Adv Wound Care (New Rochelle). 2020 Nov;9(11):623-631. doi: 10.1089/wound.2019.0965. Epub 2019 Oct 23. PMID: 33095125; PMCID: PMC7580588.

[14] Kim RB, Gryak J, Mishra A, Cui C, Soroushmehr SMR, Najarian K, Wrobel JS. Utilization of smartphone and tablet camera photographs to predict healing of diabetes-related foot ulcers. Comput Biol Med. 2020 Nov;126:104042. doi: 10.1016/j.compbiomed.2020.104042. Epub 2020 Oct 8. PMID: 33059239.

[15] Ferreira ACBH, Ferreira DD, Oliveira HC, Resende IC, Anjos A, Lopes MHBM. Competitive neural layer-based method to identify people with high risk for diabetic foot. Comput Biol Med. 2020 May;120:103744. doi: 10.1016/j.compbiomed.2020.103744. Epub 2020 Apr 8. PMID: 32421649.

[16] L. Wang, P. Pedersen, E. Agu, D. Strong, and B. Tulu, “Area determination of diabetic foot ulcer images using a cascaded two-stage SVM based classification,” IEEE Trans. Biomed. Eng., vol. 64, no. 9, pp. 2098–2109, Sep. 2017

[17] Arteaga-Marrero N, Hernández A, Villa E, González-Pérez S, Luque C, Ruiz-Alzola J. Segmentation Approaches for Diabetic Foot Disorders. Sensors (Basel). 2021 Jan 30;21(3):934. doi: 10.3390/s21030934. PMID: 33573296; PMCID: PMC7866807.

[18] Kuang B, Pena G, Szpak Z, Edwards S, Battersby R, Cowled P, Dawson J, Fitridge R. Assessment of a smartphone-based application for diabetic foot ulcer measurement. Wound Repair Regen. 2021 Mar 3. doi: 10.1111/wrr.12905. Epub ahead of print. PMID: 33657252.

[19] FS Botros, MF Taher, NM ElSayed ve AS Fahmy, "Diyabetik ayak ülserinin uzaysal ve zamansal dinamik plantar basınç kullanılarak tahmini", 2016 8. Kahire Uluslararası Biyomedikal Mühendisliği Konferansı (CIBEC) , 2016, s. 43-47, doi: 10.1109 / CIBEC.2016.7836116.

[20] Shetti NP, Mishra A, Basu S, Mascarenhas RJ, Kakarla RR, Aminabhavi TM. Skin-Patchable Electrodes for Biosensor Applications: A Review. ACS Biomater Sci Eng. 2020 Apr 13;6(4):1823-1835. doi: 10.1021/acsbiomaterials.9b01659. Epub 2020 Mar 27. PMID: 33455333.

[21] Cui C, Thurnhofer-Hemsi K, Soroushmehr R, Mishra A, Gryak J, Dominguez E, Najarian K, Lopez-Rubio E. Diabetic Wound Segmentation using Convolutional Neural Networks. Annu Int Conf IEEE Eng Med Biol Soc. 2019 Jul;2019:1002-1005. doi: 10.1109/EMBC.2019.8856665. PMID: 31946062.

[22] Adam M, Ng EY, Oh SL, Heng ML, Hagiwara Y, Tan JH, Acharya UR (2018). Ayak termogramlarında çift yoğunluklu ikili ağaç karmaşık dalgacık dönüşümü kullanılarak nöropatili ve nöropatisiz diyabetik ayağın otomatik tespiti. Kızılötesi Fizik ve Teknoloji , 92 , 270-279.

[23] Liu Q, Zhao J. (2020, July). The Classification of Diabetic Foot Based on Faster. In 2020 International Conference on Computer Vision, Image and Deep Learning (CVIDL) (pp. 585-591). IEEE.

[24] Lin C, Yuan Y, Ji L, Yang X, Yin G, Lin S. (2020). The amputation and survival of patients with diabetic foot based on establishment of prediction model. Saudi journal of biological sciences, 27(3), 853-858.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Dental Caries Diagnosis Using Artificial Intelligence

Pınar NAIBOGLU [1], Sevde GOKSEL [2, *]

[1] *Giresun University, Faculty of Dentistry, Dept. of Restorative Dentistry, Turkey*
[2] *Ankara Medipol University, Faculty of Dentistry, Dept. of Dentomaxillofacial Radiology, Turkey*

* Corresponding Author: Ankara Medipol University, Faculty of Dentistry, Turkey
Tel.: +90 312 5088829. E-Mail: sevde.goksel@ankaramedipol.edu.tr

Publication Information

Keywords :

- Artificial intelligence
- Deep learning
- Neural networks
- Dental caries

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Objectives: Dental caries is an infectious dental disease that is common all over the world. The use of artificial intelligence in dentistry has become an increasingly popular topic. The aim of this review was to evaluate the studies using artificial intelligence in the diagnosis of dental caries.
Materials and Methods: Bibliographical searches were carried out in PubMed, Scopus, Cochrane Library, and Web of Science databases using (artificial intelligence OR deep learning OR neural network OR machine learning OR machine intelligence) AND dental caries AND (diagnosis OR detection OR detect) terms on March 19, 2021. Based on the search strategy, a total of 62 articles were retrieved. Research articles that reported to use of artificial intelligence for diagnosis of caries were included in this study. Exclusion criteria were literature reviews, duplicate articles, conference abstract, studies in which data could not be collected were excluded from the analysis.
Results: 19 articles were included in the analysis. Charged coupled device (CCD) camera, periapical and bitewing intraoral digital radiographs, intraoral photographs, and near-infrared light transillumination images were used in the studies. The most used type of image was periapical radiographs. The average image databases were 888.89±1638.806 (min. 23, max. 6000). How the carious lesion was defined was stated in five of the included studies, and the type of carious lesion identified in thirteen of the included studies. Twelve of the included studies analyzed accuracy. The mean accuracy outcome was 77.3% (ranging from 20% to 99.16%).
Conclusion: In each study included in this database analysis, different neural networks and various outcome measures were used. All these variables make it difficult to compare the reliability of any neural network to diagnose caries. At the point where artificial intelligence technology has come in recent years, the techniques used in the diagnosis of caries also develop with the level of development of the age.

1. Introduction

Dental caries is an infectious, bacterial disease [1]. It is more difficult to detect caries in the initial stages than advanced stages. Dental radiographs are used to detect dental caries however diagnosis of dental caries can still be difficult for dentists [2–4].

Artificial intelligence (AI) has been an interesting area for investigators interested in mimicking human intelligence into computer systems [5]. In recent years, softwares have been developed for automatic analysis and evaluation of radiological images. These softwares have a widespread application in medicine [6]. Machine learning is the field of artificial intelligence that works by analyzing existing data relationships [7,8]. Deep learning is a subset of machine learning. Neural networks are mathematical models that mimic the way the brain works [9]. AI is being used progressively in dentistry. In this review, it was aimed to evaluate studies using artificial intelligence for caries diagnosis.

2. Materials and Methods

An electronic search was carried out in March 2021 in 4 databases (PubMed, Web of Science, Cochrane Library, and Scopus) by two researchers of the study (P.N, S.G). The search terms used were (artificial intelligence OR deep learning OR neural network OR machine learning OR machine intelligence) AND dental caries AND (diagnosis OR detection OR detect). Reviews, conference abstract, studies in which artificial intelligence is not used in the diagnosis of dental caries, studies in which data could not be collected, and duplicate studies were excluded from the study.

Information obtained from the included studies: authors, year, neural network task, image, total image database, neural network, caries definition presence, caries type and outcome metrics values [10]. The data was analyzed by SPSS for Windows 25.0 (SPSS Inc., Chicago, USA). The mean, standard deviation (SD), percentage and median values of data were determined.

3. Results

Figure 1 illustrates the study selection. 62 articles were obtained from 4 databases. 43 studies were excluded. A total of 19 studies met inclusion criteria. The information obtained from the included studies is shown in Table 1. The included studies were carried out between 2005 and 2021. Periapical images were the most used images in the studies (7/19). Image databases varied between 23 and 6000. The mean value of the data was 888.89±1638.806 and the median value was 160.00. In 5 studies, the definition of dental caries used in these studies was given in detail. Loss of mineralisation of enamel and dentin structures was considered as caries in 1 study. Caries was artificially created in 2 studies. The type of caries detected was detailed in 13 of the studies.

14 accuracy parameters were evaluated in 12 studies. The mean accuracy outcome was 77.3% (ranging from 20% to 99.16%).12 sensitivity parameters were evaluated in 10 studies. The mean sensitivity outcome was 84.33 (ranging from 59% to 100%). 10 specificity parameters were evaluated in 8 studies. The mean specificity outcome was 90.10% (ranging from 76% to 100%).

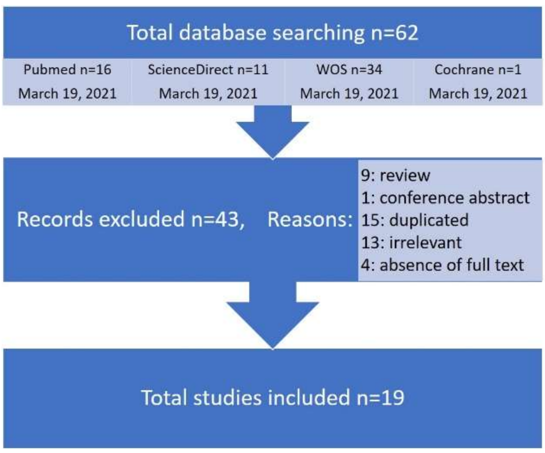


Figure 1. Flowchart.

Table 1: Main features of image database, neural network and caries of the included studies

Authors	Year	Neural Network Task	Image	Total Image Database	Neural Network	Caries Definition Presence	Caries Type	Outcome Metrics and Values
Kositbowornchai et al. [11]	2005	Detection	CCD camera and intra oral digital radiography	40	Multilayer Feed Forward Perceptron Network and Learning Vector Quantization (LVQ)	Absent	Buccal, lingual and proximal carious	For CCD; accuracy (60%), sensivity (90%), specificity (100%) for digital radiography;accuracy (20%) sensivity (80%), specificity (100%)
Kositbowornchai et al. [4]	2006	Detection and classification	CCD camera and digital radiography	49	LVQ network	Absent	Buccal or lingual caries	For CCD; accuracy (58%), sensivity (77%), specificity (81%) for digital radiography;accuracy (40%) sensivity (85%), specificity (93%)
Devito et al. [12]	2008	Detection	Bitewing	160	Multilayer perceptron neural	Absent	Sound,enamel caries, enamel-dentine junction caries and, dentinal caries	ROC (0.717)
Barbosa et al. [13]	2009	Classification	Bitewing	160	RBF	Present	Proximal enamel, enamel-dentine junction, dentin caries	ROC (0.8702)
Choi et al. [14]	2016	Detection	Periapical	475	CNN	Absent	Proximal caries	F1-score (0.74)
Sornam et al. [15]	2017	Classification	Periapical	120	Feedforward Neural Network	Absent	-	Accuracy (99%)
Lee et al. [2]	2018	Classification	Periapikal	3000	CNN	Absent	Dental caries, including enamel and dentinal carious lesions	Accuracy (82%), sensivity (81%), specificity (83%)
Singh et al. [16]	2018	Detection	Periapical	23	Artificial intelligence	Absent	Approximal surface and occlusal surface of the tooth	Sensivity (100%), specificity (100%)

Kumar et al. [17]	2018	Detection	Bitewing	6000	U-Net	Absent	-	F1-Score (61.42)

Table 1. *Cont.*

Authors	Year	Neural Network Task	Image	Total Image Database	Neural Network	Caries Definition Presence	Caries Type	Outcome Metrics and Values
Rad et al. [18]	2018	Detection	Periapical	120	Back-Propagation Neural Network	Absent	-	Accuracy (98%)
Casalengoet al. [19]	2019	Segmentation	Near-infrared transillumination	217	CNN	Absent	Proximal and occlusal caries	AUC (83.6% occlusal, 85.6% proximal)
Moutselos et al. [20]	2019	Segmentation and classification	In vivo with intraoral camera	88	Deep Neural Network Mask R-CNN	Present	Caries on occlusal surfaces	Accuracy (88.9%)
Sornam et al. [21]	2019	Classification	Periapical	120	BPNN	Absent	-	Accuracy (99.16%)
Patil et al. [22]	2019	Detection	-	120	ADA-NN	Absent	-	Accuracy (95%), sensivity (100%), specificity (90%)
Schwendicke et al. [23]	2020	Classification	Near-infrared light transillumination	226	Resnet18, Resnext50	Absent	Occlusal and/or proximal caries	Accuracy (68%), sensivity (59%), specificity (76%)
Zhang et al. [24]	2020	Detection, classification and localization	Oral photographs	3932	CNN	Present	Occlusal, buccal, labial, lingual and palatal surfaces	AUC (85.65%), sensivity (81.90%)
Geetha et al. [25]	2020	Classification	Intra-oral digital radiography	105	ANN with 10-fold cross validation	Present	-	Accuray (96.2%), ROC (0.983)
Singh et al. [26]	2020	Detection and classification	Periapical	1500	CNN-LSTM	Present	Whole tooth	Accuracy (96%), sensivity (96%), specificity (93%)
Askar et al. [27]	2021	Detection and classification	Photoragrahic images	434	SqueezeNet, a particular type of CNN	Absent	White spots	Accuracy (82%), sensivity (62%), specificity (85%)

4. Discussion

A quick and accurate diagnosis is an important factor in preventing and treating caries, which is dental caries in patients. Apart from conventional and digital radiography in the diagnosis of dental caries, fiber-optic transillumination (FOTI), laser fluorescence, digital subtraction radiography (DSR), electrical conductance measurement (ECM), tuned aperture computed tomography (TACT), ultrasonic caries detector, quantitative light-induced fluorescence (QLF) are used [2]. Artificial neural networks are mathematical models created by computer programs inspired by human neurons. Various architectures have been used in the articles included in this review. Convolutional neural network (CNN) was the most used artificial neural network in the studies.

A good description and classification of the carious lesions are necessary to analyze and compare the results achieved in each article [10]. In this review, the definition of caries was mentioned in detail in only 5 studies. The mean accuracy outcome of the articles included in the review was 77.3%. In an article that included this review, Sornam et al. presented the highest accuracy outcome as 99.16%. They used back-propagation neural network (BPNN); however, they did not define of what is meant by caries [15].

In the studies evaluated in this review, different neural networks were used and due to the different accuracy criteria used in testing existing algorithms, the accuracy of the articles cannot be compared with each other. For future studies, it is recommended to compare studies using the same neural network and the same outcome metrics with each other.

References

[1] Featherstone JDB. The science and practice of caries prevention. Journal of the American Dental Association 2000;131:887–99. https://doi.org/10.14219/jada.archive.2000.0307.

[2] Lee JH, Kim DH, Jeong SN, Choi SH. Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm. Journal of Dentistry 2018;77:106–11. https://doi.org/10.1016/j.jdent.2018.07.015.

[3] Srivastava MM, Kumar P, Pradhan L, Varadarajan S. Detection of tooth caries in bitewing radiographs using deep learning. ArXiv 2017.

[4] Kositbowornchai S, Siriteptawee S, Plermkamon S, Bureerat S, Chetchotsak D. An artificial neural network for detection of simulated dental caries. International Journal of Computer Assisted Radiology and Surgery 2006;1:91–6. https://doi.org/10.1007/s11548-006-0040-x.

[5] Sumari A, Suwandi Ahmad A, Ida Wuryandari A, Sembiring J. Brain-Inspired Knowledge-Growing System: Towards a True Cognitive Agent. International Journal of Computer Science and Artificial Intelligence 2012;2:26–36. https://doi.org/10.5963/ijcsai0201006.

[6] Khan HA, Haider MA, Ishaq H, Kiyani A, Sohail K, Muhammad M, et al. Automated feature detection in dental periapical radiographs by using deep learning. Oral Surgery, Oral Medicine, Oral Pathology and Oral Radiology 2020. https://doi.org/10.1016/j.oooo.2020.08.024.

[7] Chen YW, Stanley K, Att W. Artificial intelligence in dentistry: Current applications and future perspectives. Quintessence International 2020;51:248–57. https://doi.org/10.3290/j.qi.a43952.

[8] Wang J, Bidari S, Inoue K, Yang H, Rhoton A. Extensions of the Sphenoid Sinus. Neurosurgery 2010;66:797–816. https://doi.org/10.1227/01.NEU.0000367619.24800.B1.

[9] Chassagnon G, Vakalopolou M, Paragios N, Revel MP. Deep learning: definition and perspectives for thoracic imaging. European Radiology 2020;30:2021–30. https://doi.org/10.1007/s00330-019-06564-3.

[10] Prados-Privado M, García Villalón J, Martínez-Martínez CH, Ivorra C, Prados-Frutos JC. Dental Caries Diagnosis and Detection Using Neural Networks: A Systematic Review. Journal of Clinical Medicine 2020;9:3579. https://doi.org/10.3390/jcm9113579.

[11] Kositbowornchai S, … SS-IC, 2005 undefined. Use of artificial neural networking for detection dental caries: A pilot study. InfonaPl n.d.

[12] Devito KL, de Souza Barbosa F, Filho WNF. An artificial multilayer perceptron neural network for diagnosis of proximal dental caries. Oral Surgery, Oral Medicine, Oral Pathology, Oral Radiology and Endodontology 2008;106:879–84. https://doi.org/10.1016/j.tripleo.2008.03.002.
[13] Barbosa FDS, Devito KL, Felippe Filho WN. Using a neural network for supporting radiographic diagnosis of dental caries. Applied Artificial Intelligence 2009;23:872–82. https://doi.org/10.1080/08839510903246757.
[14] Choi J, Eun H, Kim C. Boosting Proximal Dental Caries Detection via Combination of Variational Methods and Convolutional Neural Network. Journal of Signal Processing Systems 2018;90:87–97. https://doi.org/10.1007/s11265-016-1214-6.
[15] Sornam M, Prabhakaran M. A new linear adaptive swarm intelligence approach using back propagation neural network for dental caries classification. IEEE International Conference on Power, Control, Signals and Instrumentation Engineering, ICPCSI 2017, Institute of Electrical and Electronics Engineers Inc.; 2018, p. 2698–703. https://doi.org/10.1109/ICPCSI.2017.8392208.
[16] Singh HV, Agarwal R. Diagnosis of carious legions using digital processing of dental radiographs. Lecture Notes in Computational Vision and Biomechanics, vol. 28, Springer Netherlands; 2018, p. 864–82. https://doi.org/10.1007/978-3-319-71767-8_74.
[17] Kumar P, Srivastava MM. Example Mining for Incremental Learning in Medical Imaging. Proceedings of the 2018 IEEE Symposium Series on Computational Intelligence, SSCI 2018, Institute of Electrical and Electronics Engineers Inc.; 2019, p. 48–51. https://doi.org/10.1109/SSCI.2018.8628895.
[18] Rad AE, Rahim MSM, Kolivand H, Norouzi A. Automatic computer-aided caries detection from dental x-ray images using intelligent level set. Multimedia Tools and Applications 2018;77:28843–62. https://doi.org/10.1007/s11042-018-6035-0.
[19] Casalegno F, Newton T, Daher R, Abdelaziz M, Lodi-Rizzini A, Schürmann F, et al. Caries Detection with Near-Infrared Transillumination Using Deep Learning. Journal of Dental Research 2019;98:1227–33. https://doi.org/10.1177/0022034519871884.
[20] Moutselos K, Berdouses E, Oulis C, Maglogiannis I. Recognizing Occlusal Caries in Dental Intraoral Images Using Deep Learning. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, Institute of Electrical and Electronics Engineers Inc.; 2019, p. 1617–20. https://doi.org/10.1109/EMBC.2019.8856553.
[21] Sornam M, Prabhakaran M. Logit-based artificial bee colony optimization (LB-ABC) approach for dental caries classification using a back propagation neural network. Studies in Computational Intelligence, vol. 771, Springer Verlag; 2019, p. 79–91. https://doi.org/10.1007/978-981-10-8797-4_9.
[22] Patil S, Kulkarni V, Bhise A. Algorithmic analysis for dental caries detection using an adaptive neural network architecture. Heliyon 2019;5:e01579. https://doi.org/10.1016/j.heliyon.2019.e01579.
[23] Schwendicke F, Elhennawy K, Paris S, Friebertshäuser P, Krois J. Deep learning for caries lesion detection in near-infrared light transillumination images: A pilot study. Journal of Dentistry 2020;92. https://doi.org/10.1016/j.jdent.2019.103260.
[24] Zhang B, Li S, Gao S, Hou M, Chen H, He L, et al. Virtual versus jaw simulation in Oral implant education: A randomized controlled trial. BMC Medical Education 2020;20. https://doi.org/10.1186/s12909-020-02152-y.
[25] Geetha V, Aprameya KS, Hinduja DM. Dental caries diagnosis in digital radiographs using back-propagation neural network. Health Information Science and Systems 2020;8:1–14. https://doi.org/10.1007/s13755-019-0096-y.
[26] Singh P, Sehgal P. G.V Black dental caries classification and preparation technique using optimal CNN-LSTM classifier. Multimedia Tools and Applications 2021;80:5255–72. https://doi.org/10.1007/s11042-020-09891-6.
[27] Askar H, Krois J, Rohrer C, Mertens S, Elhennawy K, Ottolenghi L, et al. Detecting white spot lesions on dental photography using deep learning: A pilot study. Journal of Dentistry 2021;107:103615. https://doi.org/10.1016/j.jdent.2021.103615.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 **||** **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Detecting Suicidal Individuals Using Artificial Intelligence

Nesime Ayşenur GÜLAYDIN [1, *]

[1] *University of Health Sciences Turkey (UHST), Hamidiye Faculty of Health Sciences Physiotherapy and Rehabilitation Department, 1st Grade Student*

* Corresponding Author: University of Health Sciences Turkey (UHST),

Publication Information

Keywords :

- Artificial intelligence
- Machine learning
- Suicide
- Covid-19

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Objective: Suicide often results from a more severe emotional pain than one can handle. In addition, there are major depressive illnesses, bipolar disorder, schizophrenia, anxiety, personality disorders such as personality, alcoholism and substance addiction as risk factors. In the aftermath of the COVID-19 outbreak, individuals show a high incidence of anxiety, depression, post-traumatic stress disorder and even suicidal behaviors. It is very important to prevent possible suicide attempts of such individuals. It is thought that research with multimodal neuropsycho-physiological features that can be included in Artificial Intelligence-based machine learning and based on AI (Artificial Intelligence) analysis will provide early detection to reduce the occurrence of serious mental illnesses and suicide attempts.

Method-Material: In this review, the articles published in the 2019-2021 research will be applied according to the application literature of Artificial Intelligence methods in chronic mental health prediction.

Results: There are methodological studies for the determination of suicidal tendency, especially for the prediction of mental disorders caused by Covid-19 and will be shared in detail in the review.

Conclusion: Machine learning approaches show promise for measurable suicide risk detection; however, many critical questions and problems remain unexplored. Potential barriers to the integration of the algorithm into clinical practice and related ethical issues are discussed. Including machine learning basics such as data needs into the algorithm by passing them through ethical filters can prevent social concerns at the first stage. In the later stages, progress can be made in line with the rights in many software.

1. Introduction

SARS-CoV-2 virus, which is also defined as COVID-19 in the literature, is a virus that emerged in Wuhan, China in the last quarter of 2019 and spread by affecting many countries virally in a short time. After the first Covid-19 case statements from China, especially Wuhan, the first cases started to be seen in Europe (especially Italy and Spain). With this rapid spread, 14 March was declared as a state of emergency in Spain and the authorities announced that the necessary measures would be taken.

In many countries where cases are beginning to occur, the measures taken to prevent viral transmission have included individuals, especially actively working individuals, in their negative emotional states. Many topics such as incomplete health information in individuals, negative news headlines made by news channels, curfews, severe health problems caused by viruses in the immediate environment, the proximity of death are the basis for emotional and mental problems that people will have difficulty coping with. These problems progress in a major sense, leading to high anxiety, depression, post-traumatic stress disorder and even suicide.

In recent studies on the 2015 Middle East respiratory syndrome (MERS) outbreak , healthcare workers are considered to be at high risk for mental illness. In this sense, especially healthcare professionals, individuals who have had a viral infection or are at risk of living, individuals who are in the risk group (for example, individuals over the age of 65 or people with chronic diseases) may encounter mental disorders that can reach suicide, as mentioned above. These individuals; It is important to diagnose suicidal tendencies in advance, to prevent suicide in the early period and to create statistical studies that can be done in this sense in the short term. In this review, there is a joint evaluation of the studies about the early diagnosis of in this suicidal individuals with artificial intelligence technology, whose development and success has been accepted by the whole world recently.

2. Results

Studies have shown that monthly suicide rates fell by 14% in the first 5 months of the pandemic (February-June 2020) in Japan. This could be due to a number of complex reasons such as generous government support, reduced working hours and school closures. On the other hand, studies have shown that there was a 16% increase in monthly suicide rates during the second wave (July-October 2020). The immediate decrease in suicide rates in Japan followed by the high increase; In individuals, the state of despair due to the fact that the pandemic process is prolonged longer than the dates predicted by health professionals, and the feeling that the existing situation will never pass, is considered as a major cause.

Based on the results of the studies carried out in line with the causes of suicidal tendency in general, it is thought that the damage caused or may be caused by the Covid-19 pandemic process may cause suicidal tendency in individuals. Factors such as anxiety, depression, alcohol-substance addiction can cause suicidal tendency, as well as an increase in the prevalence of individuals during the Covid-19 process.

3. Diagnosing Suicidal Tendency with Artificial Intelligence

Considered the father of artificial intelligence, John McCarthy says that "A computer, a computer-controlled robot or a software thinks in a way similar to the thoughts of intelligent people." defined as. The concept of Machine Learning, which was put forward in the future, was put into a mold as "It is an application area of artificial intelligence that studies algorithms that can learn by analyzing the data, determine patterns and make inferences, without the need for programming by humans. As it is known from the definitions made and today's clinical applications, artificial intelligence and machine learning are actively used in many different areas in the health sector. The field proposed in this review is included in the psychiatry service, based on the scarcity of studies in the literature. As stated above, artificial intelligence and machine learning offer a great protective-preventive approach for the early diagnosis of suicidal tendencies that may occur in individuals during the Covid-19 process, which affects the whole world. In fact, an article written in 2020 suggested that psychiatrists will enable them to redefine the occurrence of mental illnesses together with artificial intelligence and machine learning in a more objective way than is currently done by the DSM-5.

AI-based technologies in psychiatry rely on the identification of specific models within highly heterogeneous multimodal data sets. These large data sets include various psychological scales or mood rating scales, brain imaging data, genomic data, blood biomarkers, data based on new monitoring and tracking systems (e.g. smartphones), data obtained from social media platforms into the grading system. Facial data are included in the scope of attention assessment based on eye-gaze data, as well as various features based on the analysis of peripheral-physiological signals (e.g. respiratory sinus arrhythmia, startle reactivity, etc.). Based on the characteristics, it is thought that mental health disorders can be detected early enough to cure serious mental illnesses. Therefore, AI will have the power to transform a subjective diagnostic system into a common medical discipline in psychiatry, according to long-term research. It also promises a system that can act as a digital assistant if required by psychiatrists, artificial intelligence and machine learning. When examined in this sense, an application or prototype that has been studied has not been encountered by researches. The working logic described; It is a conceptual draft based on AI-based applications that are widely used and digital marketing techniques used in neuromarketing.

4. Conclusion and Evaluation

The areas of use of artificial intelligence technologies, which are increasing in importance day by day, have started to include many sectors. Among the reasons for this, it is seen that artificial intelligence technology evaluates the data in line with the most accurate results, prevents human error at the maximum level, includes less risk factors and has a fast-effective decision mechanism that is the sum of all. Among all these advantages, of course, many major and minor disadvantages also arise, but as in everything else, when approached in terms of profit and loss, the use of artificial intelligence technology in the sectoral sense is a preference.

The inclusion of artificial intelligence technology in the health sector in the developing century is a great revolution. It is actively used in many areas such as data analysis, diagnosis, treatment method tools, and its use is widespread. Although it is now seen that it is frequently used in fields such as radiology, surgery, pharmacology and molecular biology, many studies show that this field is tried to be expanded as much as possible. In this review, it is set out from the relationship of artificial intelligence with the psychiatric service. When the necessary literature reviews are made, it is striking that the number of studies on this field is scarce. In addition, the methodology has been put forward based on similar working principles rather than concrete products. It is possible to reach annual statistics calculated with many different variables in studies on suicidal individuals, which are specifically addressed, and they are sufficient in number. However, the statistics made within the framework of the covid-19 process, which affects the whole world, are not available to the public in other countries other than Japan. It is thought that among the reasons for this may be that many healthcare workers continue their professions in more intense and tiring pace within the scope of the covid-19 process. On the other hand, although it is small in number, studies have concluded that the covid-19 process, especially the part called the second wave, increases suicidal tendency due to negative emotional states on individuals. With the artificial intelligence methods whose methodology is described in the review, it is thought that these individuals can be diagnosed early and take great steps towards early initiation of the necessary treatments.

References

[1] Artificial Intelligence and Big Data in Public Health,2018, Kurt Benke and Geza Benke.
[2] Artificial intelligence in prediction of mental health disorders induced by the COVID-19 pandemic among health care workers,2020, Krešimir Ćosić, Siniša Popović, Marko Šarlija, Ivan Kesedžić , Tanja Jovanovic.
[3] Health problems in healthcare workers: A review, 2019, Aroop Mohanty,l Ankita Kabi,2 and Ambika P. Mohanty3.
[4] The mental health of health care workers in Oman during the COVID-19 pandemic,2020, Abdallah Badahdah , Faryal Khamis , Nawal Al Mahyijari , Marwa Al Balushi , Hashil Al Hatmi , Issa Al Salmi , Zakariya Albulushi , Jaleela Al Noomani .
[5] Increase in suicide following an initial decline during the COVID-19 pandemic in Japan, 2021, Takanao Tanaka, Shohei Okamoto.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Artificial Intelligence and Pediatric Nephrology; When, How?

Nida DİNÇEL [1, *], Aslı KANTAR [2], Özlem DUR [3]

[1,2,3] *University of Health Sciences Turkey, Izmir Faculty of Medicine, Dr. Behçet Uz Pediatric Diseases and Surgery Training and Research Hospital SUAM, Pediatric Nephrology Clinic*

* Corresponding Author: Izmir Bakircay University, Faculty of Medicine, Turkey

Publication Information

Keywords :

- Artificial Intelligence
- Pediatric Nephrology
- Algorithms

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Introduction: Although lots of metanalytic studies, the use of Artificial Intelligence (AI) has been fewer reported in nephrology. One side of pediatric nephrology needs early diagnosis and intervention other side requires close follow-up. In this review, we searched for the studies in the field of AI and nephrology.

Material-Method: AI, pediatric nephrology, long term follow-up, data recording, self-assessment was used as key words while searching via PubMed. Results: It was found that, algorithms can predict better than nephrologists: volumes, marker of dialysis adequacy (Kt/V), hypotension risk, cardiovascular events during dialysis, fluid volume. AI has been found useful for evaluation of protein catabolic rate, dry weight, pathogens in bacterial infections of peritoneal dialysis, prediction of decline of GFR, risk for progressive IgA nephropathy. Anemia management AI systems are programmed through personalized dosing of ESA, iron, and hemoglobin. There are also AI programmed algorithms for pretransplant patients, used for organ-matching, thus minimizing graft failure and accurately predicting mortality.

Conclusion: The aim of this study is to review all studies published on this topic. The role of AI in nephrology and the need for nephrology would indeed be “personalized medicine” are the future planned study objects.

1. Introduction

Artificial Intelligence (AI) has been reported in the aspect of medical technologies. It aims the 4P model of medicine (Predictive, Preventive, Personalized, and Participatory) [1]. One side of pediatric nephrology needs early diagnosis and intervention (such as bladder dysfunction, genetic diseases leading to chronic kidney damage), the other side requires close follow-up (such as chronic renal replacement). In this review, we searched for the studies in the field of AI and nephrology including kidney disease and dialysis and future pathways.

2. Material-Method

Artificial Intelligence, pediatric nephrology, long term follow-up, data recording, self-assessment was used as key words while searching electronic databases of PubMed.

3. Results

Artificial intelligence has been applied in several settings in clinical nephrology (Figure). There was a research by Geddes et al. deals with establishing risk for progressive IgA nephropathy (IgAN). Clinical and biological parameters such as age, sex, blood pressure, serum creatinine level, usage of antihypertensive treatment is measured at the time of IgAN diagnosis. The results showed that AI could predict the risk of progressive IgAN more accurately than nephrologists (correct predictions, 87% vs 69.4%; sensitivity, 86.4% vs 72%; and specificity, 87.5% vs 66%) [2]. Also, it has been proven useful for the prediction of the decline of glomerular filtration rate in patients with polycystic kidney disease [3].

Another study developed a network, in order to predict renal failure progression in patients with chronic kidney diseases (CKD). The model could accurately (>95%) predict the estimated glomerular filtration rate (eGFR) in 6, 12, and 18 months interval [4].

Renal Research Institute evaluated data from 28.608 patients with CKD. eGFRs, or logarithm of eGFRs (log-eGFRs) were analyzed for prediction of CKD progression into ESKD. Thus, they presented a CKD Forecaster Tool used at the point of care for nephrologists in clinical decision. This helped in-patient education and care planning for the transition from CKD to ESKD [5].

Artificial intelligence has been applied in settings in pediatric nephrology to remote home dialysis. There are few studies about recording of hemodynamic and respiratory values during dialysis treatment. The authors included 60 variables, such as patient characteristics, a historical record of physiological reactions, outcomes of previous dialysis sessions, pre-dialysis data, and the prescribed dialysis dose for the index session. The data set was used for 766,000 dialysis session recorded in the Spanish Nephro Care centers. It was found that, algorithms can predict better than nephrologists: volumes, marker of dialysis adequacy (Kt/V), and risk of hypotension and cardiovascular events during dialysis, besides prediction of session specific Kt/V, fluid volume removal and dialysis-related prescriptions [6]. Thus, AI was proved to be a better predictor than the guidelines regarding the urea removal ratio, post-dialysis BUN, or Kt/V [7].

Burlacu et al. mentioned about 2 studies by 14 pediatric patients were switched from nephrologists to AI. Results proved that AI is a superior tool for predicting dry weight in HD based on bioimpedance, blood volume monitoring, and blood pressure values [8,9].

For the treatment, anemia management AI systems are defined and programmed through personalized dosing of erythrocyte stimulating agents (ESA), iron, and hemoglobin modulation. Studies loaded the data such as erythropoietin-stimulating agents, target hemoglobin values, and iron treatment dosing. It was called as “Anemia Control Model” (ACM). This model predicted future hemoglobin values and recommended ESA dose, and AI approach led to a significant decrease in hemoglobin variability and reductions in ESA use, with also reduction in the cost of treatment [10-12].

Some other models identify responsible pathogens in bacterial infections of peritoneal dialysis cases, by generating specific biomarkers for Gram-negative and Gram-positive organisms [13]. The results were showed on 83 PD patients with peritonitis with the power of this models to analyze complex datasets in pathogen-specific inflammatory responses at the site of infection and to begin treatment earlier. This model is based on a clinical application for AI in peritoneal dialysis detecting specific immune fingerprints.

There are also some wearable systems measuring and analyzing HD and PD patients' physiological parameters by sensors to detect a pulse, temperature, blood pressure, blood leakage, electro- cardio graphic measurements, hyperkalemia, or fluid overload, real time [14-17].

There are also AI programmed algorithms for pretransplant patients, used for organ-matching, thus minimizing graft failure and accurately predicting mortality. Before the occurrence of significant serum creatinine increases, AI realizes abnormal patterns in a series of laboratory data. It leads to have a chance to detect acute rejection earlier. Network was developed based on Bayesian belief network (BBN), by loading 48 clinical variables from 5144 patients and this used for a pretransplant organ-matching tool model. It was shown that this model could predict graft failure within the first year with a specificity of 80% [18].

4. Conclusion

The aim of this study is to review all studies published on this topic. The role of AI in nephrology and the need for nephrology would indeed be "personalized medicine" are the future planned study objects. In conclusion, it was worthy that AI is not a doctor or a medical staff, it can only assist in medical decision-making. Interventions need to be thoroughly thought according to unique factors of clinical outcome.

References

[1] Briganti, G., & Le Moine, O. (2020). Artificial Intelligence in Medicine: Today and Tomorrow. Frontiers in medicine, 7, 27. https://doi.org/10.3389/fmed.2020.00027

[2] Geddes, C. C., Fox, J. G., Allison, M. E., Boulton-Jones, J. M., & Simpson, K. (1998). An artificial neural network can select patients at high risk of developing progressive IgA nephropathy more accurately than experienced nephrologists. Nephrology, dialysis, transplantation: official publication of the European Dialysis and Transplant Association-European Renal Association, 13(1), 67–71. https://doi.org/10.1093/ndt/13.1.67

[3] Niel, O., Boussard, C., & Bastard, P. (2018). Artificial Intelligence Can Predict GFR Decline During the Course of ADPKD. American journal of kidney diseases : the official journal of the National Kidney Foundation, 71(6), 911–912. https://doi.org/10.1053/j.ajkd.2018.01.051

[4] Norouzi, J., Yadollahpour, A., Mirbagheri, S. A., Mazdeh, M. M., & Hosseini, S. A. (2016). Predicting Renal Failure Progression in Chronic Kidney Disease Using Integrated Intelligent Fuzzy Expert System. Computational and mathematical methods in medicine, 2016, 6080814. https://doi.org/10.1155/2016/6080814

[5] Chaudhuri, S., Long, A., Zhang, H., Monaghan, C., Larkin, J. W., Kotanko, P., Kalaskar, S., Kooman, J. P., van der Sande, F. M., Maddux, F. W., & Usvyat, L. A. (2021). Artificial intelligence enabled applications in kidney disease. Seminars in dialysis, 34(1), 5–16. https://doi.org/10.1111/sdi.12915

[6] Barbieri, C., Cattinelli, I., Neri, L., Mari, F., Ramos, R., Brancaccio, D., Canaud, B., & Stuard, S. (2019). Development of an Artificial Intelligence Model to Guide the Management of Blood Pressure, Fluid Volume, and Dialysis Dose in End-Stage Kidney Disease Patients: Proof of Concept and First Clinical Assessment. Kidney diseases (Basel, Switzerland), 5(1), 28–33. https://doi.org/10.1159/000493479

[7] Fernández, E. A., Valtuille, R., Presedo, J. M., & Willshaw, P. (2005). Comparison of different methods for hemodialysis evaluation by means of ROC curves: from artificial intelligence to current methods. Clinical nephrology, 64(3), 205–213. https://doi.org/10.5414/cnp64205

[8] Hayes, W., & Allinovi, M. (2018). Beyond playing games: nephrologist vs machine in pediatric dialysis prescribing. Pediatric nephrology (Berlin, Germany), 33(10), 1625–1627. https://doi.org/10.1007/s00467-018-4021-4

[9] Burlacu, A., Iftene, A., Jugrin, D., Popa, I. V., Lupu, P. M., Vlad, C., & Covic, A. (2020). Using Artificial Intelligence Resources in Dialysis and Kidney Transplant Patients: A Literature Review. BioMed research international, 2020, 9867872. https://doi.org/10.1155/2020/9867872

[10] Barbieri, C., Mari, F., Stopper, A., Gatti, E., Escandell-Montero, P., Martínez-Martínez, J. M., & Martín-Guerrero, J. D. (2015). A new machine learning approach for predicting the response to anemia treatment in a large cohort of End Stage Renal Disease patients undergoing dialysis. Computers in biology and medicine, 61, 56–61. https://doi.org/10.1016/j.compbiomed.2015.03.019

[11] Barbieri, C., Bolzoni, E., Mari, F., Cattinelli, I., Bellocchio, F., Martin, J. D., Amato, C., Stopper, A., Gatti, E., Macdougall, I. C., Stuard, S., & Canaud, B. (2016). Performance of a Predictive Model for Long-Term Hemoglobin Response to Darbepoetin and Iron Administration in a Large Cohort of Hemodialysis Patients. PloS one, 11(3), e0148938. https://doi.org/10.1371/journal.pone.0148938

[12] Barbieri, C., Molina, M., Ponce, P., Tothova, M., Cattinelli, I., Ion Titapiccolo, J., Mari, F., Amato, C., Leipold, F., Wehmeyer, W., Stuard, S., Stopper, A., & Canaud, B. (2016). An international observational study suggests that artificial intelligence for clinical decision support optimizes anemia management in hemodialysis patients. Kidney international, 90(2), 422–429. https://doi.org/10.1016/j.kint.2016.03.036

[13] Zhang, J., Friberg, I. M., Kift-Morgan, A., Parekh, G., Morgan, M. P., Liuzzi, A. R., Lin, C. Y., Donovan, K. L., Colmont, C. S., Morgan, P. H., Davis, P., Weeks, I., Fraser, D. J., Topley, N., & Eberl, M. (2017). Machine-learning algorithms define pathogen-specific local immune fingerprints in peritoneal dialysis patients with bacterial infections. Kidney international, 92(1), 179–191. https://doi.org/10.1016/j.kint.2017.01.017

[14] Agarwal R. (2009). Home and ambulatory blood pressure monitoring in chronic kidney disease. Current opinion in nephrology and hypertension, 18(6), 507–512. https://doi.org/10.1097/MNH.0b013e3283319b9d.

[15] Du, Y. C., Lim, B. Y., Ciou, W. S., & Wu, M. J. (2016). Novel Wearable Device for Blood Leakage Detection during Hemodialysis Using an Array Sensing Patch. Sensors (Basel, Switzerland), 16(6), 849. https://doi.org/10.3390/s16060849

[16] Wu, J. X., Huang, P. T., Lin, C. H., & Li, C. M. (2018). Blood leakage detection during dialysis therapy based on fog computing with array photocell sensors and heteroassociative memory model. Healthcare technology letters, 5(1), 38–44. https://doi.org/10.1049/htl.2017.0091

[18] Kooman, J. P., Wieringa, F. P., Han, M., Chaudhuri, S., van der Sande, F. M., Usvyat, L. A., & Kotanko, P. (2020). Wearable health devices and personal area networks: can they improve outcomes in haemodialysis patients?. Nephrology, dialysis, transplantation : official publication of the European Dialysis and Transplant Association - European Renal Association, 35(Suppl 2), ii43–ii50. https://doi.org/10.1093/ndt/gfaa015

[18] Brown, T. S., Elster, E. A., Stevens, K., Graybill, J. C., Gillern, S., Phinney, S., Salifu, M. O., & Jindal, R. M. (2012). Bayesian modeling of pretransplant variables accurately predicts kidney graft survival. American journal of nephrology, 36(6), 561–569. https://doi.org/10.1159/000345552

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Automatic Dental Segmentation Module Supported by Artificial Intelligence for Dentistry Students Education

Ahmet KARAOGLU [1,*], Caner OZCAN [2], Adem PEKINCE [3], Yasin YASA [4], Buse Yaren TEKIN [5], Dilara OZDEMIR [5]

[1] *Sinop University, Gerze Vocational High School, Dept. of Computer Technologies, Sinop, Turkey*
[2] *Karabuk University, Faculty of Engineering, Dept. of Software Engineering, Karabuk, Turkey*
[3] *Karabuk University, Faculty of Dentistry, Dept. of Oral and Maxillofacial Radiology, Karabuk, Turkey*
[4] *Ordu University, Faculty of Dentistry, Dept. of Oral and Maxillofacial Radiology, Ordu, Turkey*
[5] *Karabuk University, Faculty of Engineering, Dept. of Computer Engineering, Karabuk, Turkey*

* Corresponding Author: Ahmet KARAOGLU
Tel.: +90 551 9351084. E-Mail: akaraoglu@sinop.edu.tr

Publication Information

Keywords :
- Dentistry
- Tooth detection
- Artificial intelligence
- Instance segmentation
- Dentistry education

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

In this study, DentiAssist, a web-based radiological image analysis and labeling application supported by artificial intelligence, was developed for the education of dentistry students. The necessary legal permissions regarding the panoramic tooth images were obtained and ten students from the Faculty of Dentistry of Karabuk University were included in the study. In the AI-based analysis of the study, Mask R-CNN was used to detect and divide the teeth, providing information about the positions of the teeth in the region of interest and the pixels of the teeth. Using the labeling module of DentiAssist software, 649 training and 279 validation data, precisely labeled by three maxillofacial radiologists, were given as input into the neural network and a feature map was created with the convolutional neural network. At the pixel level, a mask was produced for each tooth and tooth detection was carried out with the Region of Interest Alignment module. Using an equal number of 100 test images, mAP (mean average precision) was measured 97.75% because of student and artificial intelligence comparison, and 99.02% success was achieved in radiologist and artificial intelligence comparison.

1. Introduction

One of the biggest challenges in dentistry is that the maxillofacial radiologist interprets many images in limited time, and it is imperative that a quick treatment plan is presented. Human conditions such as the lack of adequate time, lack of experience and loss of concentration unquestionably reveal the necessity of the artificial intelligence-assisted automated analysis system. Deep learning models are especially used in the analysis of dental images, detection of abnormalities, image segmentation and classification. Using digital technologies in the diagnosis, imaging, treatment planning and treatment process of clinical problems shortens the time spent and helps to predict the negative situations that may occur in treatment before it occurs [1]. Thanks to its clinical applications as well as rapidly developing technology, 3D graphic models, online videos, and mobile devices (smartphones, tablet computers) are also included day by day in dentistry training. Recently, it has been revealed by researchers that the use of developing technology devices in educational activities and in almost every field influences learning performance [2].

Students and their characteristics are important in the concepts of teaching and learning. The education program designed with the strategy determined based on the characteristics of the students makes a positive contribution to the learning skills of the students. This contribution ensures that graduates have acquired the skills to meet the needs of society [3]. Academicians in the field of dentistry are required to provide training that fulfills the development criteria of the age with training plans created with up-to-date knowledge and skills for the needs of the society [4]. In the study, which evaluated the use of computer-aided systems in education in Turkish Faculties of Dentistry, it is thought that the usage rate of computer aided systems in dentistry will increase in the coming years and this will not decrease the importance of the specialist in the dentistry profession [5]. In this way, uninterrupted and sustainable education processes in the field of dentistry have been ensured. The coronavirus (Covid-19) pandemic has negatively affected education systems around the world and caused schools and universities at all levels to stop operations in general. This indicates how important it is to develop new solutions and approaches due to the longevity of the ongoing process with the COVID-19 outbreak. The closure of schools and universities forces countries to find new ways to make the education system sustainable. The education method, which we are not used to before, is developing throughout the world, and countries are producing new solutions to continue their education activities without interruption. The impact of these solutions on the quality of learning depends on the access and quality of digital resources.

The proposed DentiAssist software module is designed in a structure that will bring together dentistry students and academicians without being in the same place, especially during the period when educational institutions at all levels use distance education tools due to the pandemic. With the education module of the system, a distance learning structure has been developed with the support of artificial intelligence, in which academicians can control the labeling activities of students, interact with questions and answers, and in which the teaching processes are not interrupted in adverse situations.

2. Dental Radiography

The use of digital radiography in health enables the patient and the health officer to receive high quality images with minimum radiation [6]. As a result of the analysis on dental radiography, clinicians make an early diagnosis based on radiographic interpretation [7]. Different radiographic techniques are used in the

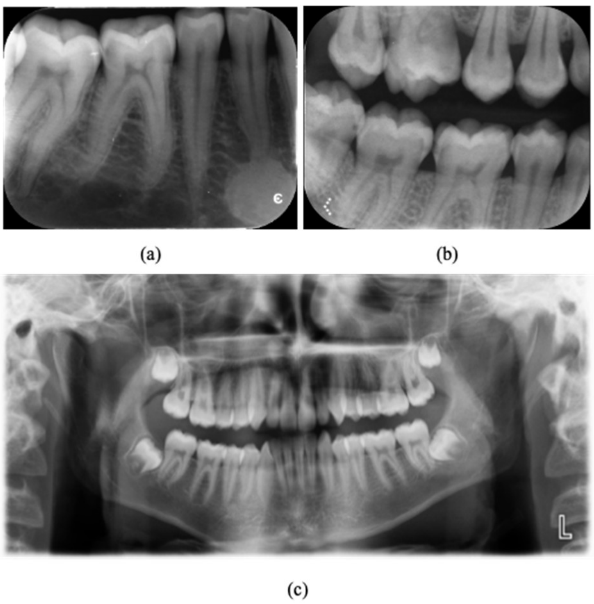


Figure 1. Types of Dental Radiography: (a) Periapical (b) Bitewing (c) Panoramic

current dental examinations performed by dentists. Radiological imaging is divided into intraoral radiography and extraoral radiography for dental images. Intraoral imaging is provided with the device placed in the mouth, while extraoral imaging such as panoramic imaging is provided to view all teeth [8]. Intraoral radiographic images are a type of imaging commonly used by dentists. Intraoral radiography provides a radiological image in which the film or sensor is placed in the mouth. There are several types of intraoral radiographs that show different aspects of the teeth to be displayed. There are three types of intraoral radiographs: bitewing, periapical and occlusal. It is used to dig into more tooth details and cavities. On the other hand, in extraoral radiography, images are taken by placing the x-ray device in a position to view the patient from the outside [9]. Some examples of extraoral radiography types are panoramic, cephalometric, and computed tomography. In extraoral radiographs, not only the teeth are in the foreground, but also the jaw and skull are displayed. Therefore, the focus of the radiograph is not only on the teeth. Fig. 1 shows the periapical, bitewing and panoramic x-ray images.

Interpretation of radiological images by maxillofacial radiologists is a process that takes time and requires attention. Dentists and maxillofacial radiologists make inferences of disease analysis in x-ray images during daily examinations. Since these workers have negative conditions such as stress and fatigue, such procedures may cause results such as incorrect analysis. Artificial intelligence applications are used to act as natural human intelligence with artificial neural networks [10]. Errors made due to the nature of human beings have been minimized and more accurate results have been obtained with the development of artificial intelligence in examinations and diagnoses on human health. With the use of computer algorithms, especially in healthcare solutions, artificial intelligence is offered at minimum cost without extra human support. In addition to these, there is also the problem of not being able to follow up regularly the treatments applied by healthcare professionals to their patients. Today, artificial intelligence plays an active role in the healthcare industry to ensure less doctor-patient contact, especially in pandemic periods such as Covid-19. The demanding and long-term analyzes performed by radiologists in the field of dentistry are reduced to short periods with AI. Artificial intelligence supported studies are carried out to detect the teeth and pathological regions in radiographic images. In many studies in the literature, teeth and problematic diseases are detected on radiological x-ray images. In the study presented by Oktay [11], the teeth were determined after finding the oral cavity with CNN using 100 panoramic images. Muresan et al. [12] classified dental problems in panoramic images with image processing techniques and deep learning. Later, with the development of image segmentation, Leite et al. [13] classified teeth by segmenting on 153 radiographic images. Poonsri et al. [14] performed tooth segmentation with template matching on dental x-ray images. In this study, the tooth area was defined with image processing techniques and then the teeth were segmented separately from the background. Thus, within the scope of artificial intelligence studies in dentistry, segmentation of tooth and non-tooth areas and problematic teeth and dental diseases are performed. As a result of artificial intelligence applications used in the field of dentistry, patient capacity and examination time have been optimized.

3. Dental Segmentation with Mask R-CNN

CNN (Convolutional Neural Networks) is an artificial neural network that is frequently used in the field of deep learning, especially for images. This neural network processes and classifies images in detail, examining them in various determined layers. However, it is the neural network that often has difficulty reaching high levels of success. R-CNN (Region Based Convolutional Neural Networks) provides a regional based detection by using pyramid-shaped features [15]. R-CNN improves the instance segmentation results by placing Region Proposal Network in floating windows through Feature Pyramid Network [16] in object detection. Because R-CNN is too costly to make the right decisions, accelerated versions such as Fast R-CNN [17] and Faster R-CNN [18] have been proposed. Mask R-CNN is a Regional-based CNN [19]. Mask R-CNN, which is a more up-to-date network compared to other neural networks in the literature, is a type of instance segmentation. Mask R-CNN extends the Faster R-CNN to add a segment using existing detection. Mask R-CNN includes a branch of convolution networks, which is a standard convolutional neural network that functions as a feature extractor to perform the sample segmentation task.

A network extracting image features such as deep residual networks [20] is preferred as the backbone network. In the ImageNet [21] dataset, residual networks were evaluated up to 152 layers, and ResNet-101 (101-layer residual network) was used. In Fig. 2, Mask R-CNN architecture is shown. As can be seen in this figure, it reduces the images it takes to the neural network to 1024x1024 dimensions so that there is no different resizing structure. Thus, without disrupting the working structure of the neural network, the same size Region of Interests (ROI) will be scanned in each input image. The RoIAlign layer is used to correct the misalignment scanned in the input by adhering to the exact positions. The 28x28 filter is used as mask size. Feature maps extracted on the network create small feature maps from RoIs created by the RoIPool method [20]. Images in the data set are passed through a two-stage RPN (Region Proposal Network). In this step, areas that are likely to be regions are kept in the RPN network. Overlap boxes are scanned for non-maximum suppression (NMS). As a result, Mask R-CNN creates a binary mask for each outputted RoI.

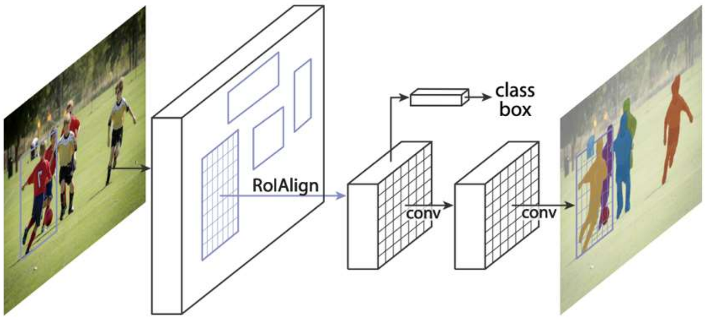


Figure 2. Architecture of Mask R-CNN [21]

4. Application

The interface design was carried out with the Bootstrap library so that the application could be viewed on all devices without any problems. The Web application is written in C# with Asp.Net, and Microsoft Sql Server is used as the database management system. JQuery, a JavaScript-based library, was used to increase the interaction of the interface with the user. When the application interface is opened, the necessary information must be entered on the "User Login Screen" for the user to log into the system. From this screen, users can log in to the system by entering their information. The user login screen is shown in Fig. 3.

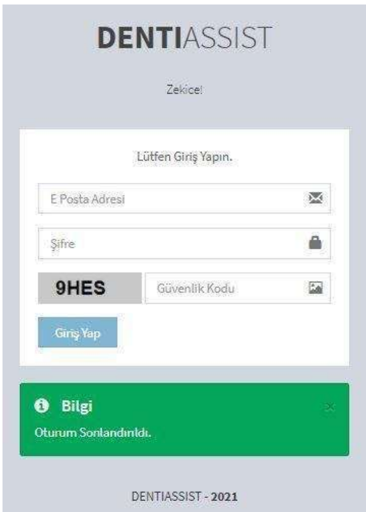


Figure 3. User Login Screen

There are three user roles. The first is the role of "administrator". The administrator role is authorized to perform all operations on the system. It can perform administrative operations such as turning the system on/off, backing up databases, viewing transaction records, and so on. The second of the user roles is the "educator" role. A user in the educator role can perform all other operations except administrative operations in the administrator role. Some of these processes can be said as creating a new project, adding images to the project created, adding new students to the system, changing student information, assigning the project to a student. The last of the user roles is the "student" role. This role is more restricted than the other two user roles. Student users can label the images in the assigned project and add questions related to the image. The system interface consists of four basic parts. The first part is the "top menu" positioned horizontally on the top edge, the second part is the "left menu" positioned vertically on the left edge, the third part is the horizontally positioned "footer" on the lower edge and the fourth part is the "content area" positioned with in the area remaining from the first three sections. In the right corner of the top menu, the picture, first and last name of the logged user are included.

In the left menu, there are referral links where users can go to the relevant screens in the system. This section is designed to take up minimal space on the screen. If the user wants, they can expand the area with these routing links from the section in the top menu. The footer shows general information about the system and software version information. The content area displays the contents of the screens from the left menu. After the user logs in to the system, the "dashboard" is displayed. This screen shows users summary information such as new questions asked, and new students recently added to the system. The dashboard screen is shown in Fig. 4.

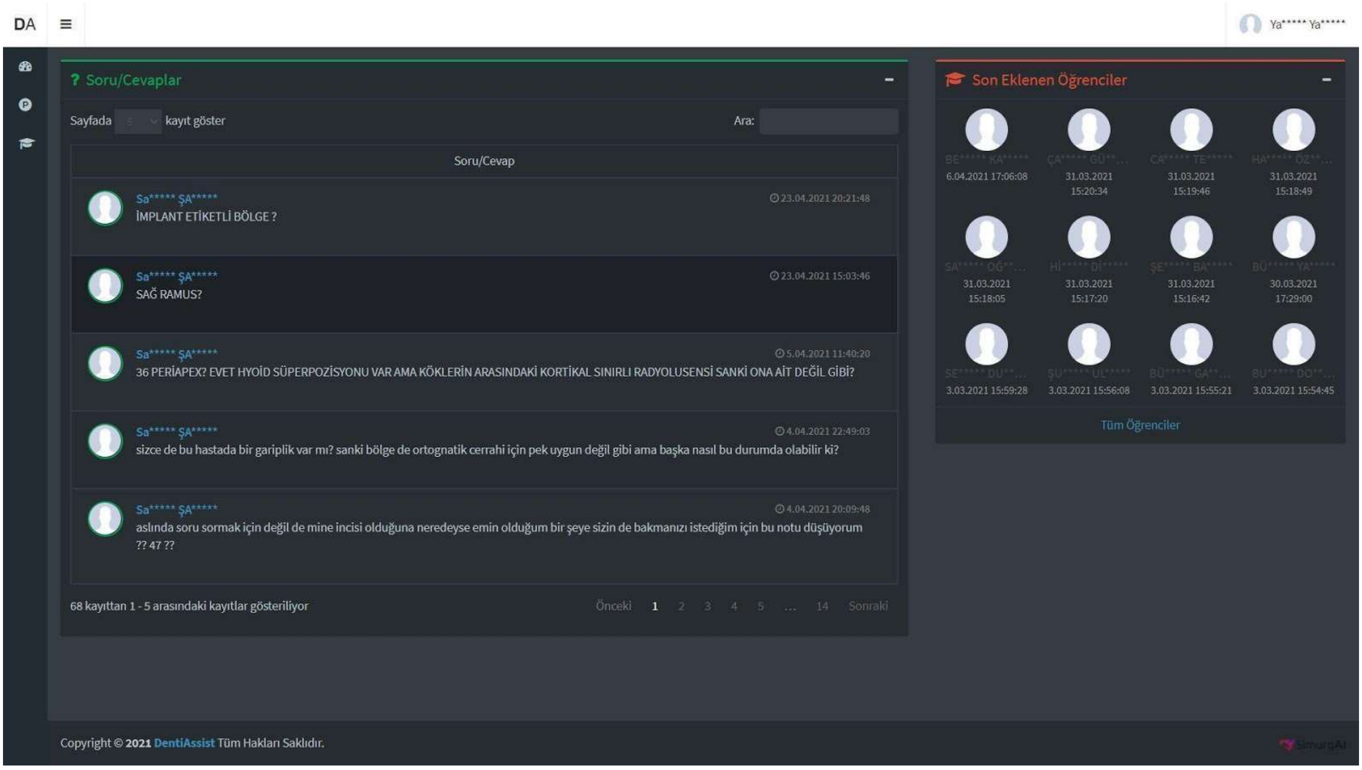


Figure 4. Dashboard

If the educator user has a question asked to him or the student user and if there is an answer to the question, they will be directed to the question and answer section of the relevant image where they can answer the question or read the answer given by clicking on the question or answer. Detailed information about the use of the question and answer section will be provided in the "Labelling Screen" section. Users can switch from the left menu to the "Projects" page. Projects allow the images to be created in groups for different purposes of use and the projects created to be assigned to the students responsively. The project screen is shown in Fig. 5. Projects created or assigned to the user are displayed on the Projects page. The name of the projects, creator, who is responsible, project description, date of creation, whether the person responsible has taken any action on the project, and if so, date and time of the most recent transaction are shown in detail. Users can sort in these areas or search by certain criteria through the search bar. A new project can be added with the "Add New Project" link in the top menu. Figure 5 shows the list of actions that can be taken on a project created. The creator or owner of the project can permanently delete the project.

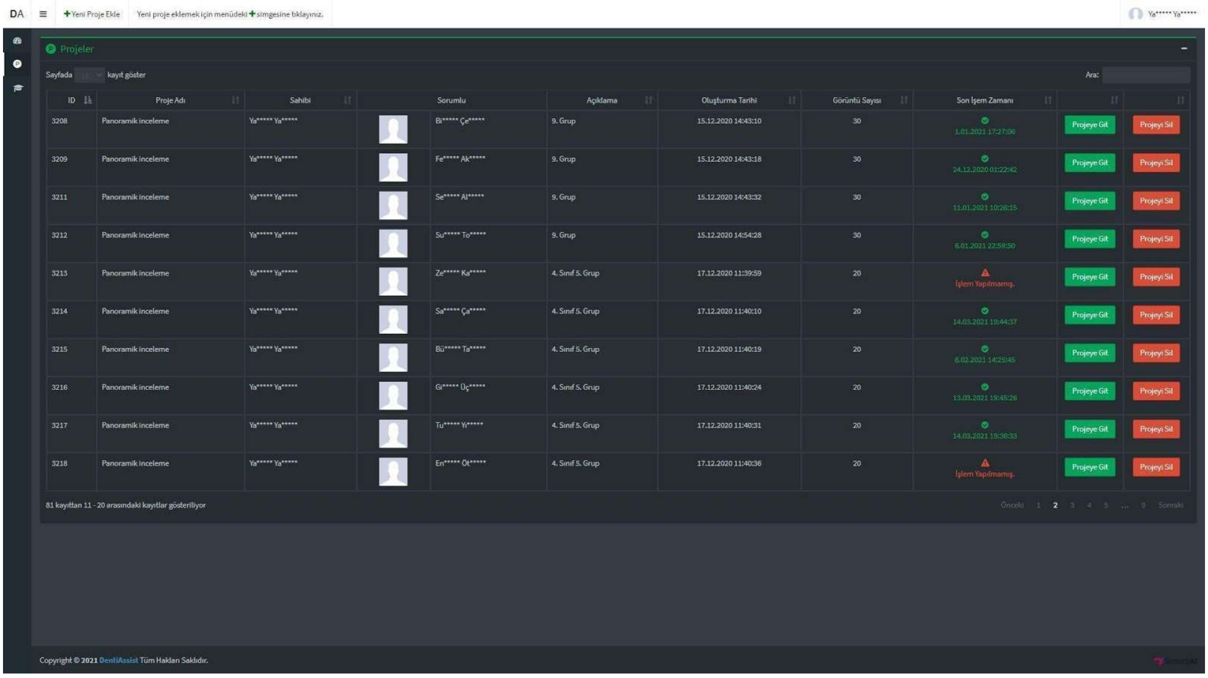


Figure 5. Project Screen

Users can switch to the screen showing the images and details within the project with the "Go to Project" link. The project details screen is shown in Fig. 6.

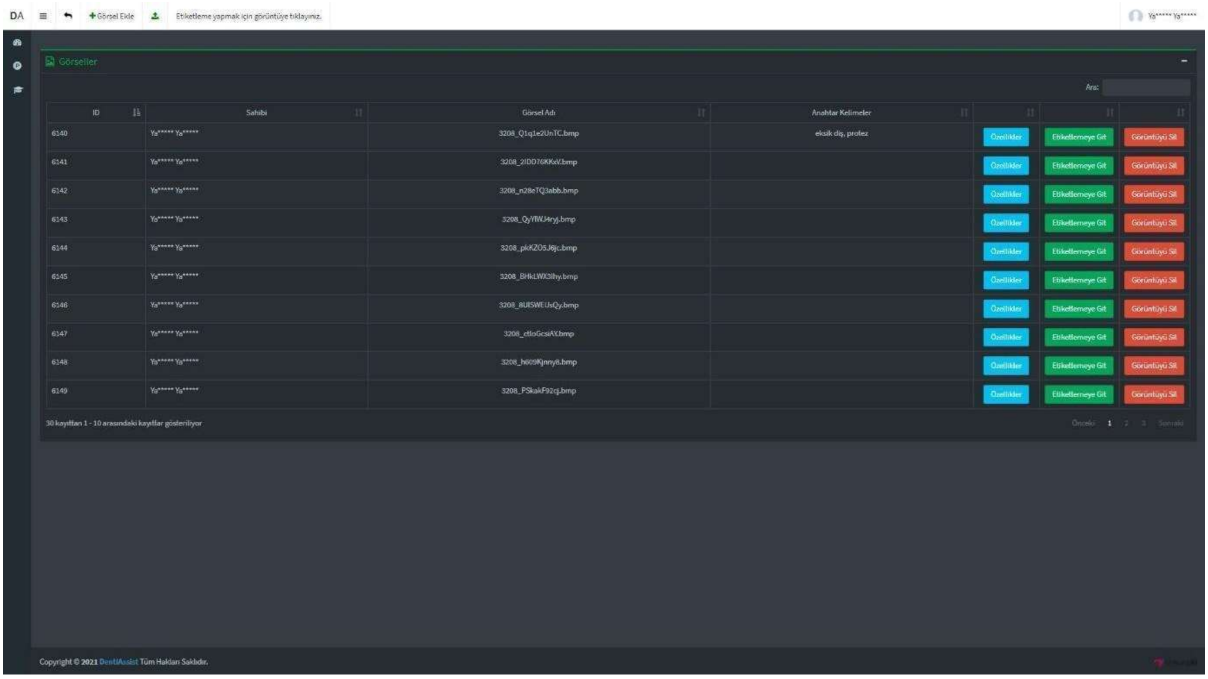


Figure 6. Project Details Screen

The project detail screen lists the images within the project. New images can be added with the "Add Image" link in the top menu. This action supports bulk image uploading. The status of the installation is visually shown to the user. When the installation is complete, the images are displayed in the list. The name of the images, who added them, the keywords are shown in detail. Users can sort in these areas or search by certain criteria through the search bar. At the end of the detailed information of each image, the actions that can be done on the image are listed. Users can permanently delete any image. Keywords can be entered from the properties link. Thanks to this feature, images with a specific common keyword can be filtered and listed. Users can switch to the screen where the images within the project are labelled with the "Go to Labeling" link. The labeling screen is shown in Fig. 7.

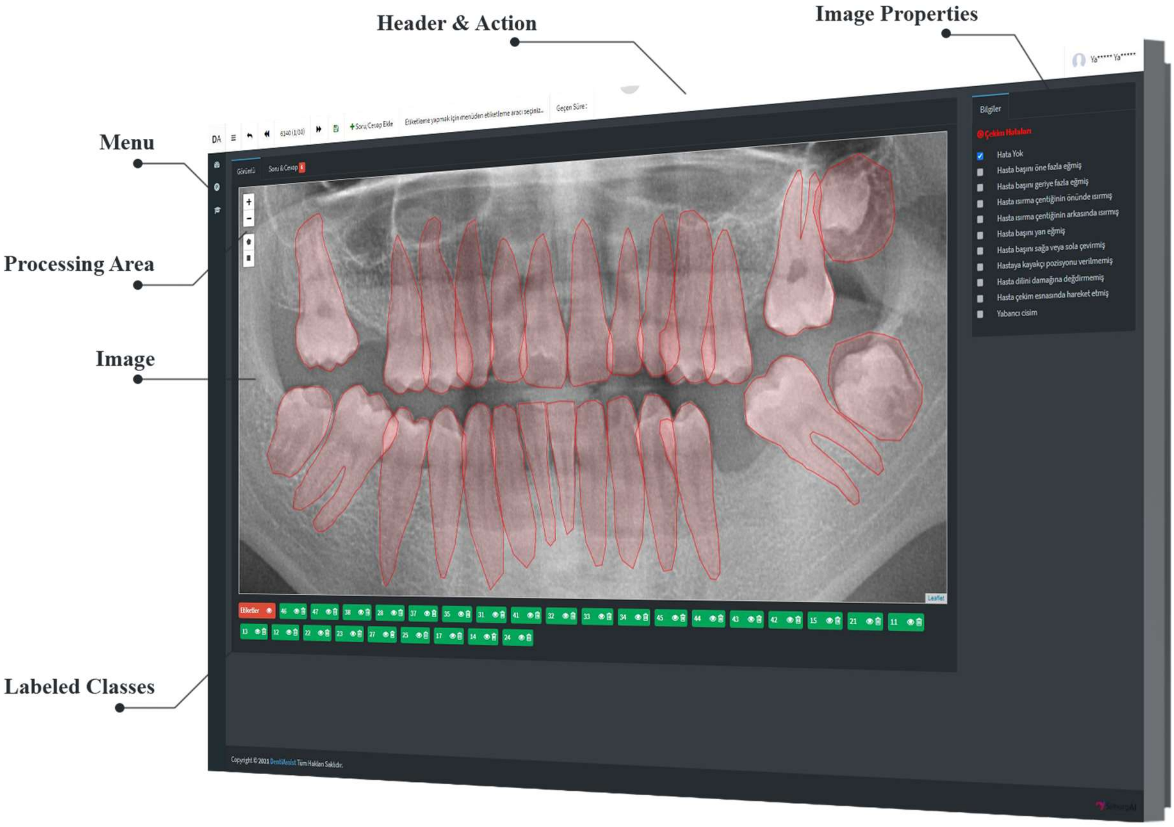


Figure 7. Labeling Screen

With the navigation buttons in the top menu, users can easily switch between images in the project. In addition, a button is positioned in this section to return to the project screen. The navigation buttons display how many images are in the project and the number of the current image and its order within the project. This menu contains a link where users can add questions about the relevant image. With this link, students can easily ask their educators questions without switching to another screen while working on the image. The questions asked here are listed on the welcome screen that opens when the user logs into the system of the educator concerned. When the user clicks on any question from this list, they are directed to the image to which the question belongs and focus on the section where the question and answer activity takes place. It performs the operation by entering the answer to the question here.

There are two sections where the relevant image on the screen is shown, labeling is done and information about the image is displayed in the content section. If the user detects any errors on the image, they select the appropriate error from the list in the information section and click the save icon in the top menu to save it. When performing labeling, the user selects one of the marking tools located on the left side of the image. These tools allow selections with rectangular and polyline selections. As soon as the user finishes labelling, the screen is shown a list of the dental template and the list of actions that can be done on the tooth, and the user selects the label that is appropriate for the region they are labeling from this list. When the label is selected, it is added to the list of tags at the bottom of the image with the label's properties. In this list, tags on the image can be completely closed to display, or label-based display can be turned on and off. The selected label can be deleted from the label list as needed. Clicking the label on the image opens in the label edit view and the label can make the necessary corrections. Clicking the label again at the end of the edit turns off the edit view. Zooming in and out on an image will be injured by the menu on the left side of the image, as well as the scroll bar on the mouse. The image can be scrolled by pressing the left mouse button simultaneously with the ctrl key on the keyboard. The time spent labeling as teeth is kept in seconds. All these operations are saved in json format to the database by pressing the save icon in the top menu. Users can switch from the left menu to the "Users" page. Authorized users can add students to the system from this screen. The users screen is shown in Fig. 8.

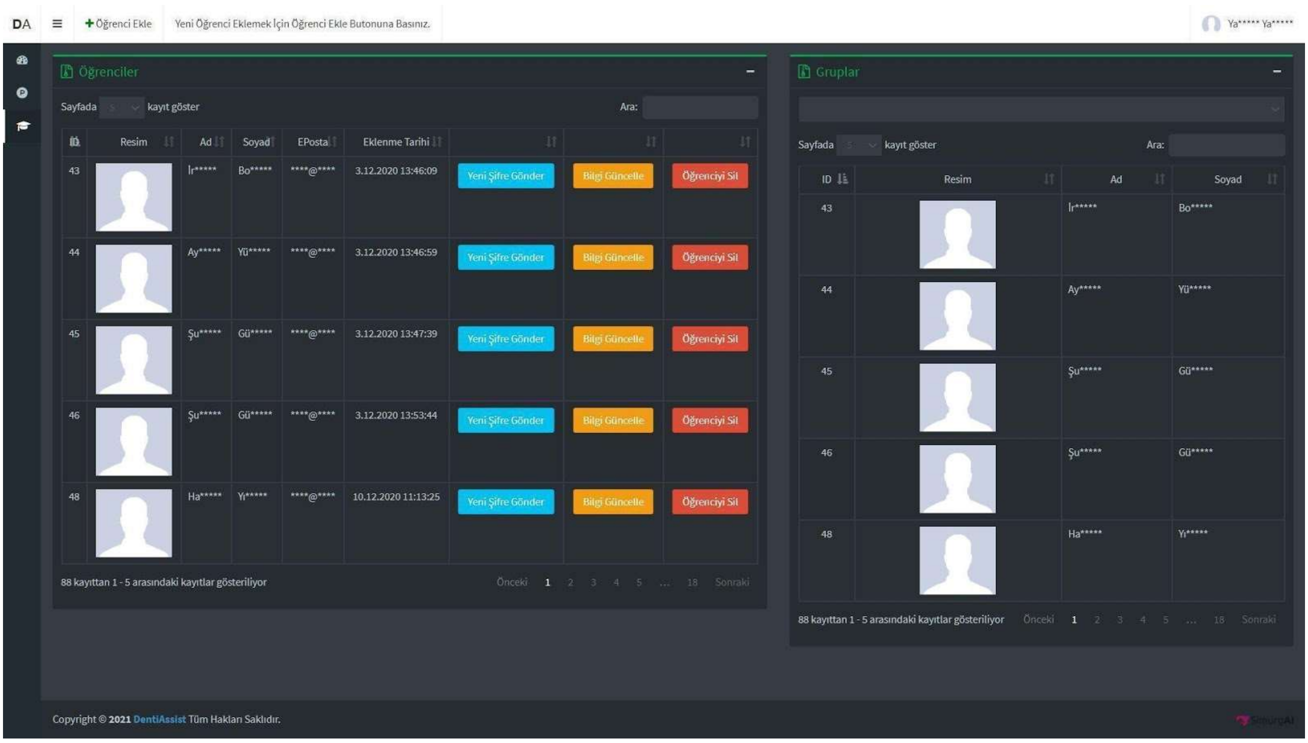


Figure 8. Users Screen

On this screen, the user can list the students they have added. New students can be added with the "Add Students" link in the top menu. It can also group specific students. A new password can be sent to each student's registered email address, student information can be edited and deleted.

5. Experimental Studies and Results

This study was performed on a computer with i9 10980XE processor and NVIDIA Quadro RTX 5000 graphics card. 649 train images randomly selected from the data set were given to the neural network. Then, verification was provided with 279 validation images in the neural network. The training was completed by selecting the 0.001 learning rate and the Adam optimization algorithm for 100 epochs. As a result of the comparison of student and artificial intelligence, using an equal number of 100 test images, the mAP (mean average precision) was measured 97.75%, and 99.02% success was achieved in the comparison of maxillofacial radiologist and artificial intelligence.

In this study, MS (Matching Score), which is frequently used in the literature, was calculated to test the suitability of the module in the proposed software. As seen in Table 1, radiologist labels are used as VGT (Value of Ground-Truth). Comparing VGT with students, MS 86.77%, AAT (Average Analysis Time) 600s and NBB (Number of Bounding Boxes) 2862; Despite the comparison of VGT and artificial intelligence, MS 85.30%, AAT 3s and NBB 2855 were found. The MS (Matching Score) value, which is one of the values seen in Table 1, comes from the IoU (Intersection over Union) expression, which is frequently used for comparison purposes in the literature. For this purpose, the similarity ratio is kept by checking the masks between the ground-truth values and the estimated values. In this way, the similarities of artificial intelligence and student results were determined, and the performance of the results was analyzed. Considering the results in Table 1, while the student completes the marking of an image in an average of 600 seconds, the developed artificial intelligence module analyzes an image in an average of 3 seconds. When the bounding boxes inferred by the student and artificial intelligence are compared, it is also tested how accurately the student analyzes the tooth images.

Table 1. Comparison of student and artificial intelligence module

	Matching Score (%)	Average Analysis Time (s)	Number of Bounding Boxes
Student	86,77	600	2862
AI Module	85,30	3	2855

In the panoramic x-ray image given in Fig. 9, the bounding boxes and matching scores shown while calculating the compared match scores of the student and artificial intelligence module are included. While the green boxes in Fig. 9 represent ground truth, the red boxes represent the student. Although there are missing teeth in this panoramic image, student and artificial intelligence have performed high accuracy analysis.

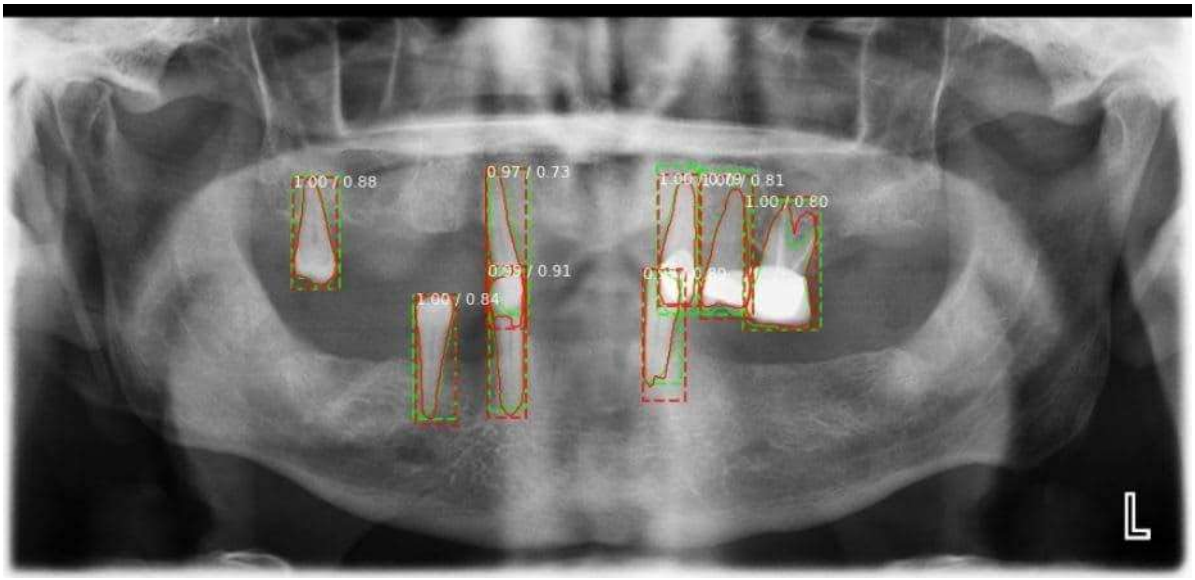


Figure 9. Comparison of matching scores of a sample tooth image

In the given Fig. 10, the masking of dental objects in a sample image with the DentiAssist segmentation module is seen. These objects are painted in a different mask color for each ROI region because of the instance segmentation.

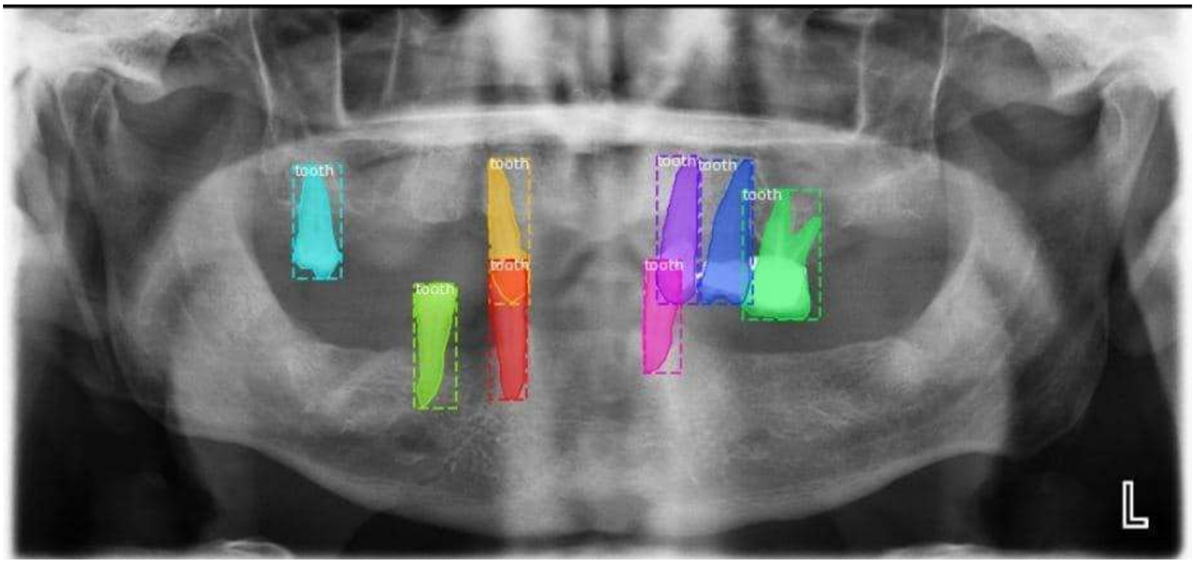


Figure 10. Panoramic image segmented with AI module of the same image

6. Conclusion and Evaluation

In this study, the segmentation module, which is an application of artificial intelligence supported radiological image analysis and labeling, was developed for the education of dentistry students. As can be understood from the experimental results of the study, when the average analysis of one radiographic image by the student and the artificial intelligence module is compared, it is seen that the analysis time of the student is much longer than the artificial intelligence. When the bounding boxes of the objects created for analysis are checked, the number of objects created by the artificial intelligence module and the number of objects created by students are close to each other. With the proposed system, it has been observed that artificial neural networks generally perform well for dental analysis in radiographic images.

As a result, when comparing the student and artificial intelligence-based segmentation module for the analysis of teeth, it was seen that both gave successful results. The artificial intelligence-based segmentation module produced results 200 times faster than the analysis time spent by a student. In addition, it is expected that it will be preferred by those working in this field in the future due to the ease, interface, and high performance of the artificial intelligence-based segmentation application. In the next studies, the sources of the problems that cause the error will be determined and the error rate will be eliminated, and the method will be improved.

References

[1] Kröger, E., Dekiff, M., and Dirksen, D. (2017), "3D printed simulation models based on real patient situations for hands-on practice", *European Journal of Dental Education*, 21 (4): e119–e125.

[2] Abdelkarim, A., Benghuzzi, H., Hamadain, E., Tucci, M., Ford, T., and Sullivan, D.(2014), "U.S. Dental Students' and Faculty Members' Attitudes About Technology, Instructional Strategies, Student Diversity, and School Duration: A Comparative Study", *Journal Of Dental Education*, 78 (4).

[3] Güven, Y. (2011), "Yüksek Öğretimde Çağdaş Yaklaşımlar, Yapısal Değişiklikler: Diş Hekimliği Eğitimi Örneği", *Yükseköğretim Dergisi*, 1 (1): 8–16.

[4] Brownstein, S. A., Murad, A., and Hunt, R. J. (2015), "Implementation of New Technologies in U.S. Dental School Curricula", *Journal Of Dental Education*, 79 (3): 259–264.

[5] Kale, E., Özçelik, T.B., (2018). "Türk Diş Hekimliği Fakültelerinde CAD/CAM Üzerine Eğitimin Değerlendirilmesi", *Acıbadem Üniversitesi Sağlık Bilimleri Dergisi,* 9(1):17-24.

[6] American Dental Association Council on Scientific Affairs (2006), The use of dental radiographs: update and recommendations. *The Journal of the American Dental Association*, *137*(9), 1304-1312.

[7] Cohen, S., & Hargreaves, K. M. (Eds.). (2011). *Cohen's pathways of the pulp*. Mosby Elsevier.

[8] Vandenberghe, B., Jacobs, R., & Bosmans, H. (2010). Modern dental imaging: a review of the current technology and clinical applications in dental practice. *European radiology*, *20*(11), 2637-2655.

[9] Aps, J. (2019). Extraoral Radiography in Pediatric Dental Practice.İ7 In *Imaging in Pediatric Dental Practice* (pp. 31-49). Springer, Cham.

[10] Maddox, T. M., Rumsfeld, J. S., & Payne, P. R. (2019). Questions for artificial intelligence in health care. *Jama*, *321*(1), 31-32.

[11] Oktay, A. B. (2017, October). Tooth detection with convolutional neural networks. In *2017 Medical Technologies National Congress (TIPTEKNO)* (pp. 1-4). IEEE.

[12] Muresan, M. P., Barbura, A. R., & Nedevschi, S. (2020, September). Teeth Detection and Dental Problem Classification in Panoramic X-Ray Images using Deep Learning and Image Processing Techniques. In *2020 IEEE 16th International Conference on Intelligent Computer Communication and Processing (ICCP)* (pp. 457-463). IEEE.

[13] Leite, A. F., Van Gerven, A., Willems, H., Beznik, T., Lahoud, P., Gaêta-Araujo, H., ... & Jacobs, R. (2021). Artificial intelligence-driven novel tool for tooth detection and segmentation on panoramic radiographs. *Clinical Oral Investigations*, *25*(4), 2257-2267.

[14] Poonsri, A., Aimjirakul, N., Charoenpong, T., & Sukjamsri, C. (2016, December). Teeth segmentation from dental x-ray image by template matching. In *2016 9th Biomedical Engineering International Conference (BMEiCON)* (pp. 1-4). IEEE.
[15] Girshick, R., Donahue, J., Darrell, T., & Malik, J. (2014). Rich feature hierarchies for accurate object detection and semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 580-587).
[16] Lin, T. Y., Dollár, P., Girshick, R., He, K., Hariharan, B., & Belongie, S. (2017). Feature pyramid networks for object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 2117-2125).
[17] Girshick, R. (2015). Fast r-cnn. In *Proceedings of the IEEE international conference on computer vision* (pp. 1440-1448).
[18] Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster r-cnn: Towards real-time object detection with region proposal networks. *arXiv preprint arXiv:1506.01497*.
[19] He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2017). Mask r-cnn. In *Proceedings of the IEEE international conference on computer vision* (pp. 2961-2969).
[20] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).
[21] Deng, J., Dong, W., Socher, R., Li, L. J., Li, K., & Fei-Fei, L. ImageNet: A large-scale hierarchical image database, 2009 IEEE Conference on Computer Vision and Pattern Recognition, pp. 248-255, 2009.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Efficientnet-B0 Based Single Stage and Multi-Scale Object Detection Model for Localization of Low-Grade Gliomas and Detection of 1p/19q Codeletion Status

Coşku ÖKSÜZ [1, *], Oğuzhan URHAN [2], Mehmet Kemal GÜLLÜ [3]

[1] *Kastamonu University, Bozkurt Vocational School, Department of Electronics and Automation, Turkey*
[2] *Kocaeli University, Dept. of Electronics and Telecommunication Engineering, Turkey*
[3] *Izmir Bakircay University, Dept. of Electrical and Electronics Engineering, Turkey*

* Corresponding Author: Kastamonu University, Department of Electronics and Automation, Turkey
Tel.: +90 366 2805803. E-Mail: coksuz@kastamonu.edu.tr

Publication Information

Keywords :

- 1p/19q codeletion
- Low-grade gliomas
- Deep learning
- Brain tumor detection

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Introduction-Objectives: In recent years, it has been revealed that the codeletion of the 1p/19q chromosomal arms in low-grade glioma (LGG) patients is an important biomarker. Accordingly, codeletion is highly correlated with a patient's positive response to treatment (chemotherapy, radiotherapy) and longer survival. Therefore, it is important to determine 1p/19q codeletion to make the correct treatment planning. For this purpose, a low complexity, single-step deep learning-based method is proposed that localizes the tumor region and predicts the codeletion simultaneously. **Materials-Methods:** In the study, the lightweight EfficientNet-B0 model is transformed into a multi-scale single-stage object detector model by inspiring the YOLO model architecture. Then, the model is trained by using the transfer learning strategy. Besides, pre-trained models with low complexity, i.e. Tiny YOLO v2, Tiny YOLO v3, and Tiny YOLO v4, are fine-tuned. **Results:** All the models are cross-validated on a public data set consisting of 159 patients with LGG (codeletion: 102, no-deletion: 57). The data set includes biopsy-proven samples. The model performance scores, namely the *log-average miss rate* and *mean average precision* (*mAP@[0.5:0.95]*), are 0.14 and 40.21%, respectively. The method predicts codeletion with 90.2% sensitivity in 67ms inference time. **Conclusions:** In the study, promising results are obtained in the prediction of 1p/19q codeletion status by a fully automatic method. The performance obtained shows that the proposed model can be used as an assistive diagnostic tool for experts. As the data sets are updated with more samples, the robustness of the model can be increased by improving the performance.

1. Introduction

Although it is known that there are more than 120 different types of primary brain tumors, gliomas attract attention due to their impact on deaths from brain tumors worldwide. Gliomas are divided into two general categories by the World Health Organization (WHO), low-grade gliomas (LGG) and high-grade gliomas (HGG). Low-grade gliomas are further classified as Grade-2 and Grade-3 [1], [2]. Considering the histopathological classification of Grade-2 and Grade-3 tumors, it is known that there are types called oligodendrogliomas and astrocytomas in Grade-2, and anaplastic oligodendrogliomas, anaplastic astrocytomas, anaplastic oligoastrocytomas, and anaplastic ependymomas in Stage-3 [3]. One of the important differences between the two categories is that LGGs are less aggressive tumors. However, the possibility of gliomas developing into high-grade glioma (Grade-4, glioblastomas) over time indicates that they have the potential to be malignant. This shows the importance of detecting gliomas at an early stage.

Until recently, the prognosis of LGGs was thought to be related to histopathological classification [4]. In the updated brain tumor classification published by the WHO in 2016, it is revealed that some molecular markers have more importance in predicting clinical outcomes [2], [5]. Accordingly, codeletion of 1p and 19q chromosomal arms in LGGs is an important factor in determining the response to chemotherapy and radiotherapy. Moreover, patients with this genetic loss have been shown to have significantly improved prognosis and overall survival compared to patients without 1p/19q deletion [6], [7].

In the current clinical routine, the status of co-deletion in chromosomal arms is determined by the fluorescence in situ hybridization (FISH) technique applied together with biopsy [8]. However, this invasive technique poses a risk to the patient. For this reason, it is a necessity to estimate the biomarkers by methods such as imaging that does not require patient intervention. In some studies [9]–[11] it is stated that factors in MR images such as heterogeneous signal intensity and unclear tumor borders carry information about codeletion status. However, evaluations made by experts based on image features can be subjective and highly variable. In [12], it is stated that the average prediction accuracy of two neurosurgeons in the estimation of codeletion is 0.43, whereas the average estimation accuracy of two neuroradiologists is 0.63. This situation reveals that there is no consensus among medical experts and the inter-observer variability is high. On the other hand, a more reliable and higher performance can be achieved with machine learning methods trained by using radiomics extracted from medical images. Classical machine learning methods are trained using the hand-crafted radiomics in studies in [4], [12]–[14] for 1p/19q prediction of codeletion status. However, finding the optimal feature set to maximize classification performance is a difficult process, and this puts the upper limit on total performance. On the other hand, with deep learning-based methods, superior performance can be obtained by learning the highly related features for the problem at hand. For the prediction of 1p/19q codeletion, methods based on deep learning have been developed in [15]–[17]. Few studies have been conducted yet and the performance achieved with the proposed methods is limited.

A method to be suggested for LGG tumor detection and prediction of 1p/19q co-deletion will be run on multiple 2D slices of the volumetric MRI data. Therefore, obtaining sufficient trade-offs in terms of speed and performance is an important requirement. For this reason, this study is inspired by the YOLO (You Only Look Once) model architecture, which is used to detect objects in natural images in real-time applications.

The main contributions of this paper are as follows:

- In some other works, the entire MRI image is used in classification. However, although it is a rare case, MRI can be containing one more tumorous region. In [18], the diffuse astrocytoma which is nothing but an LGG, and the meningioma tumors are found in the same patient. As a result, developing a method that uses the entire MRI image for classification can lead to misleading results in real-world scenarios. Therefore, an object detection-based approach has been followed to avoid this in the study.
- A single-stage and multi-scale custom object detection model is designed to localize gliomas rapidly and accurately in 2D slices of volumetric MRI data.
- The detected tumor regions are simultaneously classified by the proposed model either "with-deletion (d/d)" or "without deletion (n/n)". Since the classification is made according to the regions of interest, the reliability of the results is high.

The study is organized as follows. The proposed method is introduced in Section 2. Section 3 is devoted to experimental results. Section 4 is devoted to the discussion. Finally, Section 5 is devoted to conclusions.

2. Proposed Method

The proposed method is given in Fig. 1. As seen from Fig. 1., the method consists of a combination of two networks i.e. the feature extraction network, and the detection subnetwork. The details of the proposed method are given in subsections.

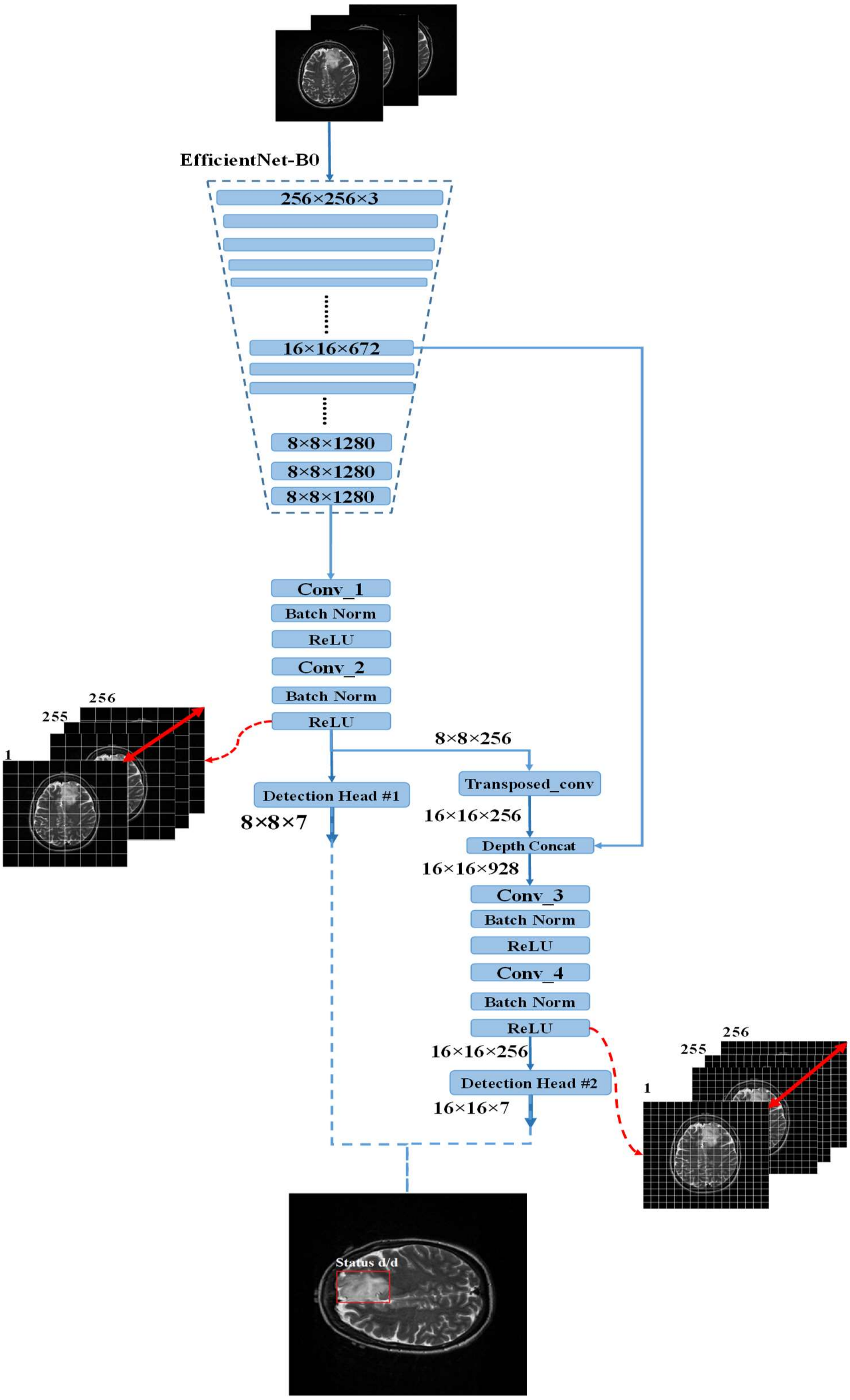


Fig. 1. The proposed LGG tumor localization framework.

2.1.Feature Extraction Network

In the study, we utilized EfficientNet-B0 model [19] as the feature extraction backbone. This model is the base model and the less complex one of the EfficientNet networks family, which consists of eight successive models. The network input is set to accept input images at 256×256×3 spatial resolutions. The down-sampling factor is adopted as 32 to include more high-level features. Thus, certain layers that are aligned for the classification task after layer *efficientnet-b0|model|head|MulLayer* are removed from the network. The obtained tensor at the output of the feature extraction network is 8×8×1280 in spatial resolution.

2.2. Detection Subnetwork

Gliomas are highly variable in size and shape. Some gliomas are very small while other tumors can be quite large. Therefore, the detection subnetwork is structured to have two detection heads to localize smaller gliomas. One anchor is used at each detection head to reduce complexity. As seen in Fig. 1, the feature maps obtained at the output of the feature extraction backbone are further processed by the convolutional, batch normalization, and ReLU layers. These layers are repeated twice in each detection head. Since the number of 256 kernels in size 3×3 is used in each convolutional layer, the resulting tensor is 8×8×256 in spatial resolution. This tensor is fed into the first detection head and then further processed to feed the second detection head. Before processing the tensor for the second detection head, it is processed by transposed convolutional layer with 256 kernels in size 8×8 to up-scale the activations maps.

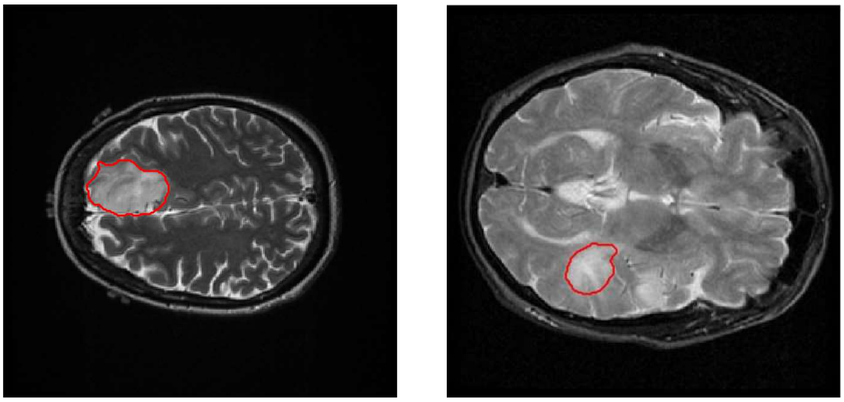
Fine-grained features are extremely important to minimize localization errors. The passthrough approach used in the YOLO v2 [20] is one of the exemplary cases. Therefore, the obtained 256 feature maps in size 16×16 are concatenated with more semantic feature maps along channel dimension using depth concatenation layer to provide fine-grained details. The semantic feature maps are fed to the depth concatenation layer from the layer, *efficientnet-b0|model|blocks_11|MulLayer* which outputs the tensor in 16×16×672 spatial resolutions. Then, the obtained 928 activation maps in size 16×16 are processed by traveling two order repeats of the convolutional layer of 256 kernels in size 3×3, the batch normalization layer, and the ReLU layer. Accordingly, the obtained tensor in size 16×16×256 is fed to the second detection head. Since there are two classes as co-deleted and non-deleted, and the number of five parameters (x, y, width, height, confidence score) to be estimated, there are seven parameters to be estimated per anchor. Therefore, a convolutional layer with 7 kernels in size 1×1 is used at each detection head. As a result, tensors at 8×8×7 and 16×16×7 spatial resolutions are obtained from the first and second detection heads, respectively.

3. Experiments and Results

In this section, experimental results are presented. Besides the proposed method, three pre-trained models with less complexity, namely Tiny Yolo v2 [21], Tiny Yolo v3 [22] and Tiny Yolo v4 [22], are used for comparison. These models are designed in accordance with the lightweight strategy by suppressing the models with more complex counterparts, Yolo v2 [20], Yolo v3 [23] and Yolo v4 [24].

3.1. Data set

In the study, *LGG-1p19qDeletion* data set [16], [25], [26] is used. This data set consists of T1C and T2 weighted MR data collected from 159 patients. The MR data for each patient is in volumetric form. There are 478 slices containing tumor regions. In the data set, 1p/19q co-deletion status of all patients is provided as proven by biopsy. The “d/d” status means that the chromosomal arms 1p and 19q are missing, while “n/n” means that neither the 1p nor 19q chromosomal arms are deleted. There are 306 slices within the status “d/d”, and 172 slices within the status “n/n”. The exemplary slices for each status are given in Fig. 2.



(a) **(b)**

Fig. 2. T2 weighted slice is given in (a) belongs to status “d/d”, while the slice given in (b) belongs to “n/n”.

3.2. Loss function, Training, Hyperparameters, and Data Augmentation

Since tumorous regions have higher contrast in T2-weighted slices, these slices are used in the model training. The 478 slices are divided into five non-overlapping folds. While the one fold is held out for the test set, the other folds are used in the training each time. The model is trained in accordance with other Yolo models by using the total loss function given in (1). While cross-entropy loss function is used to compute classification and objectness loss, the mean squared error function is used to compute bounding box loss.

$$\ell_{total} = \ell_{bbox} + \ell_{objectness} + \ell_{classification} \tag{1}$$

Each model is trained for 100 epochs with SGDM (Stochastic Gradient Descent with Momentum) optimizer. The other hyperparameters i.e., *mini batch size*, *L_2 regularization*, *penalty threshold*, and *initial learning rate ($LR_{initial}$)*, are set as 10, 5×10^{-4}, 0.5, and 10^{-3}, respectively. The learning rate is scheduled as piecewise based on iterations. The learning rate schedule is given in (2).

$$LR = \left\{ \begin{array}{cc} LR_{initial} \times \left(it/0.25\times it_{total}\right)^4, & it \leq 0.25\times it_{total} \\ LR_{initial}, & it > 0.25\times it_{total} \;\&\; it \leq 0.70\times it_{total} \\ LR_{initial}\times 10^{-1}, & it > 0.70\times it_{total} \;\&\; it \leq 0.90\times it_{total} \\ LR_{initial}\times 10^{-2}, & otherwise \end{array} \right\} \tag{2}$$

First, to stabilize the gradients at higher learning rates, the current iteration (*it*) is increased exponentially until it is less than 0.25 of the total iteration (it_{total}). Then, it is decreased step-wise.

Data is augmented at each epoch using horizontal and vertical mirroring, random translation to the right and left by 5 pixels, scaling by a randomly picked factor from [0.75 1.25], and rotating at a randomly picked angle from [-90 90].

3.3. Performance evaluation metrics

The performance evaluation techniques used in the study are *log-average miss rate (LAMR)*, *mean average precision (mAP)*, recall (TPR), precision (PPV), specificity (Spec), F_1 score, and accuracy (Acc). The *Average precision* is a commonly used metric in object detection tasks. It is measured based on the area under the precision-recall curve. This metric is important in that it summarizes the model precision as a single score obtained for varying recall thresholds. *mAP* score is computed by averaging the AP score obtained for each class. In the study, we calculated the *mAP* score as the average IoU thresholds between 0.5-0.95. *Log-average miss rate* is computed by averaging miss rate scores obtained on evenly spaced nine

FPPI (false positives per image) rates, a_i, in log-space in the interval 10^{-2} -10^{0} [27]. This metric summarizes the miss rate scores as a single score. *LAMR* and *mAP* scores are computed as given in (3). *TPR*, *Spec*, *PPV*, F_1 and *Acc* scores are computed as given in (4).

$$LAMR = \exp\left[\frac{1}{n}\sum_{i=1}^{n}\ln a_i\right],\ mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i,\ IoU = [0.5:0.05:0.95] \tag{3}$$

$$TPR = \frac{TP}{TP+FN},\ Spec = \frac{TN}{TN+FP},\ PPV = \frac{TP}{TP+FP},$$
$$F_1 = 2\times\frac{\Pr ecision \times \operatorname{Re}call}{\Pr ecision + \operatorname{Re}call},\ Acc = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

3.4. Evaluation of the Performance

The methods applied in this work are evaluated using the metrics introduced in the previous section. *mAP* and *LAMR* scores achieved at multiple thresholds are given in Table 1 for each test fold. These results indicate the effectiveness of the method. In Table 1, *LAMR* denotes the average score obtained for status "n/n", and status "d/d". The results achieved with each method at each fold are close to each other. The scores achieved on each test fold are averaged to evaluate the general performance of the models. Accordingly, the average scores indicate that Tiny Yolo v2 model underperforms about 16%, and 0.13 from other tiny models in terms of *mAP*, and *LAMR*, respectively. On the other hand, there is no significant performance difference between Tiny Yolo v3, and Tiny Yolo v4. Beyond that, the proposed method outperforms about 2%, and 0.12 from Tiny Yolo v3, and Tiny Yolo v4 in terms of *mAP*, and *LAMR*, respectively. All these suggest that the proposed method is more precise and tumor localization errors are relatively low compared to the other methods for multiple threshold values.

Table 1. The performance scores of methods obtained on each test fold.

Models	Metrics	Fold #1 95-Slices	Fold #2 96-Slices	Fold #3 96-Slices	Fold #4 96-Slices	Fold #5 95-Slices	*Avg.*
Tiny Yolo v2	*mAP (%)*	23.04	24.03	19.29	19.30	20.98	21.33
	LAMR	0.45	0.32	0.43	0.34	0.43	0.39
Tiny Yolo v3	*mAP (%)*	34.63	39.45	**38.95**	39.30	**38.82**	38.23
	LAMR	0.29	0.22	0.26	0.25	0.29	0.26
Tiny Yolo v4	*mAP (%)*	**39.75**	40.80	36.59	39.95	37.40	38.9
	LAMR	0.27	0.26	0.27	0.27	0.30	0.27
Proposed method	*mAP (%)*	37.23	**43.38**	38.49	**44.75**	37.20	**40.21**
	LAMR	**0.20**	**0.14**	**0.23**	**0.12**	**0**	**0.14**

To evaluate model classification performance, we set the IoU threshold to the commonly used value of 0.5. In Fig. 3, the evaluation process of the proposed method on each test fold, and the corresponding confusion matrices are given in detail. All the confusion matrices are summed up to see the overall performance and how the errors are distributed.

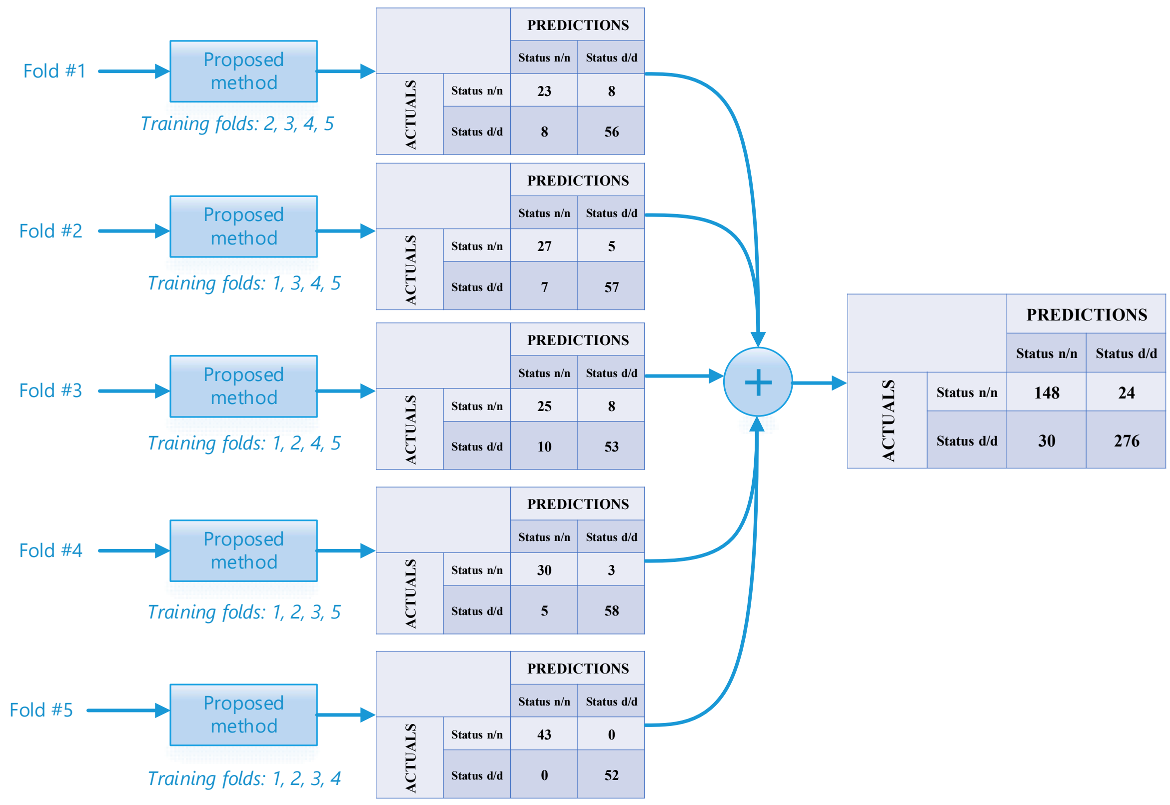


Fig. 3. Evaluation process of the proposed method on each test fold.

In Table 2, the confusion matrix is given comparatively with other methods used in the study. As seen from Table 2, the total miss classification cost is 137, 98, and 94, for Tiny Yolo v2, Tiny Yolo v3, and Tiny Yolo v4, respectively. On the other hand, it is 54 for the proposed method as seen from Fig. 3.

Table 2. The confusion matrix comparatively shows the classification results obtained from the Tiny Yolo models. The results are given in the order of v2 / v3 / v4.

n=478		PREDICTIONS	
		Status n/n	**Status d/d**
ACTUALS	**Status n/n**	136/128/126	36/44/46
	Status d/d	101/54/48	205/252/258

In Table 3, the classification results obtained based on confusion matrices are given for each method. Accordingly, the proposed method is better about 10% against Tiny Yolo v3 and Tiny Yolo v4 in terms of all metrics, while it performs better about 15% than Tiny Yolo v2. Each method is run on a notebook with RTX 2070 GPU card, and 16 GB RAM. The average inference time of the models, Tiny Yolo v2, Tiny Yolo v3, and Tiny Yolo v4, are 6ms, 20ms, 23ms, and 67ms, respectively.

Table 3. The achieved classification scores of the methods with the IoU threshold set to 0.5.

Methods	**TPR (%)**			**PPV (%)**			**Spec (%)**			**F_1 Score (%)**	**Acc (%)**	**Inference time per image**
	n/n	d/d	*Avg.*	n/n	d/d	*Avg.*	n/n	d/d	*Avg.*			
Tiny Yolo v2	79.1	67.0	*73.0*	57.4	85.1	*71.2*	67.0	79.1	*73.0*	72.12	71.34	6ms
Tiny Yolo v3	74.4	82.4	*78.4*	70.3	85.1	*77.7*	82.4	74.4	*78.4*	78.06	79.50	20ms
Tiny Yolo v4	73.3	84.3	*78.8*	72.4	84.9	*78.6*	84.3	73.3	*78.8*	78.7	80.33	23ms
Proposed	**86.0**	**90.2**	***88.1***	**83.1**	**92.0**	***87.6***	**90.2**	**86.0**	***88.1***	**87.85**	**88.70**	67ms

4. Discussion

Considering the results presented in Table 3, the reason why Tiny Yolo v2 performs poorly compared to other methods can be explained by the strength of the feature extraction backbone and the absence of multiscale detection. Therefore, the model misses the regions that especially contain smaller tumors and generates many false negatives. However, other tiny models and the proposed model are capable of capturing smaller tumors with their multiscale nature. Feature extraction backbone is an important factor in that extracting and carrying low-level and high-level features. The high-level distinctive features are not sufficiently extracted by Tiny-Yolo v3, depending on the model depth. With the slightly more complex model Tiny Yolo v4, a performance improvement is achieved thanks to a more powerful backbone. On the other hand, Efficientnet-B0 model carries the performance to the top by preserving extracted semantic information with skip connections and by extracting more complex features depending on its depth.

Table 4. Comparison of performance with other works using the same data set.

Methods	TPR (%)			PPV (%)			Spec. (%)			F_1 Score (%)	Acc (%)
	n/n	d/d	*Avg.*	n/n	d/d	*Avg.*	n/n	d/d	*Avg.*		
Voort et al. **[12]**	-	-	*73.2*	-	-	*78.7*	-	-	*61.7*	69.7	69.30
Kocak et al. **[4]**	75.8	87.5	*81.6*	70.0	90.5	*80.2*	87.5	75.8	*81.6*	79.60	83.80
Akkus et al. **[16]**	82.2	93.3	*87.8*	92.5	84.0	*88.2*	93.3	82.2	*87.8*	88.01	87.78
Ge et al. **[15]**	94.0	84.8	*89.4*	86.1	93.4	*89.7*	84.8	94.0	*89.4*	89.57	89.40
Proposed	86.0	90.2	*88.1*	83.1	92.0	*87.6*	90.2	86.0	*88.1*	87.85	88.70

In Table 4, the proposed method is compared with the works using the same data set. In work [4] and [12], classical machine learning models are trained with extracted hand-crafted features. Kocak et al. [4] extracted texture-based features from T1C, and T2 weighted images. Various classification algorithms are trained after feature selection, including Adaptive Boosting, K-NN, Naive Bayes, Neural Network, Random Forest, Stochastic Gradient Descent, and Support Vector Machine (SVM). The best performance is achieved by the neural network model. Voort et al. [12] extracted 80 features including the patient's sex and age from T1 and T2 weighted images to train the SVM model. An accuracy of 69.30% is achieved. In work [16] and [15], deep learning-based methods are proposed. Akkus et al. [16] proposed a custom CNN model using tumor regions segmented by a semi-automatic software. An accuracy of 87.78% is obtained in this study. Ge et al. [15] proposed a fusion CNN model using the entire MR image for classifying 1p/19q codeletion. In this study, the non-tumor areas on the MR image are suppressed by 1/3 using the masks defined with the data set. An accuracy of 89.40% is obtained. As seen from Table 4, deep learning-based methods are more effective than hand-crafted-based methods because the task-related features are learned. However, one drawback of the method developed by Akkus et al. [16] is that it requires tumor regions and is therefore not fully automated. Besides, the method developed by Ge et al. [15] needs manipulation of the training data. The method we proposed localizes automatically the LGGs without requiring any preprocessing on the training data, and classifies the codeletion status of 1p/19q with a high confidence score since all irrelevant regions are eliminated. Since the classification task depends on the localization task, it is a drawback of the method that it cannot be classified when the tumor is not localized. Even so, relatively good scores are achieved with our fully automated method.

In Fig. 4, the implementation results of the proposed method on several test images are shown. As seen from Fig. 4, the boxes estimated (yellow boxes) by the model are quite close to ground truth boxes (red boxes).

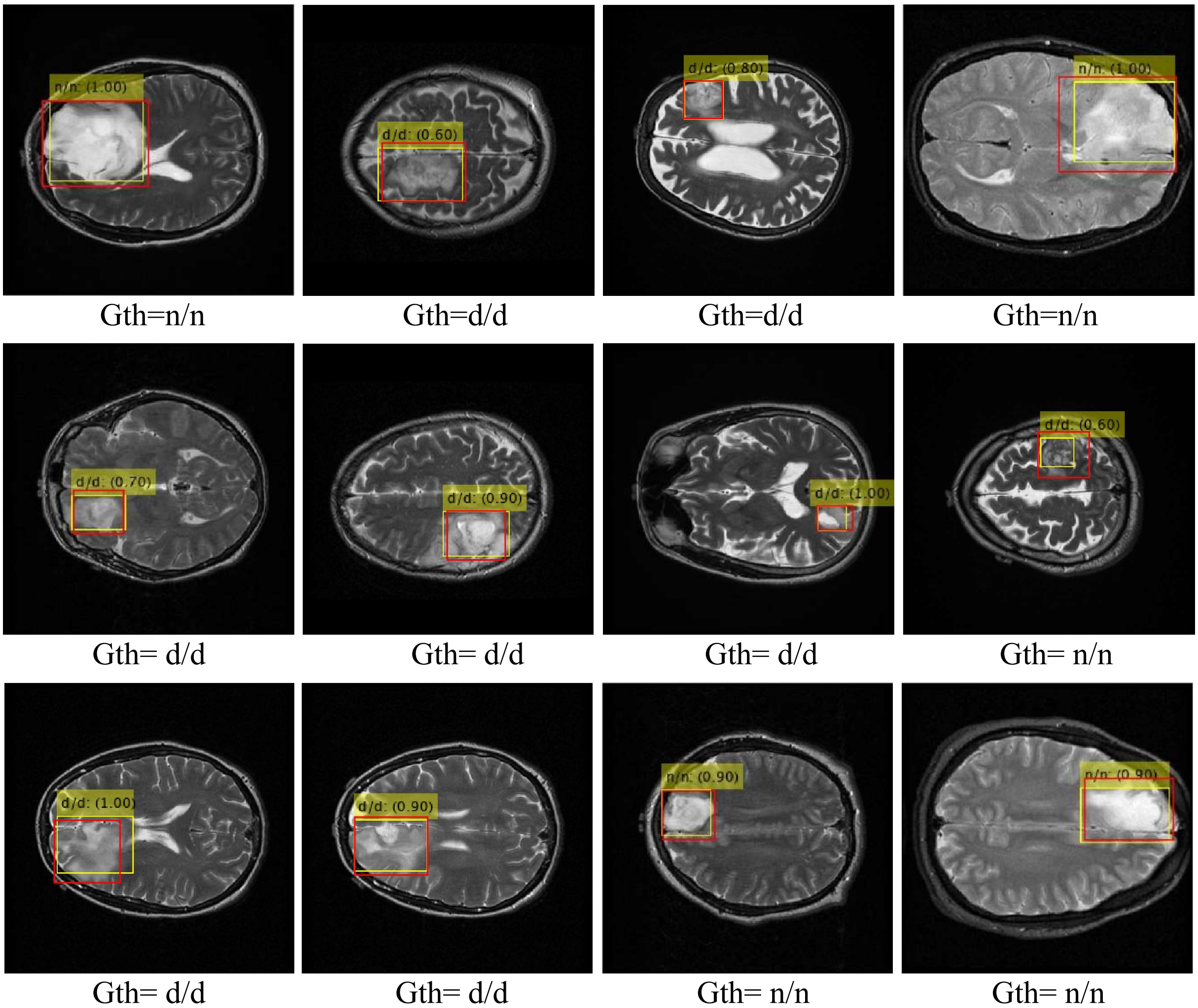


Fig. 4. Resulting MR images returned by the proposed method. The bounding box estimations made by the model are given in yellow with the corresponding classification results, and the confidence score, while the ground truth boxes are shown in red in all the images. The ground truth labels are given below each image.

5. Conclusions

In this work, we proposed a single-stage and multi-scale deep model with 14.5M parameters for tumor localization and prediction of LGG-1p/19q codeletion status. The proposed model has two detection heads each one uses single anchor. Although the achieved performance is still limited, the obtained results are promising against many other works in literature. However, performance can be further improved when the data sets are updated with more samples. We believe that the proposed method can be used as an assistive diagnostic tool for medical experts. Furthermore, tumor regions may be segmented effectively by integrating a segmentation network (or head) to the proposed model, since unrelated areas are eliminated. We plan to focus on these issues in our next study.

References

[1] V. Cuccarini et al., 'Advanced MRI may complement histological diagnosis of lower grade gliomas and help in predicting survival', J. Neurooncol., vol. 126, no. 2, pp. 279–288, Jan. 2016, doi: 10.1007/s11060-015-1960-5.

[2] The Cancer Genome Atlas Research Network, 'Comprehensive, Integrative Genomic Analysis of Diffuse Lower-Grade Gliomas', N. Engl. J. Med., vol. 372, no. 26, pp. 2481–2498, Jun. 2015, doi: 10.1056/NEJMoa1402121.

[3] R. Chen, M. Smith-Cohn, A. L. Cohen, and H. Colman, ‘Glioma Subclassifications and Their Clinical Significance’, Neurotherapeutics, vol. 14, no. 2, pp. 284–297, Apr. 2017, doi: 10.1007/s13311-017-0519-x.

[4] B. Kocak et al., ‘Radiogenomics of lower-grade gliomas: machine learning–based MRI texture analysis for predicting 1p/19q codeletion status’, Eur. Radiol., vol. 30, no. 2, pp. 877–886, Feb. 2020, doi: 10.1007/s00330-019-06492-2.

[5] D. N. Louis et al., ‘The 2016 World Health Organization Classification of Tumors of the Central Nervous System: a summary’, Acta Neuropathol. (Berl.), vol. 131, no. 6, pp. 803–820, Jun. 2016, doi: 10.1007/s00401-016-1545-1.

[6] S. H. E. Boots-Sprenger et al., ‘Significance of complete 1p/19q co-deletion, IDH1 mutation and MGMT promoter methylation in gliomas: use with caution’, Mod. Pathol., vol. 26, no. 7, pp. 922–929, Jul. 2013, doi: 10.1038/modpathol.2012.166.

[7] G. Cairncross et al., ‘Phase III Trial of Chemoradiotherapy for Anaplastic Oligodendroglioma: Long-Term Results of RTOG 9402’, J. Clin. Oncol., vol. 31, no. 3, pp. 337–343, Jan. 2013, doi: 10.1200/JCO.2012.43.2674.

[8] D. Scheie et al., ‘Fluorescence In Situ Hybridization (FISH) on Touch Preparations: A Reliable Method for Detecting Loss of Heterozygosity at 1p and 19q in Oligodendroglial Tumors’, Am. J. Surg. Pathol., vol. 30, no. 7, pp. 828–837, Jul. 2006, doi: 10.1097/01.pas.0000213250.44822.2e.

[9] J. F. Megyesi et al., ‘Imaging Correlates of Molecular Signatures in Oligodendrogliomas’, Clin. Cancer Res., vol. 10, no. 13, pp. 4303–4306, Jul. 2004, doi: 10.1158/1078-0432.CCR-04-0209.

[10] S. H. Patel et al., ‘T2–FLAIR Mismatch, an Imaging Biomarker for IDH and 1p/19q Status in Lower-grade Gliomas: A TCGA/TCIA Project’, Clin. Cancer Res., vol. 23, no. 20, pp. 6078–6085, Oct. 2017, doi: 10.1158/1078-0432.CCR-17-0560.

[11] M. P. G. Broen et al., ‘The T2-FLAIR mismatch sign as an imaging marker for non-enhancing IDH-mutant, 1p/19q-intact lower-grade glioma: a validation study’, Neuro-Oncol., vol. 20, no. 10, pp. 1393–1399, Sep. 2018, doi: 10.1093/neuonc/noy048.

[12] S. R. van der Voort et al., ‘Predicting the 1p/19q Codeletion Status of Presumed Low-Grade Glioma with an Externally Validated Machine Learning Algorithm’, Clin. Cancer Res., vol. 25, no. 24, pp. 7455–7462, Dec. 2019, doi: 10.1158/1078-0432.CCR-19-1127.

[13] P. P. Batchala et al., ‘Neuroimaging-Based Classification Algorithm for Predicting 1p/19q-Codeletion Status in IDH -Mutant Lower Grade Gliomas’, Am. J. Neuroradiol., p. ajnr;ajnr.A5957v1, Jan. 2019, doi: 10.3174/ajnr.A5957.

[14] Y. Han et al., ‘Non-invasive genotype prediction of chromosome 1p/19q co-deletion by development and validation of an MRI-based radiomics signature in lower-grade gliomas’, J. Neurooncol., vol. 140, no. 2, pp. 297–306, Nov. 2018, doi: 10.1007/s11060-018-2953-y.

[15] C. Ge, I. Y.-H. Gu, A. S. Jakola, and J. Yang, ‘Deep Learning and Multi-Sensor Fusion for Glioma Classification Using Multistream 2D Convolutional Networks’, in 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Honolulu, HI, Jul. 2018, pp. 5894–5897, doi: 10.1109/EMBC.2018.8513556.

[16] Z. Akkus et al., ‘Predicting Deletion of Chromosomal Arms 1p/19q in Low-Grade Gliomas from MR Images Using Machine Intelligence’, J. Digit. Imaging, vol. 30, no. 4, pp. 469–476, Aug. 2017, doi: 10.1007/s10278-017-9984-3.

[17] Y. Matsui et al., ‘Prediction of lower-grade glioma molecular subtypes using deep learning’, J. Neurooncol., vol. 146, no. 2, pp. 321–327, Jan. 2020, doi: 10.1007/s11060-019-03376-9.

[18] T. Tunthanathip, K. Kanjanapradit, S. Ratanalert, N. Phuenpathom, T. Oearsakul, and A. Kaewborisutsakul, 'Multiple, Primary Brain Tumors with Diverse Origins and Different Localizations: Case Series and Review of the Literature', J. Neurosci. Rural Pract., vol. 09, no. 04, pp. 593–607, Oct. 2018, doi: 10.4103/jnrp.jnrp_82_18.

[19] M. Tan and Q. V. Le, 'EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks', ArXiv190511946 Cs Stat, Sep. 2020, Accessed: Nov. 17, 2020. [Online]. Available: http://arxiv.org/abs/1905.11946.

[20] J. Redmon and A. Farhadi, 'YOLO9000: Better, Faster, Stronger', ArXiv161208242 Cs, Dec. 2016, Accessed: Mar. 20, 2021. [Online]. Available: http://arxiv.org/abs/1612.08242.

[21] 'YOLO: Real-Time Object Detection'. https://pjreddie.com/darknet/yolov2/ (accessed Mar. 20, 2021).

[22] Alexey, AlexeyAB/darknet. 2021.

[23] J. Redmon and A. Farhadi, 'YOLOv3: An Incremental Improvement', ArXiv180402767 Cs, Apr. 2018, Accessed: Mar. 20, 2021. [Online]. Available: http://arxiv.org/abs/1804.02767.

[24] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, 'YOLOv4: Optimal Speed and Accuracy of Object Detection', ArXiv200410934 Cs Eess, Apr. 2020, Accessed: Mar. 20, 2021. [Online]. Available: http://arxiv.org/abs/2004.10934.

[25] B. Erickson, Z. Akkus, J. Sedlar, and P. Korfiatis, 'Data from LGG-1p19qDeletion', 2017, doi: 10.7937/K9/TCIA.2017.DWEHTZ9V.

[26] K. Clark et al., 'The Cancer Imaging Archive (TCIA): Maintaining and Operating a Public Information Repository', J. Digit. Imaging, vol. 26, no. 6, pp. 1045–1057, Dec. 2013, doi: 10.1007/s10278-013-9622-7.

[27] P. Dollar, C. Wojek, B. Schiele, and P. Perona, 'Pedestrian Detection: An Evaluation of the State of the Art', IEEE Trans. Pattern Anal. Mach. Intell., vol. 34, no. 4, pp. 743–761, Apr. 2012, doi: 10.1109/TPAMI.2011.155.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Can We Use Artificial Intelligence in Musculoskeletal and Orthopedic Physiotherapy?

Semiha YENİŞEHİR [1, *], Erçen Büşra OYMAN [2]

[1]*Muş Alparslan University, Faculty of Health Science, Department of Physiotherapy and Rehabilitation, Muş-Turkey.*

[2]*Muş Alparslan University, Vocational School of Health Services, Department of Therapy and Rehabilitation, Muş-Turkey.*

* Corresponding Author: Muş Alparslan University, Faculty of Health Science, Department of Physiotherapy and Rehabilitation, Muş-Turkey.

Tel.: +90 232 2930000. E-Mail: s.yenisehir@alparslan.edu.tr

Publication Information

Keywords :

- Artificial intelligence
- Machine learning
- Musculoskeletal
- Physiotherapy
- Orthopedic physiotherapy

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Artificial intelligence (AI) can provide healthcare about evaluation and treatment through the advancement of care delivery, decision-making, and patient engagement. AI is the development of computer systems to solve problems associated with human intelligence. AI is used in different physiotherapy fields such as musculoskeletal, orthopedic, and neurologic. Physiotherapists and physiotherapy educators should engage in AI technology to guide physiotherapy education and clinical practice. This study aimed to compile research on the use of AI technology in musculoskeletal and orthopedic physiotherapy and rehabilitation, physiotherapy education. This review covers the main lines of the use of AI in musculoskeletal and orthopedic physiotherapy. The databases PubMed, Google Scholar, Science Direct, and PEDro were searched using related keywords, and relevant studies published by 1 March 2021 were summarized. The findings of the study indicate that there is a need for more research conducted with a multidisciplinary approach in physiotherapy in Turkey. With a multidisciplinary approach, it is thought that physiotherapists should prioritize both clinical and research studies, starting with the process of physiotherapy education.

1. Introduction

Artificial intelligence (AI) is defined as the use of complex algorithms for machines to perform cognitive functions, including problem-solving and decision-making. AI which consists of machine learning, artificial neural networks, natural language processing, and computer vision, is growing rapidly in medicine and many other fields. AI technology can take different forms such as software programs and hardware interfaces to develop a system that can learn from its data sets [1].

AI is a field of mathematical engineering that has the potential to improve healthcare through new care delivery strategies, informed decision-making, and facilitating patient participation. Machine learning (ML) is a form of AI, has two main forms as supervised and unsupervised. Supervised ML is where algorithms are provided with training data and analyzed and labeled for properties important for classification. Unsupervised ML is used to identify patterns without training. Common forms are cluster analysis (where data is grouped according to characteristic models) or association (rules are discovered where data is managed). Unsupervised learning is often applied within data mining (reviewing large databases) to make new discoveries about risk or causality where models are not obvious to clinicians [2].

AI has a promising future for the development of diagnosis and treatment methods in the field of physiotherapy and rehabilitation [2]. Physiotherapists should engage with technological innovation in the healthcare system, to guide clinical practices in different fields [2]. Thus, this study was aimed to review in light of the research studies about AI in musculoskeletal and orthopedic physiotherapy and rehabilitation in the literature.

2. Method

To determine the use of AI in the field of physiotherapy and rehabilitation, the search was made in PubMed, Google Scholar, ScienceDirect, and PEDro databases. The keywords were "artificial intelligence", "machine learning", "musculoskeletal physiotherapy", "orthopedic physiotherapy", "rehabilitation". There is no restriction regarding the starting date of the screening, and researches about the subject that was included in the determined databases until March 2021 were examined. In these studies, researches on musculoskeletal and orthopedic physiotherapy about AI are summarized. The studies on the subject have been examined and provided to be a guide for further clinical and research studies.

3. Physiotherapy and Rehabilitation Education

In the 21st-century healthcare system, physiotherapy education needs to change in order to graduate professionals suitable for physiotherapy treatments due to the possible effectiveness of AI-based technologies on physiotherapy practices [3].

The curriculum of physiotherapy and rehabilitation should be reorganized in order to integrate data science, technological, behavioral science, and human literacy across all that is considered to be core to the profession [3, 4]. An integrated physiotherapy curriculum will help clinicians learn to collaborate with high-performance algorithms while also revealing their unique human power [3].

The creativity capacity of students and personal human connections should be developed. Physiotherapy educators should take care to ensure that students know how to interpret algorithmic decisions and when to ignore them when moving to AI-based health systems [3].

4. Musculoskeletal and Orthopedic Physiotherapy

The advancement of technology in the medical field acts as a supportive workload system for physiotherapists in recent years. Virtual reality, AI and machine learning are popular and important technologies in medical applications [1]. One of the most important applications of AI and medical health big data is the management of diseases, which has attracted the attention of many countries, research institutions, and major Internet companies around the world [5].

The online applications, computer vision applications, digitalized physiotherapy solutions, proposed systems, recording video of the musculoskeletal exercises, posture detection system, and the scoring function are used for the practice of musculoskeletal physiotherapy [1]. The scoring function is used to match the performance metric with the motion quality scores and generates the benchmark score for the repetition of the exercises [1].

Machine learning applications used in longstanding pain (not exclusively musculoskeletal); outlining the use of machine learning to classify subjects to a predicted type of pain. Wearable technology provides a rich source of data for the management of chronic musculoskeletal diseases [2]. The clinical decision support systems can be used with machine learning to classify subjects. It also provides recommendations for both diagnosis and treatment. The analyzed system of machine learning can use the visual and inertial sensor data to predict the risk mechanism of injuries [2].

A web platform including a patient data module, automatic exercise protocol determination module, protocol setting module, and graphical user interface for the creation and management of an automatic exercise protocol in the field of orthopedic physiotherapy is available to patients [6].

4.1 Home-based Physiotherapy and Rehabilitation

The objective measurements to assess and monitoring exercise protocols in the home setting is necessary for management of diseases.

In a study conducted by Ar and Akgül (2014), a data set of home-based shoulder and knee exercises was created under the consultancy of physiotherapists [7]. The low-level features within machine learning classifiers were used for evidence of exercise types. The specific network for physical therapy Bayesian network is built to recognize the type of exercise by using these evidence [7]. A study of Burns et al. (2018) was aimed to develop and evaluate home shoulder physiotherapy monitoring using a commercial smartwatch. Supervised learning algorithms were used such as k-nearest neighbor (k-NN), random forest (RF), support vector machine classifier (SVC), and a convolutional recurrent neural network (CRNN). Categorical classification accuracy was above 94% for all algorithms. The best performance was reached by the CRNN algorithm (99.4%). The subject stratified cross-validation, which evaluated classifier performance on unseen subjects, yielded lower accuracy scores again with CRNN performing best (88.9%). They also reported the technical feasibility of a smartwatch device and supervised ML approach to more easily monitor and evaluate the at-home adherence of shoulder physiotherapy exercise protocols [8].

In a study by Ongvisatepaiboon et al. (2015), it was mentioned that there is a rehabilitation system that enables patients to perform their exercises at home and that this system has a design compatible with smartphones have multiple sensors, including only accelerometer, gyroscope, and magnetic field sensors. They proposed a new approach using AI to predict the angle of rotation of the shoulder using only the accelerometer sensor. It was provided with an effective recovery and an appropriate rehabilitation program, with a web-based interface, as if working with a physiotherapist [9].

4.2 Artificial Neural Network for Ultrasound Therapy

Artificial Neural Network was used for the treatment of ultrasound in physiotherapy. The length of treatment and appropriate dosage, the age of patients, the application area, the fat rate in tissue, and related factors was determined [10].

The findings obtained by means of the designed and realized embedded system were compared with data gathered from an expert. As a result, the data obtained from the designed system were found out to be in line with the existing data [10].

5. Conclusion

The findings of the study indicate that AI has been used in the field of physiotherapy and rehabilitation, especially in recent years. It is seen that there are fewer studies in this field in our country. With a multidisciplinary approach, it is thought that physiotherapists should prioritize both clinical and research studies in this field, starting with the process of physiotherapy education. In this study, research on AI in the field of musculoskeletal and orthopedic physiotherapy was focused on, and other physiotherapy and rehabilitation fields such as neurological and cardiopulmonary rehabilitation were not included. In future studies, it is recommended to conduct more comprehensive research on these subjects and to guide clinical practice and research studies.

References

[1] Godse SP, Singh S, Khule S, Yadav V, Wakhare S. Musculoskeletal physiotherapy using artificial intelligence and machine learning. Int J Innov Sci Res Technol. 2019;4(11):592-8.

[2] Tack C. Artificial intelligence and machine learning| applications in musculoskeletal physiotherapy. Musculoskelet Sci Pract. 2019;39:164-9.

[3] Rowe M, Nicholls D, Masters K. Artificial intelligence in clinical practice: Implications for physiotherapy education. Open Physio. 2019;1-6.

[4] Hodges BD. Learning from Dorothy Vaughan: artificial intelligence and the health professions. Med Educ. 2018;52(1):11-3.

[5] Ling W, Yu G, Li Z. Lower limb exercise rehabilitation assessment based on artificial intelligence and medical big data. IEEE Access. 2019;7:126787-98.

[6] Skwortsow N, Molin HP. Exercise protocol creation and management system. Google Patents; 2015.

[7] Ar I, Akgul YS. A computerized recognition system for the home-based physiotherapy exercises using an RGBD camera. IEEE Trans Neural Syst Rehabil Eng. 2014;22(6):1160-71.

[8] Burns DM, Leung N, Hardisty M, Whyne CM, Henry P, McLachlin S. Shoulder physiotherapy exercise recognition: machine learning the inertial signals from a smartwatch. Physiol Meas. 2018;39(7):075007.

[9] Ongvisatepaiboon K, Chan JH, Vanijja V, editors. Smartphone-based tele-rehabilitation system for frozen shoulder using a machine learning approach. 2015 IEEE SSCI 2015: IEEE.

[10] Işik H, Arslan S. An artificial neural network classification approach for use the ultrasound in physiotherapy. J Med Syst. 2011;35(6):1333-41.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || ISBN : 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Artificial Intelligence Applications in Autism Spectrum Disorders

Nagihan CEVHER BİNİCİ [1], Pınar DALGIÇ [2,*]

[1] University of Health Sciences, İzmir Dr.Behcet Uz Child Disease and Pediatric Surgery Training and Research Hospital, Child and Adolescent Psychiatry Unit

[2] İzmir Dr.Behcet Uz Child Disease and Pediatric Surgery Training and Research Hospital

* Corresponding author: İzmir Dr.Behcet Uz Child Disease and Pediatric Surgery Training and Research Hospital
Tel: +9 0232 4116000 E-mail:pnrdlgc@gmail.com

Publication Information

Keywords :

- Artificial intelligence
- Machine learning
- Deep learning
- Autism spectrum disorder

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Objective: Autism spectrum disorders (ASD) are neurodevelopmental disorders characterized by impaired levels of social and communication impairment, along with repetitive and stereotyped patterns of behaviour and interests (American Psychiatric Association, 2013). Current evidence indicates that best prognosis for ASD depends on early diagnosis and intensive therapeutic intervention, making early detection vital. In recent years, advanced technologies like machine learning have been used to analyze and investigate ASD to improve diagnostic accuracy, time, and quality. These machine learning methods include artificial neural networks, support vector machines, a priori algorithms, and decision trees, most of which have been applied to datasets connected with autism to construct predictive models.

Method-Material: In this review, studies using machine learning methods to recognize certain clinical features of ASD, which were published in peer-reviewed journals between 2015 and 2021, will be reviewed.

Results: There are studies evaluating clinical features such as eye contact, emotion identification, sensory hypersensitivity, sound analysis, motor movement analysis, and posture analysis for ASD, and these studies will be shared in detail in this review.

Conclusion: Although the results of studies on ASD and artificial intelligence are promising, it is one of the issues that should be further emphasized that whether it will replace clinical evaluation and what kind of results this technology may cause for children with ASD in the future. For this purpose, it is suggested that future studies concerning individuals with ASD should be carried out to expand and support the findings in the literature.

1. Introduction

Autism spectrum disorders (ASD) are neurodevelopmental disorders characterized by impaired levels of social communication and interaciton, along with repetitive and stereotyped patterns of behaviour and interests. Current evidence indicates that best prognosis for ASD depend on early diagnosis and intensive therapeutic intervention, making early detection vital.

American Academy of Pediatrics(AAP) suggests hierarchical screening for ASD at all 18-24 months old children [1,2]. Altough screening studies toward ASD detection which also supports APAs suggestion were emphasized, how it will be globally applied is discussion topic due to practical and etical challenges [3]. Because false negativity and positivity is important problem in screening tools. Observations of evaluation childs social communication and supportion these observations by the familys report increase sensitivy and specifitiy of screening tool but as you guess to evaluate every child by expert team is highly time-sink and cumbersome.

ASD is diagnosed based on clinical evaluation, pyschiatric examination and behavioral features by child and adolescent pyschiaytry specialist according to DSM-5. Interview with care-giver and pyschiatric observation of patientis is the most important step on diagnosis. Assesment tools like MCHAT (Modified Checklist for Autism), ABC (Autism Behavioral Checklist), CARS (Childhood Autism Rating Scale) and structured interviews like ADOS-2 (Autism Diagnostis Observation Schedule), ADI-R (Autism Diagnostic Interview- Revised) can be used to support clinical evaluation[4]. But applying these evaluation tools has disadvantages like loss of time and being not aviable in most clinics which study in autism. Also major part of these tools has no validity and reliability studies for implementation to Turkish. This situation emphasize that urgent need to diagnostic tools which can be applied in different cultures, cost- effective and have high validity and reliability.

In recent years, advanged technologies like machine learning have been utilized to analyze and investigate ASD to improve diagnostic accuracy, time and quality. In this literature review analysing the use of machine learning techniques in ASD diagnosis was aimed. We searched articles that investigates using artificial intelligence methods in autism spectrum disorder from 2015 to 2021. Relevant articles are recruited from Pubmed, Google Scholar and ClinicalKey databases. The searching keywords were ‘machine learning’ ‘autism spectrum disorder’ ‘artificial intelligence’ ‘deep learning’ ‘artificial neural networks’. In this review, current literature will be discussed under 4 different titles incluidng behavioral features, neuroimaging, risk prediction and differential diagnosis.

2. Behavioral Features

ASD has different behavioral aspects. According to DSM-5, features can be explained in 2 groups: social communication- interaction and restricted behaviour and interests. Deficits in communication and interaction can be shown unusal or inappropiate body language like avoiding eye contact or using facial expressions that dont fit what they are telling. There can be lack of interest in other people or sharing an interest. Also it is hard to follow social clues, understand other people’s feeling. It is possible to delay in learning how to speak or not talking at all. They may speak with atypical patterns like prosody, echolalia. Struggling to maintain a conversation is generally occured. Repetitive body movements like hand flapping, rocking and restricted interests are also frequent aspects of ASD. Insisting on samenees and hypo or hypersentiviteness to sensory stimulis are not core symptoms but when they occur, it is very challenging.

In a recent study of Abbas et al. trained two independent ML algorithms to early detection of autism spectrum disorder. First one is based on short and scrutured questionnaires such as ADI-R, ADOS, CBCL. Fort his parent-reported questionnaires, Random Forest was used to develop an algorithm. Second one is based on capturing key behaviors from short- semi structured two or three 1 minute videos. Videos were recorded at home by parents and evaluated by clinicans. Decision forest was used to develop an algorithm for videos. Then these methods were combined with logistic regression to have higher accuracy than one single assesment method[5].

Similar effort is paid for mobile applications. Thabtah proposed a mobile application called ASDTests. This app can be used by health proffesionals to help their evaluation or to individuals who wonders if they should search formal clinical diagnosis. This app is designed for each one toddlers, children, adolescents and adults by using Autism Quotient 10 and Quantitative Checklist for Autism in Toddlers. For feature selection they used Naive- Bayes and Logistic Regression. First the user completes the test by answering the 10 questions and then gives related useful data such as age, gender, etnicity etc. Finally ASDTests app makes an assignment: if final score is more than 6, this result indicates autistic and therefore the dependant variable (target class) will be assigned ‘Yes’ . However when the score is equal to 6 or smaller, then the target class will be assigned ‘No’. This is a new avenue of approach for ASD diagnosis cases to obtain faster medical referral and thus access to health, education and social support services [6].

The most important aspect of ASD diagnosis is emotion recognition. Krol et al. proposed a machine learning approach to get information about emotion recognition from eye tracking data. Eye movements from 21 individuals with autism and 23 typically developed individuals which is age- gender- IQ macthed were recorded. Three tasks were requested to complete: free-viewing, emotion recognition and brow, mouth width comparison. For emotion recognition test, they used a dataset called FACES. Six emotional expressions(suprise, anger, sadness, disgust, fear, and happiness) were choosen and each expression image was shown to each participants. Participants were asked ‘What emotion does this face express?’ also for brow-mouth task, participants were asked ‘Which of two facial features: one of the brows or the lips, were wider?’ and they choosed possible responses on the screen. They utilied Gaussian Fixation Tecniques for extacting fixation map and training machine learning algorithm. As results in the emotion recognition task, fixations of individuals with autism were positioned on lower areas of the faces and emotion recognition task performances were lower [7].

The adoption of eye-tracking methodologies has revealed behavioral and neurophysiological patterns of visual processing across ASD and comorbid neurodevelopmental disorders(NDD). Jiang et al. combined emotion recognition task performance and ET data in their study. They aimed to measure social impairment and restrictive repetitive behaviours by comparing typically developing indidivudals and ASD patients. Social impairments were measured by the SRS-2 and RRBs were measured by the RBS-R. Future investigations should enlarge sample size and include a broader age distribution, however approach of combining task data and objective measures such as ET is highly encouraging to early detection and intervention for ASD [8].

Motor function deficits are likely to be an useful autism biomarker also can be measured more directly and objectively than social or communication aspects. Even in the earliest identification of the disorder, Kanner spotted unusual motor behaviours and described affected children as “clumsy”. The ability to imitate or copy movements performed by others is also impaired in autism. Vabalas et al. investigated whether a simple imitation task could distinguish between autistic and non-autistic individuals and describe autism-specific motor differences. A motion tracker was applied to collect kinematic data and they also tracked eye movements, while participants observed the movements to copy. Participants first watched then imitated a video shown on a screen while their eye and hand movements were recorded by eye tracker and a motion tracker. For classification, Support Vector Machine (SVM) algorithm was used. In this study, they used a movement imitation task, which based on previous studies suggested good discriminability between autistic and non-autistic individuals. The results show a promise that future work could enhance diagnostic process [9].

Individuals with ASD may exhibits different postural sway characterics than typical developed individuals. Li et al purposed a machine learning approach to information of postural control patterns in children with ASD. They recruited two group of children: 5-12 years old, 25 ASD and 25 typically developing. Participants were requested to stand barefoot and held a stationary stance for 20 second in two condition: (1) eyes open, (2) eyes closed. They calculated Center of Pressure using force plate. And six machine learning methods were trained. They utilied discriminant analysis, k- nearest neighbor, naive-bayes, decision tree, support vector machine and random forest. Using machine learning methods to assess COP data is more efficient, accurate than human evaluation. Thus these methods could help the diagnosis of ASD[10].

Individuals with ASD have atypical acoustic patterns such as flat, monotonous, variable, sing-songy, pedantic, robot- or machine-like, hollow, stilted or exaggerated and inappropriate language using.[11] Such distinctive vocal characteristics are one of the earliest-occuring markers of a possible ASD diagnosis. Yankowitz et al investigated early studies on pre-linguistic vocalizations in infants and toddlers who have been or going to be diagnosed, followed by studies of paralinguistic production in pre-school and school-age children on the autism spectrum. Early vocalizations like crying, laughing, yelling, squealing, vowels, babbling are distinguishing candidates to use as clinically effective biomarkers of ASD. ASD infants and toddlers produce fewer speech-like vocalizations, more non-speech and atypical vocalizations was findings of early studies. In this study, the extended Geneva Minimalistic Acoustic Parameter Set (eGeMAPS) was used to have a standardized set of acoustic records. In pre-school or school ages, atypical prosody is highly significant paralinguistic feature. Parents were requested to record these features. For classification of ASD, Support Vector Machines were used. In summary, pre- and paralinguistic features are highly promising as clinically beneficial markers of ASD [11,12].

Autism Spectrum Disorders are associated with atypical movements described as stereotypical motor movements (SMMs) which can interfere learning and social interaction. Rad et al. built a new application of the deep learning to aid automatic SMM detection using multi-axis IMU (inertial movement units). SMMs occur without provoking stimuli and include hand waving, body rocking, and head shaking. For clinicans, it is very challenging to captured SMMs so video-based approaches are useful to analysis and it is essential develop time-efficient and accurate methods for automatic SMM detection. Inertial Measurement Units (IMUs) yield effective tools for measuring the frequency, intensity, and duration of physical activities over a time period via embedded accelerometer, gyroscope, and magnetometer sensors. Via wearable sensors, SMMs were collected in this study then used a convolutional neural network(CNN) to learn a discriminative feature space from raw data and also combined the long short-term memory (LSTM) with CNN to model the temporal patterns in a sequence of multi-axis signals. Further, they employed ensemble learning to combine multiple LSTM learners into a more robust SMM detector. In summary, results demonstrate high potentials of deep learning algorithm to handle the issues on real-time SMM detection [13].

Sensory processing is a capacity to capture, refine and integrate information through the five senses (touch, movement, smell, taste, vision, and hearing) and improving behavioral responses to the environment. Sensory processing dysfunctions have been observed as a relevant feature of ASD symptomatology; certainly it is seen over 90% of ASD individuals. In more details, they may exhibit hyper-sensitivities (overresponsiveness) and hypo-sensitivities (under-responsiveness) to a broad range of sensory stimuli. Raya et al. aimed to discriminate and predict sensory processing of ASD population versus TD population. They combined use of implicit measure called electrodermal activity (EDA) and different sensory stimuli in virtual reality (VR). Two experiments have been applied: individuals were tested in two different virtual envoriments (VE) as city and forest and three sensory stimuli conditions each—visual, visual and auditive, and visual, auditive, and olfactive stimuli- were presented. Before and during the presentation of the virtual and the sensory stimuli, EDA changes were analysed. According to this studies' results, implicit measures, such as EDA can provide valid quantitative methods to classify ASD population and improve the developing specific treatments[14].

Diagnosing ASD is more challenging in adolescents and adults compared to childhood. Küpper et al. focused on assessment of adolescents and adults by using ADOS Module 4. In this study Support Vector Machines were used to develop a machine learning algorithm. 385 adolescents and adults with ASD and 288 TD participants were recruited. Their feature selection algorithm declared five features as the most important ones. Features are A9 (Descriptive, Conventional, Instrumental or Informational Gestures), B1 (Unusual Eye Contact), B2 (Facial Expressions directed to Others), B10 (Quality of Social Response) and B11 (Amount of Reciprocal Social Communication). Although this reduced feature subset of only 5 features, AUC was equal to 0.87 (sensitivity = 0.72, specificity= 0.87). These findings support the hypotheses that accurate evaluating of adolescents and adults for ASD can be performed using smaller numbers of behavioral features, in this way complexity of the diagnostic procedure can be reducted. Although the search for objective biological markers about ASD is currently under way, the current standard of ASD diagnosis remains based on behavioral symptoms [15].

Applied behavior analysis (ABA) is one of the most well-established treatment approaches. Individuals with ASD have different responses to treatment. Stevens et al. purposed to apply Gaussian Mixture Models and Hierarchical Clustering to identify behavioral phenotypes of ASD and examine treatment response across the learned phenotypes. This study was conducted to extract behavioral phenotypes in a large sample (N=2,400) of individuals with ASD. A total of 16 unique clusters were identified. Further computational analysis found a hierarchy of 5 distinct subgroups. Within each subgroup, clusters appeared to represent different degrees of severity across developmental domains (i.e., language, social, adaptive, cognitive, executive function, academic, play, and motor skills). While it is interesting from a methodological perspective that machine learning can identify subgroups of individuals with ASD, the value of this lies in identifying ways to improve treatment response [16].

3. Neuroimaging Studies

MRI is an imaging technology that can recognize brain disorders based on brain structure. Since functional magnetic resonance imaging (fMRI) can measure brain activity so it provides data for the study of brain dysfunction disorders and has been widely used in ASD identification. MRI is not a highly accurate way to ASD identification. Wang et al. proposed a method based on multi-atlas deep feature representation and ensemble learning to identification of ASD. First, they calculate three FCs between the time series of brain regions based on three different brain atlases. Then, multi-atlas deep feature representation method based on an stacked denoising autoencoder(SDA) was selected to more discriminative feature representation. Finally, they applied a multilayer perceptron (MLP) and an ensemble learning method to combine multiple deep feature representations to complete the final ASD identification task. Their suggested method is evaluated on the Autism Brain Imaging Data Exchange

(ABIDE) dataset. They found that the AUC value is greater than 0.8. The result shows that their proposed method may be novel approach for ASD identification [17].

In the past years, a growing number of studies have aimed to detection of autism through EEG processing via machine learning (ML) systems. Grossi et al. in their recent 2 studies observed that ASD EEG signature is already present during the first months of a child's life. In 2020, they recruited 15 children and adolescents with ASD and 10 typically developing control subjects. 20 minutes of EEG data were recorded, at resting state, silent and low light environment as 10 minutes eyes-closed and10 minutes eyes open. A continuous segment of artifact-free EEG data lasting 1 minute in ASCCI format from C3 and C4 EEG channels present in 2 previous studies, was used for features extraction and subsequent analyses with advanced machine learning systems. A special hybrid system called TWIST (Training with Input Selection and Testing), coupling an evolutionary algorithm named Gen-D and a backpropagation neural network, was used to subdivide the data set into training and testing set as well as to select features yielding the maximum amount of information after a first variable selection performed with linear correlation index threshold. The findings of this study suggest that even a minor part of EEG contains precious information useful to diagnosis autism [18].

4. Risk Prediction

Autism is a multi-factorial disease, where a single risk factor can account for ethiology. Moreover, according to the complexity of risk factors, traditional statistics is often unable to grasp the core of the problem due to the strong inherent non-linearity of relationships. Like other NDDs, in ASD developing brain is more sensitive to complications during pregnancy and natal- postnatal period. Grossi et al. focused to evaluate the potential risk factors related to pregnancy, peri and early post natal period. Twenty- seven potential risk factors were asked to the mothers of forty-five autistic and of sixty- eight typically developing children. Specialized Artificial Neural Networks (ANNs) discriminated between autism and control subjects with 80.19% global accuracy when the data set was pre-processed with TWIST system selecting 16 out of 27 variables. Six factors were found significant and these factors were all more frequent in autistic group: solvents/paints occupational exposure during pregnancy ($P=.004$), stressful events during pregnancy ($P=.012$), pregnancy complications ($P=.008$), perinatal complications ($P=.047$), deficient breast-feeding after delivery ($P=.037$), and early antibiotic therapy of the newborn ($P=.047$). ANNs are computerized systems that use nonlinear statistical analysis to reveal previously unrecognized and/or weak relationships between the input and output variables, thus the use of ANNs may be an important advance research on complex disorder as autism [19].

Genetic background plays an essential role in the encouraging precision medicine. Machine learning techniques can be extensively utilized in genomic research. Particularly, deep learning has been rapidly gaining reputation in bioinformatics as well. Graph Neural Network is a family of deep learning methods and directly analyzes data structured as graphs. Zang et al. proposed a bioinformatic framework, Prioritization of Autism-genes using Networkbased Deep-learning Approaches (PANDA) and aimed to identify potential genes relate with autism across the human genome. They designed a GNN clasisifer that used the human molecular interaction network (HMIN) as input for training. For their study, they collected 732 genes of categories 1–4 from the SFARI(Simons Foundation Autism Research Initiative) database and 28 genes from OMIM(Online Mendelian Inheritance in Man) using the entry of autism. For the set of negative cases, 1,146 genes curated by brain-disease experts that have not shown any association with autism were collected. Results of this study indicates that searching proximal genes of known autism-genes may not be effective. Instead, identifying genes that share similar network characteristic with known autism-genes can be a encouraging alternative [20].

In recent studies certain retinal features were found related to autism spectrum disorder. Lai et al. developed a classification model for ASD using machine learning methods. They captured retinal images with nonmydriatic fundus camera. For classification analysis, they used machine learning and deep learning techniques. Results of analysis revealed that there were differences such as thinner retinal nerve fibre layer, exudate, hemorrhage, occlusion in retinal characteristics between ASD participants and their matched typical controls. So this differences may be used as a risk assesment tool for ASD screening [21].

5. Differential Diagnosis

ASD is a heterogeneus disorder with varied presentation and high comorbidities with other NDDs. Autism spectrum disorder (ASD) and attention deficit hyperactivity disorder (ADHD) are most common presented among NDDs. Centers for Disease Control estimates the prevalance 1.5% and 9.5%. ASD and ADHD have important behavioral overlaps such as impulsivity and struggles with social interactions and these behavioral overlaps can complicate differential diagnosis for clinicians. Duda et al. developed six machine learning algorithms on their data, using the 65 items in the Social Responsiveness Scale (SRS) as features. These algorithms aimed to diagnosis of either ASD or ADHD. Results showed that the tree-based algorithms, Decision Tree and Random Forest, were not well-suited to the classification in tihs study. In contrast, they found that four of six algorithms (SVC, LDA, Categorical Lasso and Logistic Regression) all performed with high accuracy (AUC40.96) and utilized only five behaviors from SRS. According to this study short, extensive and caregiver-directed screening measure are possible with using machine learning classifiers [22].

In adult instances with social difficulty are challenging to differiante from each other. Because they share phenotypes and have comorbid mental health conditions and common etiologies. Demetriou et al. aimed to identify apparent features of a composite test battery of cognitive and mood measures using a machine learning paradigm in clinical cohorts with social interaction difficulties. Clinical participants as autism spectrum disorder (ASD: n = 62), early psychosis (EP: n =48), or social anxiety disorder (SAD: N = 83) were recruited and compared with a neurotypical comparison group (TYP: N = 43). All participants received standardized diagnosis. Five machine-learning algorithms were used and trained with cross validation. Machine learning methods aimed to measure cognitive and executive function, lower- and higher-order social cognition and mood severity. The DSM-5 defines six cognitive domains as key domains for the assessment of neurocognitive disorders. These are complex attention, EF, learning and memory, language, perceptual–motor function, and social cognition. Their three hypotheses were that firstly, self-appraisal measures of depression and anxiety will differentiate the neurotypical group from the intances with social impairment. Second, the neurodevelopmental cases will be differentiated from the SAD sample on measures of attention, information processing, social cognition, EF, and visuomotor performance and third, the ASD and EP cases will be distinguished based on their performance on tasks of complex attention. For the first hypotheses, the control versus social impairment cases (ASD, EP, SAD) were distinguished by social cognition, visuospatial memory and mood measures. In second hypotheses, an obvious profile cluster drawn from social cognition, visual learning, executive function and mood, distinguished the neurodevelopmental sample (EP and ASD) from the SAD cohorts. For last hypotheses psychomotor speed way better than complex attention at distinguishing between the EP and ASD groups. This is the first study that utilized measures through multiple cognitive domains and affective states. These findings provide a new avenue of approach to differentiating conditions with social impairment [23].

6. Conclusion

Determining prognosis factors of ASD are early detection and intervention. As seen as in this review, applying artificial intelligence methods on ASD can be enhanced to classification. There are different ways to improve diagnosis and also evaluation the relevant topics such as risk prediction, differential diagnosis is important as diagnosis. In this research, we have seen that machine learning algorithms are applied to minimize human interruption. Altough the results of studies on ASD and artificial intelligence are promising, it is one of the issues that should be further emphasized that whether it will replace clinical evaluation and what kind of results this technology may cause for children with ASD in future. For this purpose, it is suggested that future studies concerning individuals with ASD should be carried out to expand and support the findings in the literature.

References

[1] Johnson CP, Myers S.M. 2007. Identification and evaluation of children with autism spectrum disorders. *Pediatrics*, *120*(5), 1183-1215.
[2] Hyman, SL, Levy SE, Myers SM. 2020. Identification, Evaluation, and Management of Children With Autism Spectrum Disorder, *Pediatrics*, *145*(1).
[3] Al-Qabandi M, Gorter JW, Rosenbaum P. 2011. Early autism detection: are we ready for routine screening? *Pediatrics*, *128*(1), 211-217.
[4] Sharma SR., Gonda X, Tarazi FI. 2018. Autism spectrum disorder: classification, diagnosis and therapy. *Pharmacology & therapeutics*, *190*, 91-104.
[5] Abbas H, Garberson F, Glover E, Wall DP. 2018. “Machine learning approach for early detection of autism by combining questionnaire and home video screening”, Journal of the American Medical Informatics Association, 25(8), 1000-1007.
[6] Thabtah. 2018. An accessible and efficient autism screening method for behavioural data and predictive analyses. Health Informatic Journals, 1-17
[7] Magdalena EK, Michał K, ‘A novel machine learning analysis of eye-tracking data reveals suboptimal visual information extraction from facial stimuli in individuals with autism’ 2019, Neuropsychologia, 129, 397-406
[8] Jiang M, Francis SM, Tseng A. 2020. Predicting Core Characteristics of ASD Through Facial Emotion Recognition and Eye Tracking in Youth
[9] Vabalas A., Gowen E, Poliakoff E, Casson A. J., 2020, ‘Applying Machine Learning to Kinematic and Eye Movement Features of a Movement Imitation Task to Predict Autism Diagnosis’, Scientific Reports
[10] Li Y., Mache M.A., Todd T.A., 2020, Automated identification of postural control for children with autism spectrum disorder using a machine learning approach, Journal of Biomechanics 113 110073
[11] Fusaroli R, Lambrechts A, Bang D et al. “Is Voice a Marker for Autism Spectrum Disorder? A Systematic
Review and Meta-Analysis”,2016, Wiley Online Library

[12] Yankowitz L.D. & Schultz R.T & Parish-Morris J., 2019, Pre- and Paralinguistic Vocal Production in ASD: Birth
Through School Age, Current Psychiatry Reports, 21:126
[13] Rad NM, Kia SM, Zarbo C, Laarhoven T, Jurman G, Venuti P, Marchiori E, Furlanello C. 2017, Deep Learning for Automatic Stereotypical Motor Movement Detection using Wearable Sensors in Autism Spectrum Disorders, Signal Processing
[14] Raya1 M.A., Giglioli I, Marín-Morales1 J., Higuera-Trujillo J.L, Olmos1 E., Minissi M., Garcia G.T., Sirera M. and Abad L.,2020, Application of Supervised Machine Learning for Behavioral Biomarkers of Autism Spectrum Disorder Based on Electrodermal Activity and Virtual Reality, frontiers in Human Neuroscience
[15] Küpper SS., Wolff N, Hauck F, Kliewer N, Schad-Hansjosten T, Kamp-Becker I, Poustka L, Roessner V, Schultebraucks K, Roepke S. 2020, Identifying predictive features of autism spectrum disorders in a clinical sample of adolescents and adults using machine learning,Scientific Reports, 10:4805
[16] Stevens E, Dixon DR, Novack MN., Granpeesheh D, Smith T, Linstead E. Identification and analysis of behavioral phenotypes in autism spectrum disorder via unsupervised machine learning,International Journal of Medical Informatics 129 (2019) 29–36
[17] Wang Y, Wang J., Wu F-X, Hayrat R.,Liu J., AIMAFE: Autism spectrum disorder identification with multi-atlas deep feature representation and ensemble learning, Journal of Neuroscience Methods 343 (2020) 108840
[18] Grossi E.,Valbusa G., andBuscema M.,Detection of an Autism EEG Signature From Only Two EEG Channels Through Features Extraction and Advanced Machine Learning Analysis, Clinical EEG and Neuroscience 1–8, EEG and Clinical Neuroscience Society (ECNS) 2020
[19] Grossi, E., Veggo, F., Narzisi, A., Compare, A., & Muratori, F. 2016. "Pregnancy risk factors in autism: a pilot study with artificial neural networks", Pediatric research, 79(2), 339-347.
[20] Zhang Y., Chen Y., Hu T., PANDA: Prioritization of autism-genes using network-based deep-learning approach, Wiley,Genetic Epidemiology. 2020;44:382–394.
[21] Lai M., Lee J., Chiu S., Charm J. , So W.Y.,Yuen F. P., Kwok C., Tsoi J., Lin Y., Zee B., A machine learning approach for retinal images analysis as an objective screening method for children with autism spectrum disorder, EClinicalMedicine 28 (2020) 100588
[22] M Duda, Ma R., N Haber N. and Wall DP.,Use of machine learning for behavioral distinction of autism and ADHD, Translational Psychiatry (2016) 6
[23] Demetriou EA, Park SH, Ho N, Pepper KL, Song YJC, Naismith SL, Thomas EE., Hickie I.B, Guastella AJ. Machine Learning for Differential Diagnosis Between Clinical Conditions With Social Difficulty: Autism Spectrum Disorder, Early Psychosis, and Social Anxiety Disorder, frontiers in Psychiatry, 2020

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Artificial Intelligence Applications in Diabetes Management: A Systematic Literature Review

Merve DERVİŞOĞLU [1, *], Dilek BÜYÜKKAYA BESEN [2]

[1] *Dokuz Eylül Üniversitesi Hemşirelik Fakültesi, İç Hastalıkları Hemşireliği Anabilim Dalı,*
[2] *Dokuz Eylül Üniversitesi Hemşirelik Fakültesi, İç Hastalıkları Hemşireliği Anabilim Dalı*

* Corresponding Author: Izmir Bakircay University, Faculty of Medicine, Turkey
Tel.: +90 535 6585352. E-Mail: merve.dervisoglu95@gmail.com

Publication Information

Keywords :
- Artificial intelligence
- Machine learning
- Diabetes
- Diabetes management

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Introduction-Objective: Artificial intelligence (AI) is a rapidly growing field and its applications for diabetes, which is a global pandemic, can change the approach to diagnosis and management of this disease. Machine learning has been used to create algorithms that support predictive models for the risk of developing diabetes and complications resulting from diabetes. Digital therapeutics have also proven to be important initiatives in diabetes and lifestyle management. With AI applications, biomarkers of patients can be continuously monitored, and individuals can be empowered in self-management and empowered in the care process. Healthcare professionals can benefit from AI applications as a clinical decision support system. The purpose of this review is to examine the literature on machine learning methods used in diabetes management.
Materials and Methods: The literature on artificial intelligence methods used in diabetes management was searched using PubMed, Cochrane Library, Google Scholar search engines with the keywords “artificial intelligent”, “diabetes care”, “diabetes education”. Studies from 2016-2021 were included. A total of 121 articles were selected at the beginning and the studies meeting the inclusion criteria were examined in detail.
Results: As a result of the literature reviews, AI applications used in diabetes management were used to provide better glycemic control, support carbohydrate count and weight control, early diagnosis of hypoglycemia-hyperglycemia complications, determination of retinopathy-foot ulcer risk, drug-dose calculation, strengthening self-management, it was found that it was used to predict the effect of behaviors on glucose level.
Conclusion: It is thought that health professionals will make significant contributions to diabetes care and management by following, contributing to the development and integration of artificial intelligence applications.

1. Introduction and Purpose

Artificial intelligence (AI) is a broad term defined as the theory and development of virtual systems that can mimic human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages [1,2,3]. Machine learning is a subset of artificial intelligence that provides the ability to automatically learn and develop from experiences. Machine learning can be supervised, unsupervised, semi-supervised, or reinforcement-based. The machine tries to imitate human intelligence by simulating the structure of the human brain using repetitive neural networks, thanks to deep learning [4]. In this way, by analyzing the available data, it takes part in the prediction or decision-making process like human intelligence. Growth in the field of artificial intelligence has gained momentum and its practices for diabetes can change the approach to diagnosis and management of this disease. Machine learning has been used to create algorithms that support predictive models for the risk of developing diabetes and complications resulting from diabetes. Digital therapeutics have also proven to be important initiatives in diabetes and lifestyle management. With AI applications, biomarkers of patients can be continuously monitored, and individuals can be empowered in self-management and empowered in the care process.

Health professionals can also benefit from AI applications as a clinical decision support system in diabetes management [2]. All strategies for protecting individuals with diabetes from complications include the patient's participation in diabetes management and lifestyle change. AI applications also support patients and healthcare professionals by focusing on issues such as diet, physical activity, blood glucose monitoring, drug dosage, risk of complications for effective management of diabetes [5].

The purpose of this review is to examine the current literature on artificial intelligence and machine learning methods used in diabetes management for the years 2016-2021.

2. Material and Method

In the relevant literature, PubMed, Cochrane Library, Google Scholar search engines, "artificial intelligence", "diabetes care", "diabetes education" keywords were scanned in artificial intelligence methods used in diabetes management. Studies from 2016-2021 were included. A total of 121 articles were selected at the beginning, and studies that met the inclusion criteria were examined in detail.

Inclusion Criteria:

- Serving the purpose of the study
- Machine learning and artificial intelligence methods
- In 2016-2021
- Randomized controlled and articles were included.

Exclusion Criteria:

- Studies accessed again in search engines,
- Compilations,
- Books,
- Systematic reviews,
- Studies where artificial intelligence methods are not used,
- Studies that are not specific to diabetes are not include

3. Results

It is seen that artificial intelligence and machine learning methods are used in various fields in diabetes management. Diabetes risk assessment studies can be categorized as decision support studies, studies to evaluate the risk of diabetes complications, and studies to evaluate retinopathy.

Table 1. Artificial Intelligence Applications in Diabetes Management

First Author	Title	Method	Purpose	Sample	Intervention	Research Result
Nimri et al. (2020) [6].	Insulin dose optimization using an automated artificial intelligence-based decision support system in youths with type 1 diabetes	Automated Artificial Intelligence-Based Decision Support System (AI-DSS)	It is the determination of the reliability of the automatic artificial intelligence based decision support system (AI-DSS) in adjusting the insulin dose and controlling glucose levels.	It is a six-month, multicenter, multinational, randomized controlled study conducted in 108 participants aged 10-21 years with type 1 diabetes using insulin pump therapy.	AI-DSS, n = 54; doctor group n = 54 The demographic and clinical characteristics of the randomized participants are similar. The glycemic controls of individuals in the AI-DSS group were compared with those in the physician group.	Three serious adverse events related to diabetes (two severe hypoglycemia, one diabetic ketoacidosis) were reported in the physician group and no adverse events were detected in the AI-DSS group. As a result, the use of an automated decision support tool to optimize insulin pump settings has been stated to be effective in glycemic control.
Reddy et al. (2019) [7].	Prediction of Hypoglycemia During Aerobic Exercise in Adults With Type 1 Diabetes	Model 1 is a decision tree and model 2 is a random forest model.	Developing two separate algorithms to predict hypoglycemia at the beginning of exercise.	43 T1DM individuals in model development 12 T1DM individuals were included in the model validation.	A model was developed with a data set based on 154 in-clinic aerobic exercise observations in 43 adults with T1DM. Both models were validated using an entirely new validation dataset with 90 exercise	Model 1 identified two critical characteristics that predict hypoglycemia during exercise: heart rate and glucose at the start of exercise. It has been reported to predict hypoglycemia with 79.55%

					observations collected from 12 new adults with T1DM.	accuracy if heart rate is greater than 121 in the first 5 minutes of exercise and glucose is less than 182 mg / dL at the start of exercise. Model 2 was found to achieve a higher accuracy of 86.7% by using additional features. Model 1 is intuitive and easily remembered (the 180/120 rule), while model 2 is a more complex application that requires computation, which makes it suitable for use in decision support systems such as the artificial pancreas.
Biester et al. (2018) [8].	DREAM5: An open-label, randomized, cross-over study to evaluate the safety and efficacy of day and night closed-loop control by comparing the MD-Logic automated insulin delivery system to sensor augmented	The study is a prospective, multicenter and randomized controlled trial.	Comparison of MD-Logic closed-loop system use with sensor-assisted pump (SAP) therapy in individuals with type 1 diabetes.	The sample of the study consisted of 48 (19 male, 29 female) adolescents and adults experienced in the use of sensors.	All participants used random SAP therapy or the MD-Logic system for a weekend. The carbohydrate amount of the individuals in the intervention group was entered into the bolus calculator and the rest of the insulin delivery was performed wirelessly via an automatic tablet computer. The efficiency of the system was evaluated for 60 hours	The MD-Logic system is safe and has been reported to be associated with better glycemic control than SAP (sensor-assisted pump) therapy for day and night use.

	pump therapy in patients with type 1 diabetes at home				day and night use at home on weekends.	
Robert et al. (2020) [9].	Quantification of Fluid Resolution and Visual Acuity Gain in Patients With Diabetic Macular Edema Using Deep Learning: A Post Hoc Analysis of a Randomized Clinical Trial	Post hoc analysis of a randomized clinical trial using deep learning	To study the volumetric change of intraretinal fluid (IRF) and subretinal fluid (SRF) in DME (Diabetic macular edema) during anti-vascular endothelial growth factor therapy using deep learning algorithms.	570 participants with diabetic macular edema were included.	The eyes of 570 participants with diabetic macular edema were evaluated by OCT (optical coherence tomography) volume scanning. Visual acuity was evaluated with changes in IRF and SRF volumes over 12 months using deep learning algorithms.	It is suggested that diabetic macular edema responds well to anti-vascular endothelial growth factor therapy, and that this automated spectral field optical coherence tomography (OCT) analysis can be used clinically to evaluate anatomical change during treatment.
Varadarajan et al. (2020) [10].	Predicting optical coherence tomography-derived diabetic macular edema grades from fundus photographs using deep learning	Deep Learning	Diagnosing macular edema	4035 patients in development, first clinical validation: 697 patients, second clinical validation 554 patients	Using the deep learning model in the diagnosis of diabetic macular edema	It was determined that the deep learning model had a sensitivity of 85% with a specificity of 80% (ROC-AUC of 0.89 (95% CI: 0.87-0.91)), retina specialists were found to have similar sensitivity (82-85%). The model was also found to be able to detect the presence of intraretinal fluid (AUC: 0.81; 95% CI: 0.81-0.86) and subretinal fluid (AUC 0.88; 95% CI: 0.85-0.91).

Gerendas et al. (2017) [11].	Computational image analysis for prognosis determination in DME	Machine learning (Random forest)	Determining the prognosis of patients with diabetic macular edema (DME)	The retinal layer, intraretinal cystoid fluid (IRC) and subretinal fluid of 629 patients who received anti-vascular endothelial growth factor therapy for DME were analyzed.	In this pilot study, optical coherence tomography (OCT) data were evaluated to determine the prognosis of patients with diabetic macular edema (DME).	Overall model accuracy R2 = 0.21 / 0.23 ($p < 0.001$). It was emphasized that the machine learning approach suggested for large-scale image data analysis in DME and other retinal diseases is appropriate.
Ramchandran et al. (2020) [12].	Automated vessel density detection in fluorescein angiography images correlates with vision in proliferative diabetic retinopathy	Secondary analysis of data from a prospective randomized controlled trial (Artificial intelligence algorithm)	Using an artificial intelligence algorithm to automate the detection of vessels in fluorescence angiography (FA: fluorescein angiography) images and determining the relationship between vessel density and vision in diabetic retinopathy.	42 patients from the RECOVERY study with both baseline FA images and optical coherence tomography (OCT) data were included.	An algorithm has been developed to automatically detect retinal vessels in FA images. The model developed in patients with diabetic retinopathy without significant diabetic macular edema was tested.	It has been determined that vessel density can be measured reliably from basic FA images. It has been reported that the average time for vessel detection from the FA image is 22.1 seconds. A positive correlation ($r = 0.4071$, $p = 0.0075$) was found between macular vessel density and visual acuity in patients with diabetic retinopathy. Algorithm analyzed FA images with a reliability measure (ICC) of 0.98.

Basu et al. (2018) [13].	Characteristics Associated With Decreased or Increased Mortality Risk From Glycemic Therapy Among Patients With Type 2 Diabetes and High Cardiovascular Risk: Machine Learning Analysis of the ACCORD Trial	Machine learning	To provide information on intensive glycemic therapy among patients with type 2 diabetes and high CVD risk by identifying characteristics associated with the risk of death in the ACCORD study.	Participants were individuals from the Action to Control Cardiovascular Risk in Diabetes (ACCORD) study aged between 40 and 79 years. (n = 10,251)	The machine learning method of gradient forest analysis was applied to understand the change in all-cause mortality in the Action to Control Cardiovascular Risk in Diabetes (ACCORD) study (n = 10,251), whose participants were between 40 and 79 years of age with type 2 diabetes.	In the lowest risk group (HGI <0.44, BMI <30 kg / m2, age <61 years) there was a 2.3% reduction in absolute risk of mortality attributable to intensive therapy. In the highest risk group (HGI (observed minus expected HbA1c derived from prerandomization fasting plasma glucose) ≥0.44), it was found to have an absolute risk of death of 3.7% attributable to intensive treatment. It has been found that some groups may have benefited, as well as some groups that were likely to suffer from intensive glycemic therapy; About two thirds (n = 6.395) experienced neither benefit nor harm. As the risk of benefit and harm differs between individuals with type 2 diabetes, outcomes support existing guidelines advocating individualized treatment decisions and also emphasize making such

						guidelines functional in clinical practice.
Faruqui et al. (2019) [14].	Development of a Deep Learning Model for Dynamic Forecasting of Blood Glucose Level for Type 2 Diabetes Mellitus: Secondary Analysis of a Randomized Controlled Trial	Secondary Analysis of a Randomized Controlled Trial (Deep Learning)	The aim of the study is to dynamically estimate daily glucose levels in T2DM patients based on daily mobile health lifestyle data, including individuals' previous day diet, physical activity, weight, and glucose level.	It was conducted with 10 T2DM patients who were overweight or obese.	A deep learning model was developed to predict the glucose levels of the individuals on the previous day with the data obtained from 10 overweight and obese T2DM patients (daily monitoring of diet, physical activity, weight and blood sugar).	Individuals' glucose level is difficult to predict as it is determined by multiple factors. However, it has been reported that mobile health data can be used to develop effective personalized prediction plans for T2DM management using machine learning methodologies.
Perez Gandia et al. (2018) [15].	Decision Support in Diabetes Care: The Challenge of Supporting Patients in Their Daily Living Using a Mobile Glucose Predictor	Randomized controlled pilot study, decision support system (DSS)	Determining the impact of a decision support (DSS) system based on mobile glucose estimation	It was conducted with 12 T1DM individuals treated with an insulin pump.	Determination of the results of the group using a decision support system based on glucose estimation in the management of hypoglycemia or hyperglycemia events	It has been reported that type 1 diabetes using the mobile glucose estimation based decision support (DSS) system has an effect on the decision process and patients have high confidence in glucose estimation. No clear benefit in glucose control was noted, but no hypoglycemic events were observed. One limitation of this study is that participants have to manually save

						their CGM measurements in the DSS application. It is reported that ensuring that CGM readings are automatically integrated into DSS can prevent errors.
Doupis et al. (2018) [16].	Mobile-based artificial intelligence significantly improves type 1 diabetes management	Mobile applications	To investigate the effectiveness of the mobile application "D-Partner" (a mobile-based application serving as a self-management tool for individuals with type 1 diabetes) in glucose management in patients with type 1 diabetes.	The study was conducted with 24 patients (14 men, 10 women) with type 1 diabetes.	Based on the data imported by the patient, it transmits a bolus wizard (with food database), a basal insulin titration manager, as well as multiple automatic notification, alert and reward messages. In addition, the "D - Partner" serves as a telemedicine tool; It can share information about meals, insulin dose, glucose measurements, blood pressure, body weight and laboratory values online with the healthcare professional.	It was found that the HbA1c level of the intervention group decreased significantly compared to the control group (p = 0.01). In addition, the incidence of hypoglycemia was found to be significantly lower in the intervention group (p = 0.04). D-partner is a mobile-based self-management application that can contribute to better management of type 1, and it has been found to improve the quality of life of individuals.

Gracey et al. (2018) [17].	Improving medication adherence by better targeting interventions using artificial intelligence-A randomized control study	Double blind randomized controlled trial (artificial intelligence supported)	Artificial intelligence medicine Determining the effect on compliance	There are 14,377 people in the Control Group, 5,423 in the Traditional Group and 24,527 in the AI Group.	In the study, patients were randomly divided into three groups. Control, Traditional and AI group. There was no intervention for the patients in the control group. Patients in the Traditional Group provided traditional support. Patients in the AI Group received live calls and direct mail to patients, and faxes to prescribers.	Patients in the AI Group had a 6.11% higher drug compliance than the Control Group (p-value = 0.04); It was reported that patients in the AI Group had a 7.8% higher adherence to treatment than the Traditional Group. (p - value = 0.08)
Fan et al. (2020) [18].	AI-based prediction for the risk of coronary heart disease among patients with type 2 diabetes mellitus	Artificial intelligence-based prediction	Estimating the risk of coronary heart disease in individuals with type 2 diabetes	The data set of 1,273 T2DM patients with and without coronary heart disease formed a sample of 1,253 new T2DM patients to validate the performance of the presented model.	The reliability of the model confirming the coronary artery disease risk of individuals with artificial intelligence-based type 2 diabetes was tested.	The result was determined that the model reached 0.77 (fivefold cross validation) in the training dataset and 0.80 AUC in the test dataset. It was reported that the Model reached 0.71 AUC in model validation.
Alfonsi et al. (2020) [19].	ISPY: a pilot study of a novel carbohydrate counting smartphone app for youth with type 1 diabetes	Artificial intelligence supported mobile application	Determination of the functionality of the mobile application supporting KH (carbohydrate) counting	T1DM 44 people between the ages of 10-17 were included in the study.	The intervention group of the employee used the application supporting the ISpy HR count developed and the application accuracies were compared with the control group.	Compared with the control group, the intervention group improved carbohydrate counting accuracy (total grams per meal) over the 12-week study period (p = 0.007). It has also been found that the carbohydrate estimate of a

						particular item is false more than 10g from the true value, decreasing by 9.9% (p = 0.047) Participants using ispy were reported to show accuracy and positive acceptability in carbohydrate counting. Since iSpy has the potential to improve diabetes management, it has been suggested to be replicated in a larger study
Avari et al. (2021) [20].	Safety and feasibility of the PEPPER adaptive bolus advisor and safety system; a randomized control study	Decision support system based on artificial intelligence technology	Determining the impact of the Patient Empowerment system on glycemic outcomes with Predictive Personalized Decision Support (PEPPER)	It was conducted with 54 individuals with Type 1 diabetes.	The Patient Empowerment system with Predictive Personalized Decision Support (PEPPER) provides personalized bolus advice for people with Type 1 diabetes. The system generates predictive glucose alerts, alarms, and provides individualized HR recommendations. It also includes an adaptive insulin advice system (based on case-based reasoning, artificial intelligence methodology), along with a security system that includes bolus insulin restriction. The glycemic control of	It has been reported that the group using the PEPPER system has a higher perception of hypoglycemia. The PEPPER system was found to be safe, but it was found that the glycemic results did not change when compared with the control group. Further studies have been proposed to confirm the overall effectiveness.

					the intervention group using PEPPER for 12 weeks was evaluated.	

4. Conclusion

Artificial intelligence applications that emerged to support diabetes management aim to increase the control of the individual on his disease, quality of life and comfort. Repeating the developed artificial intelligence algorithm studies by increasing the number of samples, increasing the sensitivity and specificity of the developed products, developing systems that can read information directly from the devices such as bluetooth connection to reduce the margin of error of systems that develop recommendations based on manual information input of the patient, renew the infrastructure of the systems that provide recommendations to the healthcare professional in line with the updated guidelines. is required. In addition, it is recommended to write algorithms that provide individualized recommendations for the clinical course of the disease and to design the systems that make risk assessment by increasing the accuracy and sensitivity to prevent unnecessary further examinations.

Health professionals should also be informed about these technological developments, integrate these systems into the care process and take part in the development of these services.

References

[1] Artificial intelligence Definition of artificial intelligence in English by Oxford Dictionaries. Oxford Dictionaries English. Erişim Tarihi:18.04.2021
https://en.oxforddictionaries.com/definition/artificial_intelligence .

[2] Ellahham S. (2020). Artificial intelligence in diabetes care. The American journal of medicine, 133(8):895-900. doi: 10.1016/j.amjmed.2020.03.033.

[3] Broome, D. T., Hilton, C. B., & Mehta, N. (2020). Policy implications of artificial intelligence and machine learning in diabetes management. Current diabetes reports, 20(2), 1-5.

[4] Singla R, Singla A, Gupta Y, Kalra S. (2019). Artificial intelligence/machine learning in diabetes care. Indian journal of endocrinology and metabolism, 23(4), 495.

[5] Reusch, J. E., & Manson, J. E. (2017). Management of type 2 diabetes in 2017: getting to goal. Jama, 317(10), 1015-1016.

[6] Nimri, R., Battelino, T., Laffel, L. M., Slover, R. H., Schatz, D., Weinzimer, S. A., ... & Phillip, M. (2020). Insulin dose optimization using an automated artificial intelligence-based decision support system in youths with type 1 diabetes. Nature medicine, 26(9), 1380-1384.

[7] Reddy, R., Resalat, N., Wilson, L. M., Castle, J. R., El Youssef, J., & Jacobs, P. G. (2019). Prediction of hypoglycemia during aerobic exercise in adults with type 1 diabetes. Journal of diabetes science and technology, 13(5), 919-927.

[8] Biester, T., Nir, J., Remus, K., Farfel, A., Muller, I., Biester, S., ... & Nimri, R. (2019). DREAM5: An open-label, randomized, cross-over study to evaluate the safety and efficacy of day and night closed-loop control by comparing the MD-Logic automated insulin delivery system to sensor augmented pump therapy in patients with type 1 diabetes at home. Diabetes, Obesity and Metabolism, 21(4), 822-828.

[9] Roberts, P. K., Vogl, W. D., Gerendas, B. S., Glassman, A. R., Bogunovic, H., Jampol, L. M., & Schmidt-Erfurth, U. M. (2020). Quantification of fluid resolution and visual acuity gain in patients with diabetic macular edema using deep learning: a post hoc analysis of a randomized clinical trial. JAMA ophthalmology, 138(9), 945-953.

[10] Varadarajan, A. V., Bavishi, P., Ruamviboonsuk, P., Chotcomwongse, P., Venugopalan, S., Narayanaswamy, A., ... & Webster, D. R. (2020). Predicting optical coherence tomography-derived diabetic macular edema grades from fundus photographs using deep learning. Nature communications, 11(1), 1-8.

[11] Gerendas, B. S., Bogunovic, H., Sadeghipour, A., Schlegl, T., Langs, G., Waldstein, S. M., & Schmidt-Erfurth, U. (2017). Computational image analysis for prognosis determination in DME. Vision research, 139, 204-210.
[12] Ramchandran, R., Bawany, M. H., Ding, L., Sharma, G., Wykoff, C. C., & Kuriyan, A. E. (2020). Automated vessel density detection in fluorescein angiography images correlates with vision in proliferative diabetic retinopathy. Investigative Ophthalmology & Visual Science, 61(7), 5312-5312.
[13] Basu, S., Raghavan, S., Wexler, D. J., & Berkowitz, S. A. (2018). Characteristics associated with decreased or increased mortality risk from glycemic therapy among patients with type 2 diabetes and high cardiovascular risk: machine learning analysis of the ACCORD trial. Diabetes Care, 41(3), 604-612.
[14] Faruqui, S. H. A., Du, Y., Meka, R., Alaeddini, A., Li, C., Shirinkam, S., & Wang, J. (2019). Development of a deep learning model for dynamic forecasting of blood glucose level for type 2 diabetes mellitus: secondary analysis of a randomized controlled trial. JMIR mHealth and uHealth, 7(11), e14452.
[15] Pérez-Gandía, C., García-Sáez, G., Subías, D., Rodríguez-Herrero, A., Gómez, E. J., Rigla, M., & Hernando, M. E. (2018). Decision support in diabetes care: the challenge of supporting patients in their daily living using a mobile glucose predictor. Journal of diabetes science and technology, 12(2), 243-250
[16] Doupis, J., Papandreopoulou, V., Glykofridi, S., & Andrianesis, V. (2018). Mobile-Based Artificial Intelligence Significantly Improves Type 1 Diabetes Management. Diabetes Jul 2018, 67 (Supplement 1) 1058-P; doi: 10.2337/db18-1058-P.
[17] Gracey, B., Jones, C. A., Cho, D., Conner, S., & Greene, E. (2018). Improving Medication Adherence By Better Targeting Interventions Using Artificial Intelligence-A Randomized Control Study. Value in Health, 21, S76.
[18] Fan, R., Zhang, N., Yang, L., Ke, J., Zhao, D., & Cui, Q. (2020). AI-based prediction for the risk of coronary heart disease among patients with type 2 diabetes mellitus. Scientific reports, 10(1), 1-8.
[19] Choi, E., Alfonsi, J., Arshad, T., Sammott, S. A., Pais, V., Stinson, J., & Palmert, M. (2020). 158-LB: iSpy: A Pilot Study of a Novel Carbohydrate Counting Smartphone App for Youth with Type 1 Diabetes.Diabetes 2020 Jun; 69(Supplement 1): https://doi.org/10.2337/db20-158-LB
[20] Avari, P., Leal, Y., Herrero, P., Wos, M., Jugnee, N., Arnoriaga-Rodríguez, M., Reddy, M. (2021). Safety and feasibility of the PEPPER adaptive bolus advisor and safety system: a randomized control study. Diabetes Technology & Therapeutics, 23(3), 175-186.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

The Use of Artificial Intelligence in Education of Nursing and Midwifery Students

Berrak MIZRAK ŞAHİN [1,*], Esra Nur KABAKCI [2]

[1] *Eskisehir Osmangazi University, Faculty of Health Sciences, Dept. of Nursing, Turkey*
[2] *Eskisehir Osmangazi University, Faculty of Health Sciences, Dept. of Midwifery, Turkey*

* Corresponding Author: Eskisehir Osmangazi University, Faculty of Health Sciences, Nursing Department, Meselik Campus, 26480 Eskisehir, Turkey
Tel.: +90 222 239 37 50/1109. E-Mail: bmizrak5@hotmail.com

Publication Information

Keywords :

- Artificial Intelligence
- Education
- Midwifery
- Nursing

Category : Special Issue

Received :
Accepted : 26.05.2021

ABSTRACT

Artificial intelligence is used to describe a branch of computer science that explores the abilities of machines to learn how to imitate intelligent human behavior The use of artificial intelligence in education is important due to its effects such as improved efficiency, global learning, customized / personalized learning, smarter content creation, and effectiveness and efficiency in education management Technologies such as curriculum and content development, virtual reality, web-based platforms, video conferencing, robotic applications, audio-visual files and 3-D technology that do this are among the areas where artificial intelligence is applied in education. These programs that include artificial intelligence can enable the development of non-technical skills such as improving clinical judgment skills, teamwork, decision-making and communication in nursing and midwifery education.

1. Introduction

Information technology is changing rapidly and challenging traditional pedagogy. The presence of especially mobile phones, tablets and related applications in digital technology enables students to access information whenever and wherever they want [1]. In nursing and midwifery disciplines, educators seek to find accessible and innovative teaching and learning methods for the academic and clinical development of students [2]. The use of technology in clinical simulation education with the rapid growth of technology in nursing and midwifery education [2] as well as the use of artificial intelligence, virtual reality, and computer games in educational applications has also led to a global increase [3].

Artificial intelligence is used to describe a branch of computer science that explores the abilities of machines to learn how to imitate intelligent human behavior [4]. The technological method by which computers produce a solution on a task or question without any programming is machine learning [5]. Learning methods such as speech recognition, visual perception and / or decision making can be carried out with instructions loaded into computer simulation programs [3,4]. The use of artificial intelligence in education is important due to its effects such as improved efficiency, global learning, customized / personalized learning, smarter content creation, and effectiveness and efficiency in education management [6]. Technologies such as curriculum and content development, virtual reality, web-based platforms, video conferencing, robotic applications, audio-visual files and 3-D technology that do this are among the areas where artificial intelligence is applied in education [6]. These programs that include artificial intelligence can enable the development of non-technical skills such as improving clinical judgment skills, teamwork, decision-making and communication in nursing and midwifery education [2].

The use of facial analysis to assess pain in those living with severe dementia is an example of the use of computer-assisted artificial intelligence. With this system, facial expressions recognition technology is used to detect the presence of pain in people with severe dementia [7].

Another area where artificial intelligence is applied and used in education is web-based platforms. The use of these platforms in education enables the relevant materials to be accessed from anywhere in the world, to benefit from other aspects of artificial intelligence such as language translation tools, and in this way, interactive and personalized learning by helping the student in a shorter time [6].

Virtual reality application, which is another field where artificial intelligence is applied, is a technology that is increasingly used and attracted attention in nursing and midwifery education. Theoretical and clinical training in nursing and midwifery turns into learning facilitating applications through with virtual reality applications. In virtual reality, practitioners allow them to repeatedly try educational applications involving clinical skills and critical events. These applications provide a safe and accessible learning environment that can increase patient safety [2]. Butt et al. [8] developed a virtual reality program designed to provide sterile technique during urinary catheterization. Virtual reality has been used as an environment to reduce the incidence of catheter-associated urinary tract infections in this application. With head-worn screens and tactile glove equipment, students receive feedback on their violations and performances in maintaining a sterile area from the educators who follow them [8].

Machine learning, a subset of artificial intelligence, uses techniques and various algorithms that mimic people's decisions. Artificial intelligence-based analytical and machine learning algorithms are used in clinical practice areas that support nurses and midwives in making clinical decisions for their patients [9]. However, social robots are increasingly being used to provide companionship to residents living in long-term nursing homes under the supervision of nurses. These robots have natural language processing capabilities that enable them to understand, analyze, manipulate data and generate language [10]. These technological developments are expected to cause significant changes in nursing / midwifery practices in the next decade. Nurse / midwife educators will be at the forefront of these changes [9].

Transformation of the nursing / midwifery curriculum will enable nurses / midwives to be equipped with informatics competencies in the future. Artificial intelligence and machine learning technology in education will be used more in clinical settings and will be required to provide digital and data literacy competencies. Strong nurse / midwife leaders will be needed to adopt these developing technological developments and to prepare nurse / midwife educators for new pedagogies that prepare students to use these developing technologies [4,9].

2. References

[1] Chang, C.-Y., Lai, C.-L., & Hwang, G.-J. (2018). Trends and research issues of mobile learning studies in nursing education: A review of academic publications from 1971 to 2016. Computers & Education, 116, 28-48.
[2] Fealy, S., Jones, D., Hutton, A., Graham, K., McNeill, L., Sweet, L., & Hazelton, M. (2019). The integration of immersive virtual reality in tertiary nursing and midwifery education: A scoping review. Nurse education today, 79, 14-19.
[3] Harmon, J., Pitt, V., Summons, P., & Inder, K. J. (2020). Use of artificial intelligence and virtual reality within clinical simulation for nursing pain education: A scoping review. Nurse education today, 104700.
[4] Clancy, T. R. (2020). Artificial Intelligence and Nursing: The Future Is Now. JONA: The Journal of Nursing Administration, 50(3), 125-127.

[5] Robert, N. (2019). How artificial intelligence is changing nursing. Nursing management, 50(9), 30.
[6] Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: a review. Ieee Access, 8, 75264-75278.
[7] Atee, M., Hoti, K., Parsons, R., & Hughes, J. D. (2018). A novel pain assessment tool incorporating automated facial analysis: interrater reliability in advanced dementia. Clinical interventions in aging, 13, 1245.
[8] Butt, A. L., Kardong-Edgren, S., & Ellertson, A. (2018). Using game-based virtual reality with haptics for skill acquisition. Clinical Simulation in Nursing, 16, 25-32.
[9] Buchanan, C., Howitt, M. L., Wilson, R., Booth, R. G., Risling, T., & Bamford, M. (2021). Predicted Influences of Artificial Intelligence on Nursing Education: Scoping Review. JMIR Nursing, 4(1), e23933.
[10] Papadopoulos, I., Koulouglioti, C., & Ali, S. (2018). Views of nurses and other health and social care workers on the use of assistive humanoid and animal-like robots in health and social care: a scoping review. Contemporary nurse, 54(4-5), 425-442.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || ISBN : 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Using Machine Learning in Pathological / Physiological Classification of Oncological FDG PET Whole Body Images

Sertaç ASA [1 *]

[1] *Istanbul University-Cerrahpasa, Faculty of Medicine, Dept. of Nuclear Medicine, Turkey*

* Corresponding Author: Istanbul University-Cerrahpasa, Faculty of Medicine, Turkey
Tel.: +90 (212) 414 30 00. E-Mail: asa@iuc.edu.tr

Publication Information

Keywords :

- Machine learning,
- FDG PET,
- Oncology

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Objective: We evaluated the use of FDG PET whole-body images in oncology patients in pathological/physiological differentiation with image classification using visual recognition data.

Method: A total of 60 whole body maximum intensity projection (MIP) images obtained with FDG PET for oncological imaging indication were included in the study. Whole-body MIP images of the patients were processed with semi-automatic segmentation on the workstation program (GE AW Volume Share 5, GE Medical Systems). Brain, heart, and bladder structures with variable and high FDG distribution were removed from the image with this method. IBM Watson program was used for machine learning and analysis of the data. Two groups (MIP negative and MIP positive) were defined for image classification. A total of 20 images were used to create the training (train) data. Afterward, images showing 20 known pathological distributions and images with 20 physiological distributions were used for the sampling.

Results: Values with a confidence value of 80% in image classification were accepted as correct. According to the defined classification analysis, 17 of 20 images known as pathological in the sample images were classified as correct and 3 as false (85%). In addition, 19 of the 20 images known to have a physiological distribution were classified correctly and 1 false (95%).

Conclusion: Visual recognition-based machine learning seems successful in distinguishing pathological/physiological images and has a promising future in current medical practice, especially in oncological imaging.

1. Introduction

F-18 fluorodeoxyglucose (FDG) is a positron-emitting radiopharmaceutical that represents the glucose metabolism in the cells. Cancer cells generally show high FDG affinity(1**).** For this reason, FDG Positron Emission omography (PET) has wide clinical use for metabolic characterization, staging, restaging, and treatment response evaluation in oncological imaging(2-5).

When F-18 FDG is injected intravenously, it distributes the body similar to the glucose molecule. FDG passes into the cell via glucose transporters. Then it is phosphorylated by the hexokinase enzyme but does not participate in other glycolysis reactions. Consequently, it accumulates in the cell. Physiological FDG distribution is seen in the brain, heart, kidneys, ureters, bladder, bowels, and liver. In the pathological condition, focal increased uptake (over the liver uptake) is observed. Pathological conditions, focal increased uptake which is above liver in any region within the examination area is observed.

Whole-body FDG imaging is performed with PET/CT or PET/MRI devices. 3 dimensional PET and fusion images are obtained. In addition, a maximum intensity projection image(MIP) is acquired **(figures 1a and b).** These images are evaluated by nuclear medicine physicians. As the workload of physicians increases, the possibility of misinterpretation of the images increases. Therefore, supportive automated systems are needed to prevent such situations.

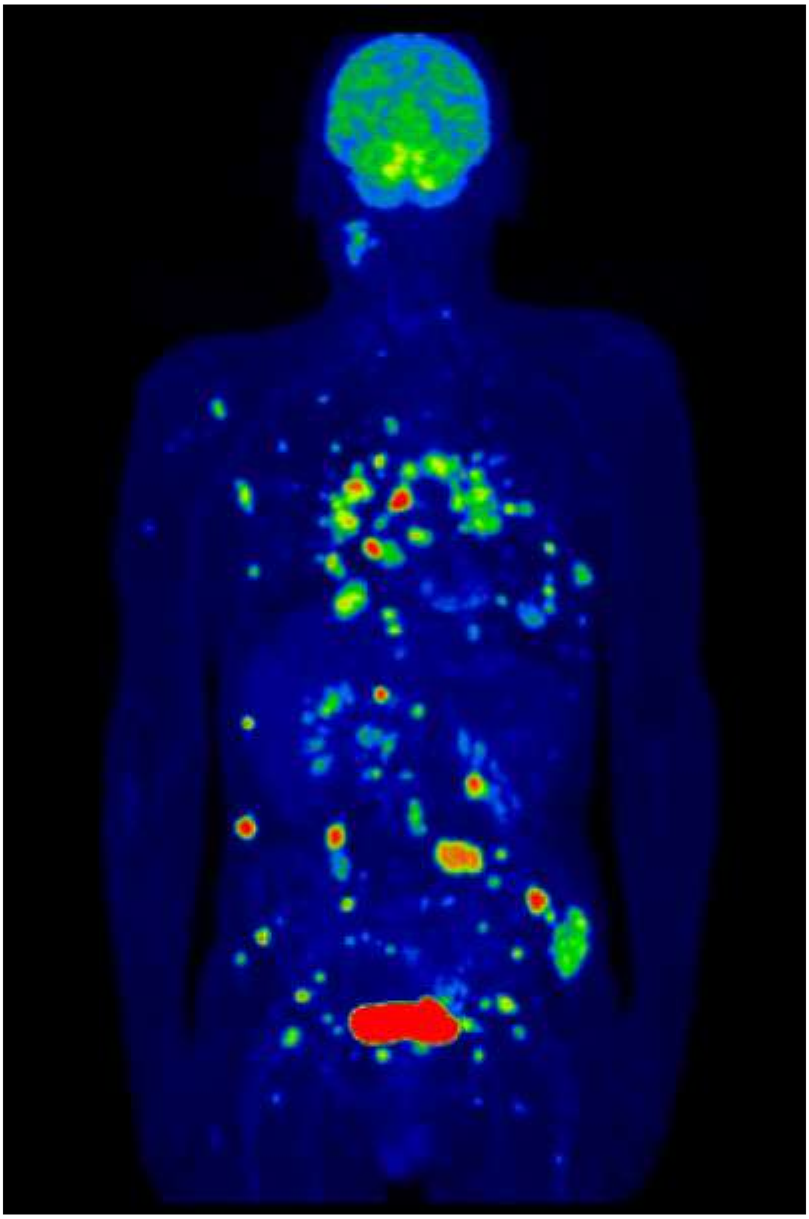


Figure 1a. Physiological Maximum intensity projection image

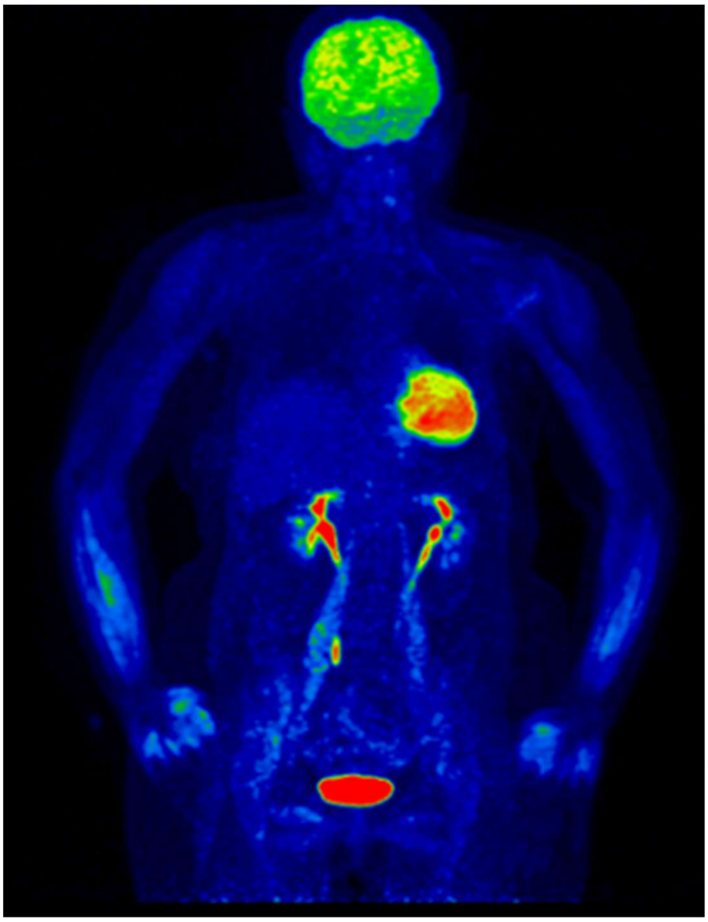


Figure 1b. Pathological Maximum intensity projection image

The use of machine learning, one of the artificial intelligence methods, in medicine is increasing day by day. Machine learning uses convolutional neural networks (CNN) in visual recognition models. The number of studies using convolutional neural networks in medical imaging is increasing. Recent studies are using CNN in the evaluation of pulmonary tuberculosis on plain radiography(6), covid-19 infection with thorax CT(7), and age estimation with brain MR(8). In addition, there are also studies in which CNN has been used successfully in FDG PET imaging (9-11).

For this purpose, we evaluated the use of FDG PET whole body maximum intensity projection images in oncology patients in pathological/physiological differentiation with image classification using visual recognition data.

2. Materials and Methods

Patients who applied for oncological imaging were asked to fast for at least 4 hours before intravenous FDG injection for PET imaging. Imaging was done on the PET device within 45-120 minutes after the injection in our department. Whole-body imaging covered between vertex and mid femur.

A total of 60 whole body MIP images, 30 positive and 30 negatives, confirmed by a nuclear medicine specialist, were used in the study. Since FDG showed variable and high distribution from patient to patient in the brain, heart, and bladder, these structures were extracted from the MIP images with the semi-automatic segmentation program in the workstation **(figure 2)** (GE AW Volume Share 5, GE Medical Systems). The obtained images were recorded in jpeg format as 400x600 pixels.

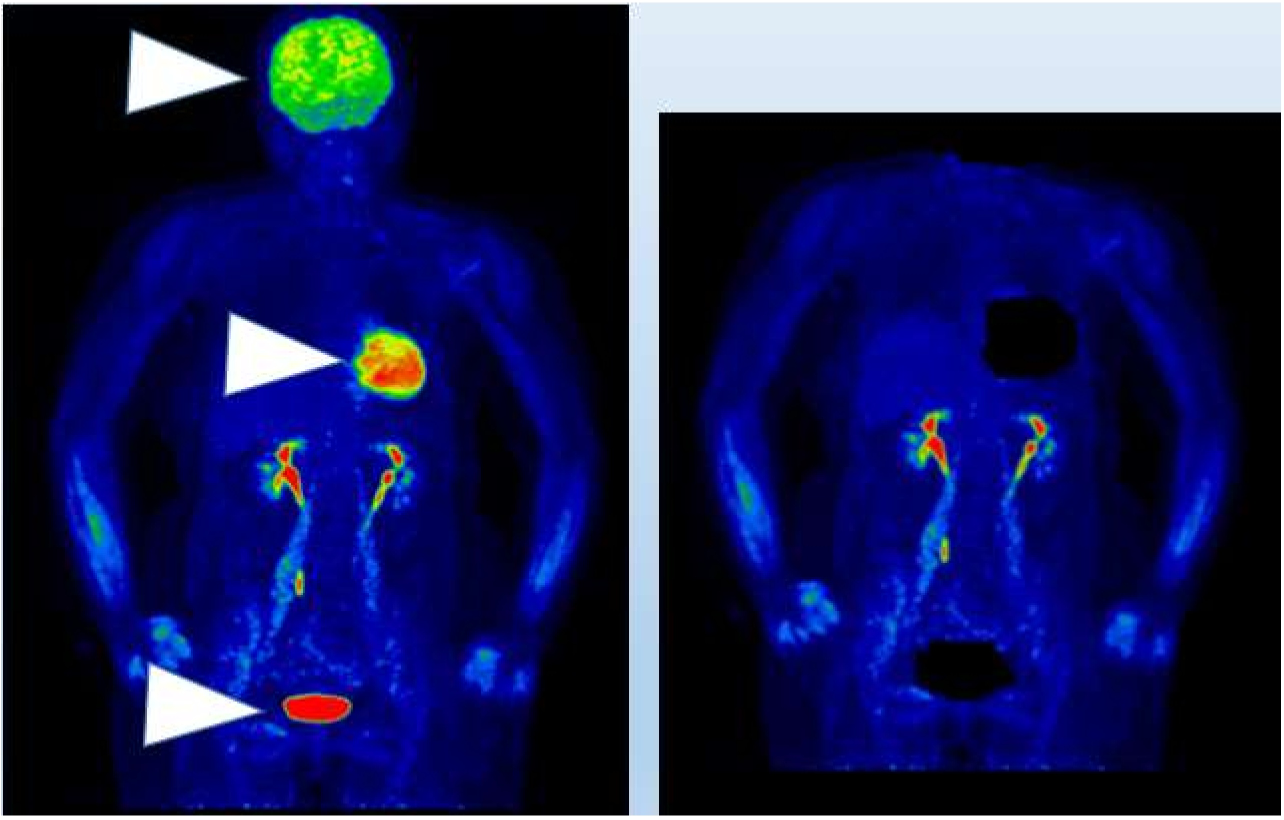


Figure 2. The brain, heart, and bladder were extracted from the MIP images with the semi-automatic segmentation program in the workstation (arrowheads).

Twenty images (33.3%) were used as training and 40 (66.6%) as samples. Images were identified as negative and positive with custom classification for machine learning to IBM Watson program's visual recognition application. After the training, the sample images were evaluated by the program. The obtained confidence scores were recorded. Images with a confidence score of ≥80 and consistent with the nuclear medicine expert's comment were considered correct.

3. Results

According to the defined classification analysis, 17 of 20 images known as pathological in the sample images were classified as correct and 3 as false (85%) **(figures 3a and b).** In addition, 19 of the 20 images known to have a physiological distribution were classified correctly and 1 false (95%). The median value of confidence score in 36 patients with correct results was 91% (range: 80%-92%).

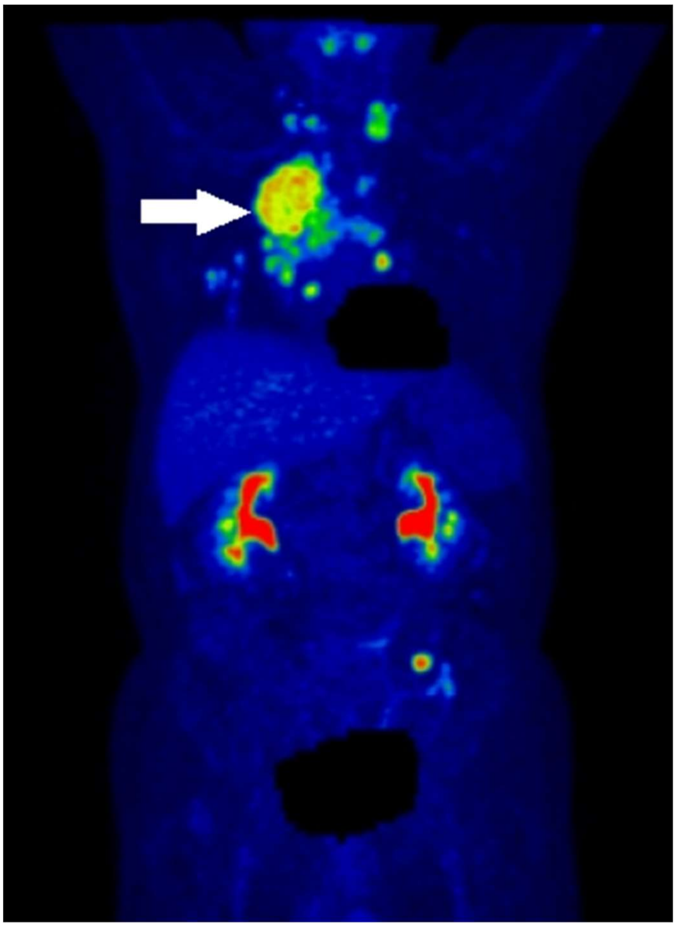


Figure 3a. The pathological activity was detected in the primary massive tumor of the right lung central region of the patient who underwent FDG PET for lung cancer indication (arrow). In addition, metastatic lymph nodes showing pathological activity in the surrounding area were observed. Correct classification was made with a confidence score of 91%.

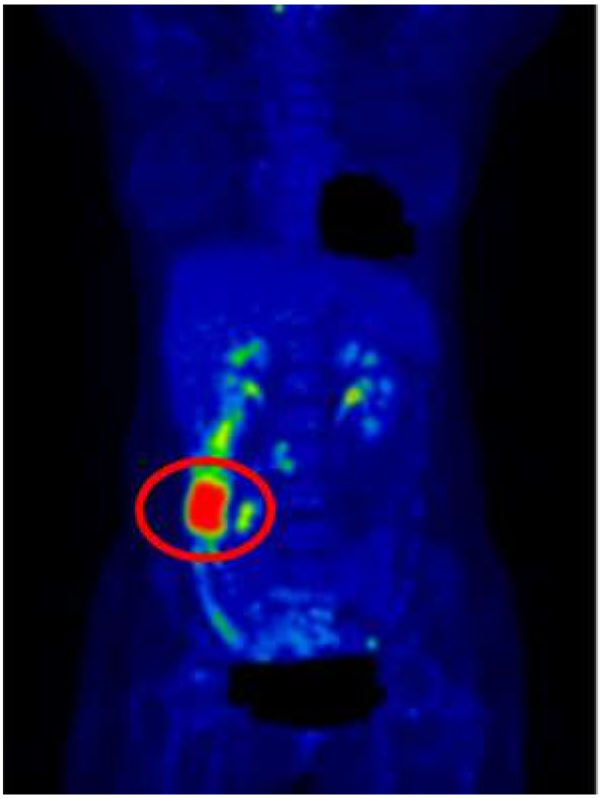


Figure 3b. The primary tumor in the right colon in the abdomen of the patient who underwent FDG PET for the indication of colon cancer showed pathological activity. In addition, metastatic lymph nodes showing pathological activity in the surrounding area were observed (circle). Correct classification was made with a confidence score of 87%.

4. Conclusion and Evaluation

In our study, we determined that 95% of the physiological images and 85% of the pathological images of the patients who performed PET with oncological indication with visual recognition-based machine learning were classified correctly.

In the study of Kawauchi et al., 94.4% of the physiological images and 94.4% of the pathological images were correctly classified by a CNN-based system(9). According to our study, the rate of pathological classification appears higher (94.4% vs 85%). The main reason for this difference is the use of more patient data compared to our study (3485 vs 60). Despite this, our study showed similar performance in physiological classification (94.4% vs 95%).

Figure 4. The pathological activity was identified in the primary tumor of the right lung central region and metastatic supraclavicular lymph node of the patient who underwent FDG PET for lung cancer indication(circle). The incorrect classification was made due to the small number of lesions and small sizes.

To explain the classification error, we examined cases that were incorrectly predicted. Although the small size and low activity involvement lesion in one case were pathological, it was mislabeled and classified physiologically **(figure 4)**. On the other hand, a patient who was negative but had a confidence score below 80 according to the standard reference was evaluated as incorrect.

Although we only used whole body MIP images in our study, we obtained high correct classification. If organ and lesion-based segmentation is performed, we estimate that it will be more successful than the current values. In addition, we think that more prosperous results will be obtained by expanding the training data. Also, processing data with fully automatic systems will increase the feasibility of the application.

Visual recognition-based machine learning seems successful in distinguishing pathological/physiological PET images and has a promising future in current medical practice, especially in oncological imaging. For improved outcomes, prospective studies using advanced algorithms with larger data are needed.

References

1. Warburg O. On the origin of cancer cells. Science. 1956;123(3191):309-14.
2. Ben-Haim S, Ell P. 18F-FDG PET and PET/CT in the evaluation of cancer treatment response. Journal of Nuclear Medicine. 2009;50(1):88-99.
3. Seam P, Juweid ME, Cheson BD. The role of FDG-PET scans in patients with lymphoma. Blood, The Journal of the American Society of Hematology. 2007;110(10):3507-16.
4. Kandathil A, Kay FU, Butt YM, Wachsmann JW, Subramaniam RM. Role of FDG PET/CT in the eighth edition of TNM staging of non–small cell lung cancer. Radiographics. 2018;38(7):2134-49.
5. Paydary K, Seraj SM, Zadeh MZ, Emamzadehfard S, Shamchi SP, Gholami S, et al. The evolving role of FDG-PET/CT in the diagnosis, staging, and treatment of breast cancer. Molecular imaging and biology. 2019;21(1):1-10.
6. Lakhani P, Sundaram B. Deep learning at chest radiography: automated classification of pulmonary tuberculosis by using convolutional neural networks. Radiology. 2017;284(2):574-82.
7. Singh D, Kumar V, Kaur M. Classification of COVID-19 patients from chest CT images using multi-objective differential evolution–based convolutional neural networks. European Journal of Clinical Microbiology & Infectious Diseases. 2020;39(7):1379-89.
8. Ueda M, Ito K, Wu K, Sato K, Taki Y, Fukuda H, et al., editors. An age estimation method using 3D-CNN from brain MRI images. 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019); 2019: IEEE.
9. Kawauchi K, Furuya S, Hirata K, Katoh C, Manabe O, Kobayashi K, et al. A convolutional neural network-based system to classify patients using FDG PET/CT examinations. BMC cancer. 2020;20(1):1-10.
10. Lu D, Popuri K, Ding GW, Balachandar R, Beg MF, Initiative AsDN. Multiscale deep neural network based analysis of FDG-PET images for the early diagnosis of Alzheimer's disease. Medical image analysis. 2018;46:26-34.
11. Ypsilantis P-P, Siddique M, Sohn H-M, Davies A, Cook G, Goh V, et al. Predicting response to neoadjuvant chemotherapy with PET imaging using convolutional neural networks. PloS one. 2015;10(9):e0137036.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Benefits of Remote Treatment Service in Community 5.0 Framework

Kezban ÖZÇELIK KAYNAK [1 *], Barış ÖZTUNA [2]

[1] *Izmir Bakircay University, Turkey*
[2] *Cankiri Karatekin University, Department of Economics and Administrative Sciences, Turkey*

* Related Author: Izmir Bakırcay University, Turkey
Tel: +90 232 2930000. E-Mail: kezban.kaynak@bakircay.edu.tr

Publication Information

Keywords :
- Health,
- Artificial intelligence,
- Industry 4.0,
- Society 5.0,
- Technology

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

This study aims to make predictions about how technology and artificial intelligence can be used in the field of health.

Society 5.0 aims to liberate society from passivity and use technology more effectively for the benefit of the society, for its well-being, and thus for a greater transformation of society. With the transfer of artificial intelligence to technology, social transformation will be facilitated within a wide range of sectors from military and security-oriented fields, sectoral areas for production and service, personal care and patient attendance, occupational safety areas. Health service delivery is expected to be one of the sectors that will be affected.

1. Introduction

This study makes predictions on how technology and artificial intelligence can do in the field of health, and includes studies and applications carried out in different countries concerning this matter. The combination of the tools of Industry 4.0 and the advantages of Society 5.0 (Super Smart Society) lends itself beneficial in the field of health, especially for the elderly, creating the opportunity to be treated without going to the hospital with sensors, artificial intelligence, and health data with the harmony of people and technological tools. In this way, the density of patients in hospitals can be decreased, the productivity of health workers can be increased, and the treatment of patients in remote and provincial areas can be facilitated.

Physical distance rules, movement limitations, which became mandatory with the Covid-19 pandemic, have made the importance of technological and digital advances inevitable in the field of health. The use of artificial intelligence in this field brings many advantages. In particular, the possibility of the spread and/or spread of infectious diseases such as COVID-19 has made studies inevitable regarding the comprehensive use of artificial intelligence as an important method in the field of screening, prediction, contact monitoring and drug development.

2. Artificial Intelligence in Health

It is a technology that can process artificial human beings without the need for human beings. Artificial intelligence is not limited to robotics and digitals. The philosophical dimension of artificial intelligence also exists, and for this technology to advance, the basic structure must be well known (Suucu and Ataman, 2020:41). Since the 1970s, artificial intelligence has been known to create major advances in medical decision-making, early diagnosis and treatment, drug development and many more (Long, 2020:82). Health care providers need to experience digital transformation in order to expand their service range, increase employee productivity, improve medical decision-making processes, increase patient satisfaction, reduce operating costs and be competitive (Işık, 2019: 1982).

The advancement of technology always positively affects the quality of life. New technologies in terms of health enable the improvement of treatment processes, communication with patients and processes related to health protection. High-speed internet connection, mobile connection solutions have digitized transactions such as appointments, follow-ups and reporting in healthcare, and physical needs have been fulfilled for the retention of this and similar data thanks to cloud computing. Digitalization enables the use of artificial intelligence. Using methods such as machine learning with artificial intelligence, new methods are introduced in the field of health in processes such as diagnosis, treatment and rehabilitation (Akalin and Veranyurt, 2020: 132). Artificial intelligence provides training opportunities for health workers with systematic programs for educational purposes. Thanks to the data analyses to be carried out, the information is kept up to date. Intensive infection zones can be scanned and used to solve possible crises by estimating the need for hospital occupancy, bed and health workers. In the future, artificial intelligence will become an important technology against all epidemics by making life easier in health management. By reducing social and economic problems in the fight against many diseases, it will also allow for the implementation of policies supporting basic health services (Bananas and others, 2020: 182). Among the biggest reasons for the increased interest in the applications of artificial intelligence are improving diagnosis and treatment methods, preventing medical errors and improving the quality of health services (Uysal and Ulusinan, 2020:56).

Technologies such as "Cloud Computing", "Big Data", "Internet of Things", "Augmented Reality", "3D Printers", "Artificial Intelligence" and "Data Analytics", which are widespread in many sectors, have caused major changes in all the processes of the health sector. This technological change occurs as a result of the need for new specialties in the health sector. These technological advances lead to the formation of new professions in the field of health. These professions include telemedicine systems specialist, health big data analyst, clinical business analyst, augmented/virtual reality assisted surgical planner, plastic/reconstructive and aesthetic surgery 3D printer specialist, virtual hospital manager, deep learning specialist, synthetic organ designer, voice assistant designer providing epigenetic counseling and healthcare content (Önder et al., 2019:72).

In this century of digital age, it is of great importance for health institutions, which aim to meet the changing care needs of people, to adapt to changes at the global level, to protect their assets and to compete. For this reason, they need to be ready for artificial intelligence, which is expected to have an important place in the future of the health sector along with all other sectors (Eskin Legless and others, 2020:463).

3. Remote Treatment Services within the Framework of Society 5.0

After the transition of societies from hunting to agriculture, industry and information society, the stage that has survived to the present day is shaped by Society 5.0 (Super Smart Society) put forward by the Japanese. It is a model that centers on human beings and allows them to live in prosperity using digital environments and artificial intelligence. It comes across as an inclusive model that provides all kinds of needs of individuals in the required quantity and time, especially the elements that facilitate human life. The balancing nature of the model's home and work life is also of great importance (Saracel and Aksoy, 2020: 32). Society 5.0 is not an individual concept, but a joint venture that is social. The main player in this society is not technology, but human beings. Society 5.0 reassessed the interest in social progress among the stakeholders of society, and environmental theorists defined social responsibility primarily as the desire of natural and social welfare (Bee, 2021: 475).

One of the biggest problems of Japanese society today concerns the increasing size of the aging populations and ways to help older individuals using the technological advances (artificial intelligence, robotics, big data and cloud computing). Japan aims to prevent and mitigate disasters with Community 5.0 (Oztuna, 61-62). As a result of technological advances in the field of Society 5.0 health, they aim to make health services accessible to the elderly and those living in remote places.

There is a need for further studies to be carried out on mobile health services, which is a new field but will gradually increase in importance in the future projection and become an important market. Incentives for portable and wearable medical technologies to be used in mobile health should be provided, R&D projects should be supported (Bektaş and Simsek, 2016: 183). The fact that hospitals can reach people more quickly with internet platforms, that online interviews and interagency agreements can be realized, and that the process is carried out digitally in many areas with decision support systems raises other issues in the hospital management process. Managers can access and analyze data outside the hospital and make decisions according to this information. The fact that job interviews can be held independently of time and space is also an advantage for hospital managers (Kaya and Gemlik, 2021: 62).

Although tele-medicine application was used for diagnosis and treatment procedures with information and communication tools for long distances in health services from the 1960s to the 2000s, it is now used as a component of the concept of e-Health. In countries such as Norway, Canada, USA and Russia, systems such as "e-Health, mHealth and Tele-medicine" are used to reduce the problems experienced by individuals living in places with geographical and economic disadvantages. In this way, health follow-ups, diagnosis and treatments of people living in the countryside who have difficulty accessing quality health services have become as doable as possible (Kilic, 2017: 206-207). It is thought that tele-medical applications will be a remedy for health institutions and health workers. With advances in technology, tele-medical applications have been launched to make health services accessible, reduce costs and increase effectiveness. Even if this practice is thought to lead to improved patient living standards and quality of health care, the lack of patient safety can reduce the quality of care. Promotional and educational activities such as education and public spotlight are among the strategies to be implemented to increase the confidence and usage rates of individuals. Therefore, it is a necessity to plan training activities and increase the usage rates of these people in relation to tele-medical applications (Korkmaz and Hoşman, 2018: 262).

There are many examples of this issue in the world. Philippines-based TheraWee is a telerehabiliation platform designed for pediatric therapy services that can provide support and expertise in addressing child developmental concerns and provide access to rehabilitation services for neurodevelopmental disorders. TheraWee is a community teletherapy platform that helps children with disabilities find, connect, and receive quality therapy services remotely. It is a platform for parents to be more proactive about child development and for developmental disorders (autism, learning disabilities, down syndrome, etc.), to receive medical services for early intervention (Therawee, 2021). Another example is Intelehealth, a telemedicite platform that connects patients and frontline healthcare professionals with patients to provide remote primary health care in countries such as India. Their mission is to improve access to affordable and quality healthcare for all (Intelehealth, 2021).

4. Conclusion and Evaluation

Society 5.0, whose ideal is to create a "Super Smart Society", brings radical changes in economic and social life with big data analysis, artificial intelligence applications, cybersecurity, internet of things, robotic solutions, industry 4.0, virtual reality, augmented reality.

With the prolonged life expectancy, some countries face a gray tsunami (density of the elderly population). Therefore, it is very important to harmonize the elderly population with technology. Providing as few applications as possible to health institutions with technological infrastructures aimed at minimizing the risk of transmission during the pandemic period has fulfilled a very important task of protecting health workers and reducing physical mobility. For all these reasons, we can say that especially in a global pandemic such as COVID-19, technology, artificial intelligence and data science have become a critical point to help societies address the pandemic effectively.

References

1. Akalın, B., Veranyurt, Ü. (2020). Sağlıkta Dijitalleşme ve Yapay Zeka. SDÜ Sağlık Yönetimi Dergisi. 2(2). 131-141.
2. Arı, E., S. (2021). Süper akıllı toplum: Toplum 5.0. Dokuz Eylül Üniversitesi Sosyal Bilimler Enstitüsü Dergisi. 23 (1). 455-479.
3. Bektaş, G., Şimşek, F. (2016). İleri Yaş Sağlık Turizminde Mobil Sağlık Hizmetlerinin Önemi. Health Care Acad J. 3(4). 179-185.
4. Eşkin Bacaksız, F., Yılmaz, M., Ezizi, K., Alan, H. (2020). Sağlık Hizmetlerinde Robotları Yönetmek. SHYD. 7(3). 458-465
5. Intelehealth (2021). Telemedicine for last mile health. https://www.intelehealth.org/
6. Işık, T. (2019). Sağlık İletişi Bağlamında Kullanım Şekilleri Açısından Dijital Algı ve Önemi. Atatürk Üniversitesi Sosyal Bilimler Enstitüsü Dergisi. 23 (Özel Sayı). 1979-1994.
7. Kaya, N. ve Gemlik, H.N. (2021). Hastane Yöneticilerinin Hastanelerin Dijitalleşmesine Bakış Açıları Üzerine Nitel Bir Araştırma, Journal of Academic Perspective on Social Studies, (1), 59-71.
8. Kılıç, T. (2017). E-Sağlık, İyi Uygulama Örneği; Hollanda. Gümüşhane Üniversitesi Sağlık Bilimleri Dergisi. 6(3). 203-217.
9. Korkmaz, S., Hoşman, İ. (2018). Sağlık Sektöründe Tele-Tıp Uygulamaları: Tele-Tıp Uygulama Boyutlarını İçeren Bir Araştırma. Usaysad Dergisi. 4(3). 251-263.
10. Muz F., N., Ö., Kılınç, A, Önsüz M., F. (2020). COVID-19 Pandemisinde Yapay Zekanın Kullanımı. ESTÜDAM Halk Sağlığı Dergisi. 2020;5(COVID-19 Özel Sayısı). 178-83.
11. Önder G., Önder E. & Özdemir M. (2019). Gelişmekte Olan Teknolojiler Sonucu Sağlıkta Oluşacak Yeni Meslekler. Gümüşhane Üniversitesi Sosyal Bilimler Enstitüsü Elektronik Dergisi, 10(Ek Sayı), 71-80.
12. Öztuna, B. (2019). TOPLUM 5.0 (SÜPER AKILLI TOPLUM). Bursa: Ekin Yayınevi.
13. Saracel, N., Aksoy, I. (2020). Toplum 5.0: Süper Akıllı Toplum. Social Sciences Research Journal. 9 (2). 26-34.
14. Sucu, İ., Ataman, E. (2020). Dijital Evrenin Yeni Dünyası Olarak Yapay Zeka ve Her Fimi Üzerine Bir Çalışma. Yeni Medya Elektronik Dergi – eJNM. 40-52.
15. Therawee (2021). What is TheraWee. https://www.therawee.ph/
16. Uysal, B., Ulusinan, E. (2020). Güncel Dijital Sağlık Uygulamalarının İncelenmesi. Selçuk Sağlık Dergisi. 1. 46-60.
17. Uzun, T. (2020). Yapay Zeka ve Sağlık Uygulamaları. İzmir Kâtip Çelebi Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi. 3(1). 80-92.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || ISBN : 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

An Artificial Intelligence Approach Specific to Rheumatoid Arthritis: Digital Coaching

Hatice TEL AYDIN[1], Döne GÜNAY [2] *

[1] *Sivas Cumhuriyet University Faculty of Health Sciences Nursing Department*
[2] *Sivas State Hospital*

* Corresponding Author: Döne GUNAY, Sivas State Hospital, Turkey
E-Mail: donegunay@gmail.com

Publication Information

Keywords :

- Artificial intelligence,
- Digital coaching,
- Rheumatoid arthritis,
- Disease emanagement,
- Nursing

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Chronic diseases are conditions that negatively affect the quality of life of the individual. Although it is observed at a lower rate than many chronic diseases, Rheumatoid Arthritis (RA) has a significant impact on the individual, society, and health care system due to the fact that it is frequent among individuals who are young and at productive age. RA treatment consists of using pharmacological and non-pharmacological treatments together within a multidisciplinary team approach. In the field of Rheumatology, Artificial Intelligence is advancing in areas such as providing medication options with machine learning, electronic diagnosis, prediction of disease activity, image interpretation through deep learning, and determination of genetic predisposition. It is observed that a number of adaptation problems have occurred with the preventive measures against pandemic during the Covid-19 pandemic in terms of Access to health care and planning and follow-up of treatments for individuals with RA who use immunosuppressive agents. In the solution of these problems, telemedicine practices and digital coaching, which have gained strategic importance, particularly with the impact of the Covid-19 pandemic, can be referred to in the light of advancements in the field of health care technology. Nursing care and follow-up care for individuals with RA can be provided in the digital environment within the framework of digital coaching. In this review study, it was mentioned how the treatment and care of individuals with RA, which has a significant place among chronic diseases, can be shaped through digital coaching within the scope of artificial intelligence Technologies and telemedicine.

1. Introduction

Chronic diseases; these are conditions that generally last a year or longer, require continuous medical intervention and limit daily living activities [1]. Chronic diseases are diseases that adversely affect the quality of life of the individual, require advanced expertise, have fatal complications or can lead to disability, and are costly to follow-up and treat [2]. Chronic diseases are lifelong, so managing chronic diseases is very difficult for patients and caregivers [2]. According to the "2019 Global Health Forecasts" report published by the World Health Organization in 2020, non-communicable diseases (such as cancer, heart disease, diabetes) constitute 7 of the top 10 causes of death in the world [3]. Chronic diseases appear as a serious health problem for our country as well. In the study published by WHO in 2018, where the profiles of the countries in terms of Non-Communicable Diseases (NCD) were stated; It was stated that NCDs were responsible for 89% of all deaths in Turkey in 2016 [3], and in the report showing the development of NCDs published by WHO in 2017, the rate of early death due to NCDs in Turkey was 17% [4]. In addition, the COVID-19 pandemic, which has affected the whole world in 2019, targets individuals with chronic diseases.It has been determined that individuals with chronic diseases are more susceptible to being infected due to Covid-19, and the general health status of individuals with chronic diseases among individuals infected with Covid-19 is more negatively affected [5].

One of the chronic diseases, Rheumatoid Arthritis (RA) is an inflammatory and autoimmune disease [6]. Individuals with a diagnosis of RA experience symptoms such as pain, fatigue, insomnia, and limitation of movement, and may have difficulties in performing daily life activities [7]. RA is an important health problem due to its high prevalence in young females, the loss of work force and disability it causes in as little as 2 years after the diagnosis of the disease is determined. The social burden is significant when compared with the treatment plan consisting of high-cost drugs and the complications caused by the disease, according to the prevalence in the population [8]. RA has a disease course with attacks and remission periods, and the aim of treatment is to prevent joint damage by providing complete remission [7]. The effective treatment process of individuals diagnosed with RA includes pharmacological and non-pharmacological processes in a multidisciplinary team approach. The treatment plan in RA consists of highly costly and immunosuppressive options that may cause serious health problems for the individual, the application process requires training and follow-up, rather than just one drug option, the desired effect is achieved by using several drug options together [8, 9]. However, individuals diagnosed with RA cannot be followed with appropriate monitoring intervals (in the world and in our country) due to the small number of health professionals specialized in the field of Rheumatology [10]. This situation prevents the progression of the disease and can make it difficult to control the disease. It causes labor loss both individually and socially and high cost drug options directly and indirectly increase the cost burden of RA [11,12].

The reflections of technological developments in the field of health continue impressively. Since its use in the field of healthcare, computers where patient data are stored offer the meaningful results of artificial intelligence technology from the existing information load (big data) about patients, again on the basis of evidence, which are suggestions for the benefit of patients [13,14]. Artificial intelligence; It is defined as the theory and development of computer systems that can complete tasks that typically require human intelligence, such as visual perception, speech, recognition, decision making, and / or language translation [14]. Simply put, it is the ability of a machine to imitate intelligent human behavior [13,14]. Machine learning, a common method of reflection of Artificial Intelligence in healthcare, is a field of computer science that uses algorithms to develop predictive models from large data sets [13]. Traditional statistics focus on summarizing data, understanding statistical relationships between variables, and estimating population parameters in the most accurate way. In contrast, the main goal of most machine learning methods is prediction performance on unseen data. The most common focus of artificial intelligence in rheumatic and musculoskeletal diseases is machine learning [15]. Therefore, machine learning can act as a sharp scalpel to examine big data, reveal new patterns and therefore improve treatment options in rheumatology. In the field of rheumatology, innovations in drug treatment plans in recent years have increased the importance of targeted treatment options [16]. Differences between patients can be seen in the clinical course. Technology options such as artificial intelligence, machine learning, and deep learning are expected to provide the application of treatment shaped according to the differences between individuals with rheumatic diseases and determine the disease activity [15,16]. Within the framework of artificial intelligence applications in the field of rheumatology, electronic diagnosis and estimates that affect the treatment and follow-up as a result of examining the existing relationship with genetic codes in the development and course of rheumatic diseases are mentioned. In addition, the subfield of machine learning, deep learning, is increasingly used for image interpretation in musculoskeletal radiology [15].

Nurses are healthcare professionals directly affected by the reflection of developing technology on healthcare services. Nursing care can be shaped by artificial intelligence applications in the provision of health services that have changed by the developing technology options. In the literature, artificial intelligence tools are used in chronic disease management in areas related to nursing care; Decision support systems, collecting patient information, creating appropriate discharge instructions for the patient in planning the discharge process from the hospital, and digital coaching when lifestyle changes are needed. In the treatment of patients with chronic pain and depression in one of these studies [17], loaded on a tablet; It used an artificial intelligence application that recognizes and responds to verbal and non-verbal inputs, produces verbal and nonverbal output, deals with speech functions (such as getting and giving feedback), giving signals showing the state of the speech, and also adding new propositions to the speech content. In the results of working; It was concluded that the compliance with the recommendations offered to the sick individuals to reduce stress was complete (100%), and the compliance with the healthy nutrition recommendations was high (89%). Another study [18] tested the use of artificial intelligence as a way to reduce feelings of loneliness and isolation in older adults. On a satisfaction scale ranging from one (low satisfaction) to seven (high satisfaction), it was determined that those using artificial intelligence expressed above-average satisfaction with 4.4 points. In another study, two virtual nurses (designed as separate races) were identified through artificial intelligence tools. He contributed to patient care to review patients' care plans and treatments [19]. As a result of the study, it was concluded that satisfaction with care provided was at similar rates compared to actual nursing care, and that being of a different race did not affect patient satisfaction in nursing care provided in digital environment via artificial intelligence.

The basic strategy adopted in coping with chronic diseases in the world and in our country has been to gain individuals the healthy lifestyle behaviors that prevent the occurrence of diseases [20]. In the presence of chronic disease, in the case of RA, individuals; It is expected to ensure compliance with treatment, to avoid possible complications, to eliminate lack of information, to attend health checks regularly, to recognize the symptoms of the disease, and to control behaviors that may be related to symptom severity [8]. In the light of all this information, it may be beneficial to provide health coaching to individuals with chronic diseases by an expert health professional.

Health coach; is a health professional who is specific for chronic diseases and aims to provide the individual with disease management skills by supporting health education and health promotion behaviors in order to increase the well-being of the individual and to facilitate the achievement of health-related goals [22,23]. The Health Coach helps ensure that patients develop the knowledge, skills and confidence needed to manage their chronic conditions and improve their health. The health coach is involved in empowering patients to take a central role in managing the disease and to engage in self-management activities at home, work, and schools where they spend most of their lives [20].

Considering the lifestyle changed by technological possibilities and the pandemic conditions affecting the whole world, technologies that allow the sustainability of treatment and care in cases where there is no physical access to the patient in chronic disease management play an important role. In this context, it may be possible to benefit from health coaching services in digital environment from applications created by using artificial intelligence technology by health professionals who are experts in their fields [21]. With digital coaching of individuals; ensuring compliance with treatment plans, eliminating the lack of information, early intervention in side effects that may be caused by specific drug options, increasing the quality of life with symptom management, increasing awareness of possible complications, referring to appropriate consultations, preventing movement limitation with suggestions for increasing physical activity, increasing the motivation of the individual It can be kept away from behaviors that may affect disease activity [21, 24]. In an article discussing the digital coaching model presented with artificial intelligence in the management of chronic diseases [25]; It is stated that the chronic nature of chronic diseases causes difficulties for individuals to cope. It is mentioned that the short examination periods in the hospital environment may be insufficient to reach the data that will shape the treatment and care in the fight against the disease that affects all aspects of life in a complex structure. In addition, it is stated that digital coaching is important in order to provide instant and continuous determination of data on individuals about the disease, and to provide care recommendations regarding the results obtained from individuals, to gain disease management skills, to obtain the results of interventions, and to observe the development of individual skills in the process [25].

Individuals with a diagnosis of RA can benefit from applications created using artificial intelligence technology through healthcare professionals in disease management through digital coaching. In addition, it may be beneficial to monitor RA patients using immunosuppressive agents in the COVID-19 pandemic with a digital coach within the scope of telemedicine technology due to the limited number of healthcare professionals in the field of rheumatology and the lack of appropriate follow-up frequency [24]. With digital coaching, individuals with RA can increase their self-efficacy, contribute to reducing disease activity, achieving remission, and reducing the cost burden of the disease [24]. In a study presented for the first time at the EULAR 2017 meeting where digital coaching was followed in the care of individuals with RA [26]; Individuals diagnosed with RA were followed up for 12 weeks by calling individuals every week through a digital health coach. During this follow-up, personalized to individuals with RA; Consultancy was provided on the subjects of ensuring the adaptation of the individual to the treatment in his / her environment, gaining healthy lifestyle behaviors, providing motivation, providing diet and exercise suggestions, following the symptoms of the disease, and supporting the individuals in terms of positive behavioral changes. As a result of the research; It has been determined that individuals diagnosed with RA have increased their disease management skills and their disease symptoms have decreased.

2. Result

As a result, nurses are seen as an integral part of technological developments in the field of healthcare. Nurses take an active role in the creation and implementation of technologies related to healthcare services. In this context, it is expected that technology will not be seen as an alternative among nurses in terms of the opportunities it offers, and technological developments will take its place as an opportunity to allocate more time for independent nursing interventions in patient care.

Individuals with chronic diseases should be given long-term medical care. RA constitutes an important burden among chronic diseases with its aspects such as cost, disability, and early labor loss. Developing health technologies in the field of rheumatology; Under the title of artificial intelligence, machine learning brings the interpretation of deep learning to processes carried out with clinical experience and knowledge such as determining drug options, predicting disease activity, and interpreting images. Thanks to artificial intelligence applications in nursing interventions; decision support systems, collecting patient information, creating appropriate discharge instructions for the patient and adapting to lifestyle changes. It has reached a strategic position in telemedicine applications during the Covid-19 pandemic in the follow-up and care of individuals with RA. In this context, as a result of advances in health technologies, nursing care can be effectively offered to RA diagnosed individuals using immunosuppressive agents with a digital coaching approach.

References

1. Centers for Disease Control and Prevention (CDC), About Cronic Disease, 2021. https://www.cdc.gov/chronicdisease/about/index.htm#:~:text=Chronic%20diseases%20are%20defined%20broadly,disability%20in%20the%20United%20States. Erişim: 22 Nisan, 2021.
2. Ambrosio, L.,SenosiainGarcía, J. M., Riverol Fernández, M., Anaut Bravo, S., Díaz De CerioAyesa, S., UrsúaSesma, M. E., Caparrós, N., &Portillo, M. C. (2015). Livingwithchronicillness in adults: a conceptanalysis. *Journal of clinicalnursing*, *24*(17-18), 2357–2367. https://doi.org/10.1111/jocn.12827
3. Global Health Estimates, 2019 https://www.who.int/data/global-health-estimates Erişim: 14 Mart, 2021.
4. Natıonal Household Health Survey In Turkey Prevalence Of Noncommunıcable Dısease Rısk Factors 2017 https://www.who.int/ncds/surveillance/steps/WHO_Turkey_Risk_Factors_A4_TR_19.06.2018.pdf Erişim: 20 Mart, 2021.
5. Yu, X.,&Yang, R. (2020). COVID-19 transmission through a symptomatic carriers is a challenge to containment. Influenza Other Respi Viruses, 14, 474-475.
6. Arnett, F. C.,Edworthy, S. M., Bloch, D. A., McShane, D. J., Fries, J. F., Cooper, N. S., Healey, L. A., Kaplan, S. R., Liang, M. H., &Luthra, H. S. (1988). TheAmericanRheumatismAssociation 1987 revisedcriteriafortheclassification of rheumatoidarthritis. *Arthritisandrheumatism*, *31*(3), 315–324. https://doi.org/10.1002/art.1780310302
7. Smolen, J. S.,&Steiner, G. (2003). Therapeuticstrategiesforrheumatoidarthritis. *Nature reviews. Drugdiscovery*, *2*(6), 473–488. https://doi.org/10.1038/nrd1109
8. Smolen, J. S.,Aletaha, D., &McInnes, I. B. (2016). Rheumatoidarthritis. *Lancet (London, England)*, *388*(10055), 2023–2038. https://doi.org/10.1016/S0140-6736(16)30173-8
9. Pisetsky D. S. (2017). Advances in theTreatment of RheumatoidArthritis: CostsandChallenges. *North Carolina medicaljournal*, *78*(5), 337–340. https://doi.org/10.18043/ncm.78.5.337
10. Felson DT, Smolen JS, Wells G*,* et al. (2018). American College of Rheumatology/European League Against Rheumatism Provisional Definition of Remission in Rheumatoid Arthritis for Clinical Trials *Annals of the Rheumatic Diseases*;**70:**404-413.
11. Nicholl K. (2017). The role of thebiologicsnursespecialist in rheumatology. *British journal of nursing (Mark Allen Publishing)*, *26*(7), 390.
12. Packham, J.,Arkell, P., Sheeran, T. *et al.* (2017). Patientexperiences, attitudesandexpectationstowardsreceivinginformationabout anti-TNF medication: a quantitativestudy. *ClinRheumatol* **36,** 2595–2600https://doi.org/10.1007/s10067-017-3642-5
13. McGrow K. (2019). Artificialintelligence: Essentials fornursing. *Nursing*, *49*(9), 46–49. https://doi.org/10.1097/01.NURSE.0000577716.57052.8d
14. Frith K. H. (2019). ArtificialIntelligence: WhatDoesItMeanforNursing?. *Nursingeducationperspectives*, *40*(4), 261. https://doi.org/10.1097/01.NEP.0000000000000543
15. Hügle, M.,Omoumi, P., vanLaar, J. M., Boedecker, J., &Hügle, T. (2020). Appliedmachinelearningandartificialintelligence in rheumatology. *Rheumatologyadvances in practice*, *4*(1), rkaa005. https://doi.org/10.1093/rap/rkaa005
16. Kothari, S.,Gionfrida, L., Bharath, A. A., & Abraham, S. (2019). ArtificialIntelligence (AI) andrheumatology: a potentialpartnership. *Rheumatology (Oxford, England)*, *58*(11), 1894–1895. https://doi.org/10.1093/rheumatology/kez194
17. McCue, K.,Shamekhi, A., Bickmore, T., Crooks, D., Barnett, K. Haas, N., … Gardiner, P. (2015). A feasibilitystudytointroduce an embodiedconversationalagent (ECA) on a tablet computerinto a groupmedicalvisit. *Annual Meeting of theAmericanPublicHealth Association.* https://apha.confex.com/apha/143am/webprogram/Paper329324.html

18. Bickmore, T.,Pfeifer, L., &Jack, B. (2013). Takingthe time tocare: Empoweringlowhealthliteracyhospitalpatientswithvirtualnurseagents. *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems (CHI)*. Boston, MA. Retrieved from http://relationalagents.com/publications/CHI09.VirtualNurse.pdf
19. Zhou, S.,Bickmore, T., Paasche-Orlow, M., &Jack, B. (2014). Agent-userconcordanceandsatisfactionwith a virtualhospitaldischargenurse. *Intelligent Virtual Agents*
20. Haskett, T. (2006). Chronicillnessmanagement: Changingthesystem. Home HealthCare Management Practice, 18: 492-496. 74
21. Barbosa, S.,Abbott, P., & Dal Sasso, G. (2021). Nursing in theDigitalHealthEra. *Journal of nursingscholarship : anofficialpublication of SigmaThetaTau International HonorSociety of Nursing*, *53*(1), 5–6. https://doi.org/10.1111/jnu.12620
22. Palmer, S.,Tubbs, I. andWhybrow, W. (2003). Health coaching to facilitate the promotion of healthy behaviour and achievement of health-related goals. 41. 91-93. 10.1080/14635240.2003.10806231.
23. WHO; Digital Health (2018), https://www.who.int/health-topics/digital-health-test-version#tab=tab_1 Erişim;20 Nisan 2021.
24. Krusche, M.,Burmester, G. R., &Knitza, J. (2020). Digital crowd sourcing: unleashing its power in rheumatology. *Annals of the rheumatic diseases*, *79*(9), 1139–1140. https://doi.org/10.1136/annrheumdis-2020-217697
25. TahriSqalli, Mohammed& Al-Thani, Dena. (2019). AI-supportedHealthCoaching Model forPatientswithChronicDiseases. 452-456. 10.1109/ISWCS.2019.8877113.
26. Ghosh I, Srivastava U, Burton BS, Garcia-Espinosa MA, Patel D, Rasulnia M.(2017).Assessing the Impact of a Digital Health Coaching Program for Patients with Rheumatoid Arthritis [abstract]. *Arthritis Rheumatol.*; 69 (suppl 10). https://acrabstracts.org/abstract/assessing-the-impact-of-a-digital-health-coaching-program-for-patients-with-rheumatoid-arthritis/.

AITA

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || ISBN : 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Triage and Artificial Intelligence in the COVID 19 Pandemic

Ahu PAKDEMİRLİ [1, *], Dilek ORBATU [2], Senem ALKAN ÖZDEMİR [3],
Elif GÜLER KAZANCI [4], Demet ALAYGUT [5]

[1] *University of Health Sciences , Gulhane School of Medicine, Department of Physiology, Turkey*

[2] *University of Health Sciences Dr. Behçet Uz Children's Education and Research Hospital Department of Pediatrics, Turkey*

[3] *University of Health Sciences Dr. Behçet Uz Children's Education and Research Hospital Department of Neonatology, Turkey*

[4] *Health Sciences University Bursa Faculty of Medicine Vice Dean, Turkey*

[5] *University of Health Sciences Tepecik Training and Research Hospital Department of Pediatric Nephrology, Turkey*

* Corresponding Author: Dr. Behçet Uz Children's Education and Research Hospital Department of Pediatrics, Turkey
Tel.: +90 505 755 65 79. E-Mail: drdilekorbatu@gmail.com

Publication Information

Keywords :

- Triage,
- Artificial inteeligence,
- Covid 19

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Triage means selection, separation, and elimination as a word. It is a method of classifying individuals according to the urgency of their current situation and putting them in order according to their urgency of intervention. In a situation like a pandemic, in addition to classification and prioritization, it is also necessary to allocate existing resources in the most beneficial way. It is important to distinguish patients who are likely to be infected with the COVID 19 pandemic with rapid and effective triage. This is critical for both effective treatment of patients and proper allocation of hospital resources. The increase in computing power and big data have enabled deep learning to be used successfully in many medical applications. It is important to group the cases quickly in the picture of infection, such as Covid 19, where rapid assessment is required, risk determination and appropriate management are required. In this sense, digitalization and artificial intelligence applications gain importance. An example of this in my epidemic management, "Hayat Eve Sığar" mobile application developed by the Ministry of Health. In addition to providing person-based follow-up in the prevention of the epidemic, it has been an important protective system that provides information about personal tracking, zone tracking and risk status by continuously updating. This system has also helped the radiation teams and preventive healthcare providers to travel, with whom they can travel, and the health status of the person and those around him. In the conventional approach, in order to facilitate the physician's evaluation of multiple parameters together and to guide the patient within a certain algorithm, many demographic data, geographical location, symptoms, laboratory test results of the individuals will be processed with an artificial intelligence-based approach, scoring the patients from the first application of the patient and creating an algorithm. It is important that the use of triage based on artificial intelligence becomes widespread. The most radical change in post-pandemic health policies will be the provision of digitalization in health and the applications of artificial intelligence to both the decision-maker and the implementer platform of the healthcare service provider.

1. Introduction

Triage refers to the fast selection and coding process performed at the scene and in every health institution where they are transported, in order to determine the priority treatment and transplantation in cases where there are a large number of patients or injured people. It was first administered by Napoleon's chief of surgery, Dominic Jean Larrey. Its aim is to leave soldiers seriously injured due to insufficient health resources to die, and to intervene in the lesser wounded, to return them back to the battlefield. The military triage system has gradually turned into a civil disaster and emergency unit triage.

First, in 1964, Weinerman et al. Published the first civil triage system. After that, triage systems gradually developed.

It enables the determination of the urgency of patients in emergency services, preventing conflict among people and ensuring that patients who need to be intervened with priority benefit from health services earlier. Thus, it is possible for critically ill patients to overcome their life threats and to apply the treatment and care of all patients with urgency more quickly. The correct triage applied in the hospital reduces the waiting time of the patients and the wounded and ensures that they receive appropriate medical care and treatment. While applying triage, the selection of the patient or the injured person should be made according to scientific and vital criteria. An effective triage system should have the characteristics of simple, time-efficient, predictive accuracy, reliability, and least error.

Why is a triage system required? Due to the necessity of organizing the available resources in war, collective accidents and disasters, situations where out-of-program patient admissions are high, population increase increases the number of urgent admissions, patients in need of urgent care need to leave because of the high number of non-urgent patient admissions.

Routine emergency room triage takes place in 3 ways. 1) Non-Professional Triage (Traffic Cop) Secretary done by the security guard. According to the patient's complaint; 'Patient' or 'not patient' decision is made and the patient is put on hold or for examination. 2) Indiscriminate or Rapid Triage is performed by a nurse, doctor, paramedic or paramedic. With the complaint, "very urgent", "urgent" and "non-urgent" decision is made in the light of objective and subjective data. It is taken to the appropriate area. 3) Comprehensive Triage is applied by the triage nurse, doctor or people trained in these matters.

The complaint is evaluated with subjective and objective findings and limited physical examination. The urgency is determined with four and five triage scales, and the information is documented.

Pandemics or pandemic diseases are the general name given to epidemics (epidemics) that spread over a wide area such as a continent or even the entire world surface. Pandemic is derived from the Ancient Greek words “pan”, meaning all, and “demos”, meaning people. According to the definition of WHO (World Health Organization), a pandemic is deemed to have started only when the following 3 conditions are met: The emergence of a disease that the population has not been exposed to before, The disease causing the disease to infect humans and cause a dangerous disease, The spread of the disease factor easily and continuously among people A disease or medical condition cannot only be considered a pandemic because it is widespread and kills large numbers of people, but must also be contagious. For example, although cancer is a disease that causes many deaths in humans, it is not called a pandemic because it is not contagious. (It should be noted that some types of cancer can be caused by infectious factors).

In December 2019, a new pathogen, SARS CoV-2, appeared in China (1). The acute respiratory distress syndrome (ARDS) epidemic caused by this novel coronavirus (COVID-19) has turned into a global pandemic with the reporting of local transmission cases shortly after the detection of cases from abroad in the affected countries (2). The World Health Organization (WHO) announced that as of March 11, 118 thousand cases were seen in 114 countries and 4 thousand 291 people died (3). For this reason, he declared COVID-19 a pandemic disease. The first COVID-19 case in our country was detected on March 11, 2020. The basic control of this disease is based on rapid identification, appropriate risk assessment, isolation of possible cases and prevention measures for the spread of the virus (4, 5). In this great effort to prevent the COVID-19 pandemic, the role of emergency room doctors, supported by hospitals and infectious diseases specialists, is enormous. Emergency service physicians at the front line must diagnose and isolate potential case patients early in order to detect possible cases of COVID-19. Identifying these patients is challenging, as individuals with COVID19 can be relatively asymptomatic in the early stages of the disease or present with atypical symptoms. The early stages of COVID-19 may therefore be indistinguishable from ARDS caused by common respiratory viruses (6). Therefore, case definitions are important in guiding emergency physicians about the triage of potential possible cases. Given the importance of patient-to-patient transition in the hospital, its role as a line of defense in identifying suspected COVID-19 cases in the emergency department and ensuring their isolation at first arrival is crucial (7) The increase in computing power and big data have enabled deep learning to be used successfully in many medical applications. It is important to group the cases quickly in the picture of infection, such as Covid 19, where rapid assessment is required, risk determination and appropriate management are needed. In this sense, digitalization and artificial intelligence applications gain importance. An example is "Hayat Eve Sığar" (HES) mobile application developed by the Ministry of Health of the republic of Turkey. In addition to providing person-based follow-up in the prevention of the epidemic, it has been an important protective system that provides information about personal tracking, zone tracking and risk status by continuously updating. This system has also helped the radiation teams and preventive healthcare providers to travel, with whom they can travel, and the health status of the person and those around him. In the conventional approach, in order to facilitate the physician's evaluation of multiple parameters together and to guide the patient within a certain algorithm, many demographic data, geographical location, symptoms, laboratory test results of the individuals will be processed with an artificial intelligence-based approach, scoring the patients from the first application of the patient and creating an algorithm. It is important that the use of triage based on artificial intelligence becomes widespread. The Finnish Startup firm provides online triage services to its patients in Hull and York, England. It aims to improve access to primary health care and reduce waiting times with the artificial intelligence symptom checker. It is possible to see similar examples in the world.

Approximately 60,000 patients in Yorkshire, Finland have been given access to online triage technology from Finland-based Clinical Healthcare Solutions. Haxby Group is a healthcare provider managing surgery in Hull and York. This group was the first in the UK to adopt the Clinical Access online system, which offers patients an online assessment using an artificial intelligence (AI) powered symptom control device. Clinical algorithms can identify the underlying health problem, recognize its urgency, and guide the patient to the right point of care. Complex cases are sent directly to the Haxby Group's emergency care team so they can decide on the urgency of the case and how to treat it.

The system was initially introduced to patients in two of the Haxby Group's York surgeries, and the average of weekly online inquiries increased from 0.1% at the beginning to 24% within two months after the implementation of the new system. According to a survey of the UK National Health Authority (NHS), patients across the country have difficulty reaching their physicians. The Online Clinic system aims for physicians to review their patients' queries and call them back for a care plan the same day and schedule a face-to-face meeting for patients in need. It also provides healthcare professionals with information that enables them to start the necessary treatment as soon as possible. It is estimated that by 2020, the size of patient data worldwide will reach 25,000 petabytes (1 petabyte = 1024 terabytes). When such a large amount of data is combined with the deep learning method, great improvements can be made in the diagnosis of diseases. In the USA, 300 million radiological examinations are required each year for diagnostic purposes. As this number increases, it becomes difficult for radiologists to evaluate these examinations more effectively and accurately. The newly developed artificial intelligence application can determine the priorities of incoming patients by scanning according to their clinical findings and direct them to the most appropriate doctor. Thus, a medical image can be interpreted within milliseconds, 10,000 times faster than a radiologist.

2. Conclusion

In conclusion, the most radical change in post-pandemic health policies will be the provision of digitalization in health and the applications of artificial intelligence to both the decision-maker and the implementer platform of the health service provider.

References

1. Zhou P, Yang XL, Wang XG, Hu B, Zhang L, Zhang W, et al. A pneumonia outbreak associated with a new coronavirus of probable bat origin. Nature. 2020;579(7798):270-3.
2. Pongpirul WA, Pongpirul K, Ratnarathon AC, Prasithsirikul W. Journey of a Thai Taxi Driver and Novel Coronavirus. N Engl J Med. 2020;382(11):1067-8.
3. https://covid19.who.int/
4. Thompson RN. Novel Coronavirus Outbreak in Wuhan, China, 2020: Intense Surveillance Is Vital for Preventing Sustained Transmission in New Locations. J Clin Med. 2020;9(2). pii: E498. DOI: 10.3390/jcm9020498.
5. Wu X, Zhou H, Wu X, Huang W, Jia B. Strategies for qualified triage stations and fever clinics during the outbreak of COVID-2019 in the county hospitals of Western Chongqing. Journal of Hospital Infection. Pii: S0195- 6701(20)30120-1 DOI: https://doi.org/10.1016/ j.jhin.2020.03.021.
6. Huang CL, Wang YM, Li XW, Ren L, Zhao J, Hu Y, et al. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. Lancet. 2020;395(10223):497-506.
7. Wang D, Hu B, Hu C, Zhu F, Liu X, Zhang J, et al. Clinical Characteristics of 138 Hospitalized Patients With 2019 Novel Coronavirus-Infected Pneumonia in Wuhan, China. JAMA. 2020. DOI: 10.1001/jama.2020.1585. [Epub ahead of print]

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

A Clinical Decision Support Method and Mobile Application for Remote Monitoring of Diabetic Patients

Canan TALAYHAN [1, *], Adnan KAVAK [2]

[1] *Kocaeli University, Faculty of Engineering, Dept. of Computer Engineering, Turkey*
[2] *Kocaeli University, Faculty of Engineering, Dept. of Computer Engineering, Turkey*

* Corresponding Author: Kocaeli University, Faculty of Engineering, Turkey
Tel.: +90 546 2168677. E-Mail: canan.t.talayhan@gmail.com

Publication Information

Keywords :

- Covid-19,
- Diabetes,
- Remote patient monitoring,
- Decision support,
- Medical IoT

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Recently, due to the Covid-19 pandemic, remote patient care and monitoring systems have become important especially for patients with chronic diseases such as diabetic patients. Daily insulin dosage adjustment of home care diabetic patients is done by themselves or their caregivers based on periodic glucose measurements. This requires home care patients to be frequently in contact with the health expert (doctor, nurse). In this study, we propose a decision support method for dynamic adjustment of daily insulin dosages of diabetic patients, and also present implementation of a mobile application for remote monitoring. The proposed decision support method is based on existing information provided as forms to patients in diabetes clinics. The developed application has properties such as recording of glucose measurements, monitoring of these measurements, notification of insulin dosage adjustment as a result of decision support algorithm, appointments, and direct messaging with an expert.

1. Introduction

Due to the COVID-19 pandemic that has affected the whole world in recent years, people do not leave their homes to reduce the spread of the virus and prefer not to go to hospitals unless there is an emergency case. Diabetes patients who need long-term follow-up and treatment are among the people most affected by this condition. Unfortunately, diabetics require lifelong insulin supplements, and adjustment of insulin dosage is a critical issue. With the developing technologies, remote patient monitoring (RPM) systems allow vital parameters of the patient to be monitored continuously. As a result of remote real-time monitoring and easy access to the doctor, glycemic control goals can be achieved and diabetes follow-up can be effectively controlled [1].

Clinical Decision Support Systems (CDSS) is a health information technology system designed to provide clinicians and other healthcare professionals with clinical decision support (CDS), that is, aid in clinical decision-making tasks [2]. Clinical decision support systems are divided into non-knowledge-based clinical decision support systems and knowledge-based clinical decision support systems.

Knowledge-based clinical decision support systems consist of three parts: a knowledge base, an inference engine, and a communication mechanism. [3] The knowledge base contains rules and relationships of compiled data, mostly in the form of IF-THEN rules. The inference engine combines the rules in the knowledge base with the patient's data. The communication mechanism allows the system to show the results to the user and get input into the system [4]. These systems have qualified information about disease detection, treatment options, which drug should be used, and they help physicians to evaluate the patient in the best way by combining up-to-date information with specific patient information. Non-knowledge-based clinical decision support systems use machine learning methods. This eliminates the need for rule writing and expert input. However, most healthcare professionals do not use these results directly for diagnosis for reliability and accountability reasons, as machine learning-based systems cannot explain the reasons for their results [4].

Georga et al. have proposed a predictive model of short-term glucose homeostasis based on machine learning to prevent hypoglycemic events and long-term hyperglycemia. Data mining approaches are used as a tool to explain and predict long-term glucose control and the incidence of diabetic complications [5].

Kavak and Inner have presented end-to-end remote patient monitoring system called as ALTHIS which was designed and developed to transfer vital measurement values of patients to the hospital information system in real-time to ensure effective patient-doctor interaction, to make necessary notifications in critical situations [6]. There are four main modules included in ALTHIS: "Patient Assistant Module" mobile applications running on Android or IOS mobile devices, "Measuring Station" running on a touch screen PC, universal Windows platform application software that can work in integration with other hospital information systems. “Server and Monitoring System” and “Wearable Patient Monitoring Module”. As an ALTHIS application study, they focused on the monitoring of blood glucose measurements of diabetic patients. According to the measurements, a doctor-centered decision support system has been implemented for patients to use insulin.

Among Covid-19 cases, 20% - 50% of the cases are diabetic patients [7]. Based on this statistic, Joshi et al. have developed a mobile application referred to as intelligent Glucose Meter (iGLU) so that people who could not leave the house during the COVID-19 process could also remotely control their blood glucose levels. .
Joshi et al have also developed IGLU application, using which diabetic patients can measure their blood glucose in a non-invasive way. Its innovation is that it detects glucose molecules in the vein, measures blood, and automatically sends it to the cloud with near-infrared spectroscopy and machine learning algorithms without finger piercing [8].

iLog or SmartLog recommends the patient's food to be eaten for the patient-specific diet program. It detects the calories of food through the photo uploaded to the system and reports it to the patient [9,10].

As can be seen, many studies and researches have been carried out to make the lives of diabetes patients easier, especially during COVID-19 pandemic. In this study, we propose a decision support method that can be integrated into remote monitoring of diabetic patients based on the insulin dose forms manually presented to the patients in the diabetes clinic and implementation on a mobile application.

2. Insulin Dose Adjustment Decision Support Method

As can be seen from the system diagram in Figure 1, diabetic users record their daily blood glucose values via the mobile application on their Android phone. As a result of these stored records, the knowledge base of the decision support system is integrated into the application, operates the rules within it, and helps patient adjust his/her insulin dosage dynamically.

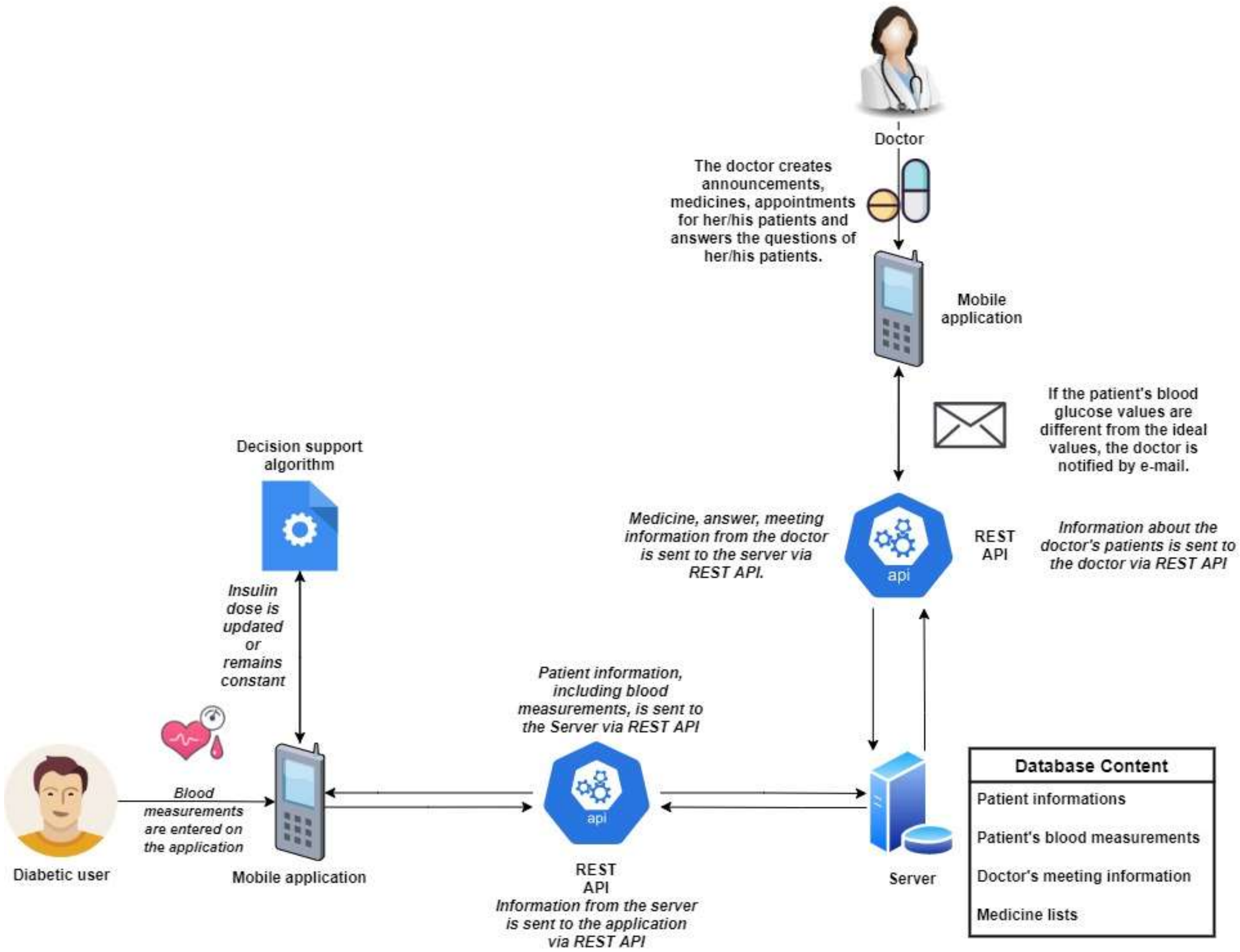


Figure 1. System diagram

The decision support mechanism is implemented daily for morning (t = 1), noon (t = 2), evening (t = 3), 11:00 p.m. (t = 4) and 03:00 a.m. (t = 5) times. It checks the blood glucose measurements for the last 3 days. Two separate blood glucose records are kept for the morning, noon, and evening times as fasting and full stomach cases. Single blood glucose measurement value (usually full stomach case) is kept for 11:00 p.m. and 03:00 in the morning. As the user enters blood measurements, the algorithm starts to run.

As a result of flows in the diagrams in Figure 2 and Figure 3, the patient is informed that the insulin dose should be increased if the blood glucose values are above the ideal values for 3 consecutive days or the insulin dose should be decreased if it is below the ideal values. The parameters in the Figure 2 and Figure 3 and their meanings are given in Table 1.

The summary of these 3 days is sent to the doctor automatically by e-mail. In addition, if the blood glucose decreases below 70 at any time, the insulin dose should be reduced the next day. If the fasting blood glucose in the morning is higher than 200 milligrams per deciliter, blood glucose should be checked at 03:00 a.m. All dosage adjustment values recommended by the model can be accessed by the doctor of the patient/user.

Table. 1

day	Number of day
t	1 (morning), 2 (noon), 3 (evening), 4 (23:00 p.m.), 5 (03:00 a.m.)
ins (day; t)	The insulin dose of the relevant day and meal
T_{TKS}	Instant blood glucose value for full stomach condition
T_{AKS}	Instant blood glucose value for fasting condition
O_{TOK}	Optimum blood glucose value for full stomach condition
O_{AC}	Optimum blood glucose value for fasting condition

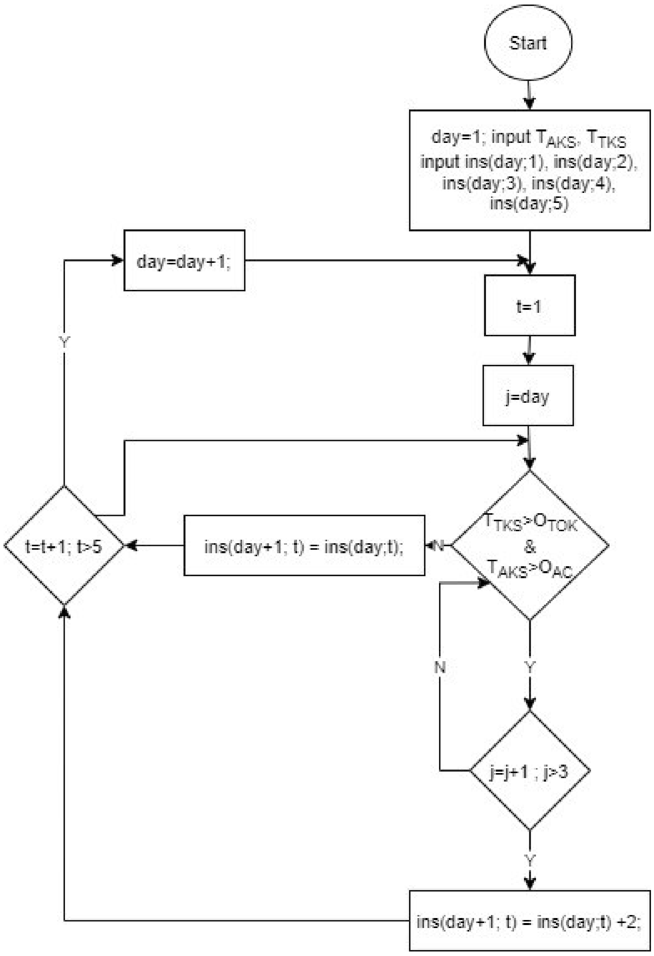


Figure 2. Flow diagram of the decision support in cases where blood glucose is greater than ideal values

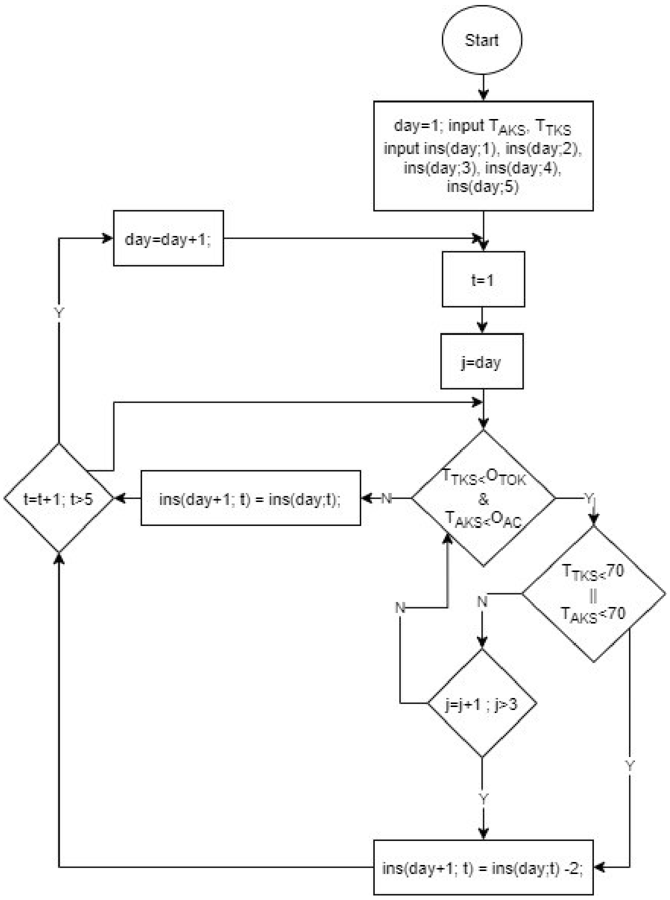


Figure 3. Flow diagram of the decision support in cases where blood glucose is lower than ideal values.

3. Diabetes Monitoring Mobile Application

The decision support method proposed in this study has been implemented into the Android mobile application. PHP was used in the mobile application and MySQL was preferred because it has built-in support as a database.

Figures 4 through 9shows screenshots of the developed mobile application. After the user registers and logs in, the main page appears. On the main page, the patient's "Appointments (Randevularim)", "Medicines (Ilaclarim)", "Enter Measurement (Olcum Gir)", "Measurement History (Olcum Gecmisim)", "Graphic (Grafik)", "Ask a Question (Soru Sor)", "Answers and Announcements (Cevaplar ve Duyurular)" titles are available as shown in Figure 4.

Figure 4. Mobile application main page

When the user enters her/his measurements from the screen in Figure 5, the user is asked for confirmation. If the user is sure that the values, she/he has entered are correct and approved, these data are recorded in the database. Patient information, including blood glucose values, is sent to the Server via REST API. If the user wants to change the values despite her/his approval, she/he can enter the measurement again. Old values in the database are updated with the new values.

Figure 5. User measurement entry page

From the "My Measurement History" button, the user can view her/his records in detail as in Figure 6.

Figure 6. User measurement history page

When the user presses the graphic button, she/he can view the history of the last added records as shown in Figure 7. With the morning, noon, evening, and night buttons, the user can easily follow up his/her recordings.

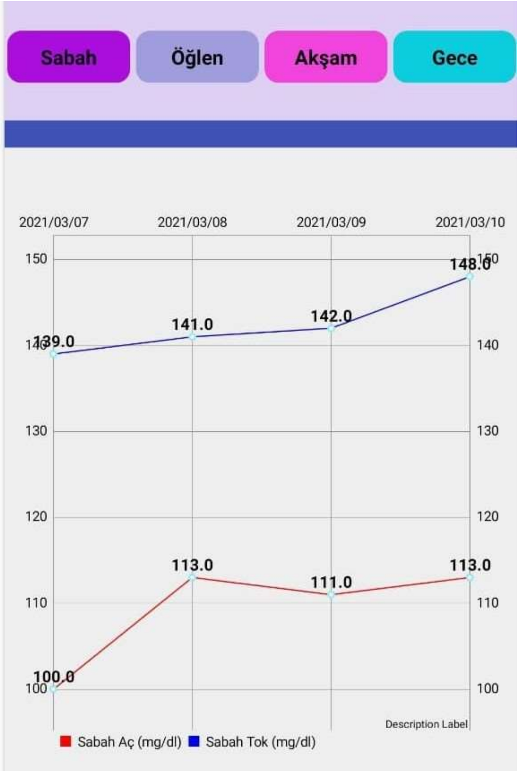


Figure 7. User graphic page (morning)

If the blood glucose values differ from the ideal values as in Figure 7, the dose increase/decrease warning generated as a result of running decision support algorithm is sent to the doctor as an e-mail message as shown in Figure 8. The warning also appears as a notification in the mobile application as shown in Figure 9.

Figure 8. Screenshot of the information e-mail sent to the doctor

Figure 9. Dose increase warning screenshot to the patient

As you can see in Figure 1, diabetic user can enter blood values via the mobile application and adjust the insulin dose with the decision support system. In the server, there is personal information of the patient, blood measurements, information about the doctor, meeting information, and medicine lists in the database. The doctor can access this information via the mobile application on her/his phone and contact the patient when necessary, add medicine and display it.

4. Conclusion

In this paper, a study on remote patient monitoring, which gained importance especially with the COVID-19 outbreak, is presented. In this study, a clinical decision support system based on manual form information used in the clinic is proposed for remote monitoring of diabetic patients. This proposed method has also been implemented on an Android-based mobile application. The developed mobile application is designed as a platform where the patient can enter daily blood glucose measurements, arrange their appointments, and also directly message the relevant specialist (doctor, nurse, etc.).

In the future work, this study can be expanded for gestational diabetes mellitus (GDM) patients. The most recent and relevant approaches for remote GDM management were presented in the study [11], but none of them provided a dynamic insulin adjustment for GDM patients. This led us to the development of a goal specific telemedicine decision support system for a GDM patients.

References

1. Katalenich, B., Shi, L., Liu, S., Shao, H., McDuffie, R., Carpio, G., Thethi, T., & Fonseca, V. (2015). Evaluation of a Remote Monitoring System for Diabetes Control. Clinical Therapeutics, 37(6), 1216–1225. https://doi.org/10.1016/j.clinthera.2015.03.022
2. Clinical decision support system. (2021). In Wikipedia. https://en.wikipedia.org/wiki/Clinical_decision_support_system
3. Dehghani Soufi, M., Samad-Soltani, T., Shams Vahdati, S., & Rezaei-Hachesu, P. (2018). Decision support system for triage management: A hybrid approach using rule-based reasoning and fuzzy logic. International Journal of Medical Informatics, 114, 35–44. https://doi.org/10.1016/j.ijmedinf.2018.03.008
4. Berner, E. S. (Ed.). (2007). Clinical Decision Support Systems: Theory and Practice (2nd ed.). Springer-Verlag. https://doi.org/10.1007/978-0-387-38319-4
5. Georga, E. I., Protopappas, V. C., Mougiakakou, S. G., & Fotiadis, D. I. (2013). Short-term vs. long-term analysis of diabetes data: Application of machine learning and data mining techniques. 13th IEEE International Conference on BioInformatics and BioEngineering, 1–4. https://doi.org/10.1109/BIBE.2013.6701622
6. Kavak, A., & İnner, A. B. (2018). ALTHIS: Design of An End to End Integrated Remote Patient Monitoring System and a Case Study for Diabetic Patients. 2018 Medical Technologies National Congress (TIPTEKNO), 1–4. https://doi.org/10.1109/TIPTEKNO.2018.8596906
7. Joshi, A. M., Shukla, U. P., & Mohanty, S. P. (2021). Smart Healthcare for Diabetes During COVID-19. IEEE Consumer Electronics Magazine, 10(1), 66–71. https://doi.org/10.1109/MCE.2020.3018775
8. Joshi, A. M., Jain, P., Mohanty, S. P., & Agrawal, N. (2020). iGLU 2.0: A New Wearable for Accurate Non-Invasive Continuous Serum Glucose Measurement in IoMT Framework. IEEE Transactions on Consumer Electronics, 66(4), 327–335. https://doi.org/10.1109/TCE.2020.3011966
9. Sundaravadivel, P., Kesavan, K., Kesavan, L., Mohanty, S. P., & Kougianos, E. (2018). Smart-Log: A Deep-Learning Based Automated Nutrition Monitoring System in the IoT. IEEE Transactions on Consumer Electronics, 64(3), 390–398. https://doi.org/10.1109/TCE.2018.2867802
10. Rachakonda, L., Mohanty, S. P., & Kougianos, E. (2020). iLog: An Intelligent Device for Automatic Food Intake Monitoring and Stress Detection in the IoMT. IEEE Transactions on Consumer Electronics, 66(2), 115–124. https://doi.org/10.1109/TCE.2020.2976006
11. Pais, S., Parry, D., Petrova, K., & Rowan, J. (2017). Acceptance of Using an Ecosystem of Mobile Apps for Use in Diabetes Clinic for Self-Management of Gestational Diabetes Mellitus. Studies in Health Technology and Informatics, 245, 188–192.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Healthy-Unhealthy Classification Using Respiratory Sounds and Shapley Values of Features

Fevzi Yasin KABABULUT [1] *, Damla GÜRKAN KUNTALP [1], Mehmet KUNTALP [1]

[1] *Dokuz Eylul University, Dept. of Electrical Electronic Engineering, Turkey*

* Corresponding Author: Dokuz Eylul University, Faculty of Electrical Electronic Engineering, Turkey
Tel.: +90 505 7683927. E-Mail: fevziyasin.kababulut@ogr.deu.edu.tr

Publication Information

Keywords :
- Machine learning algorithms,
- Shapley value,
- Lung diseases,
- Binary classification

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Due to the effects of prolonged human life and modern living conditions, respiratory diseases have been increasing throughout the world. Therefore, it is important to correctly diagnose these diseases by simple and automated methods. In this study, five different machine-learning algorithms are examined for classifying respiratory sounds as healthy or unhealthy using three different feature sets, namely, Power Spectral Density (PSD), Variance of PSD and Mel Frequency Cepstral Coefficients (MFCC). Two different performance criteria are used to evaluate the classification performance. The classification results of the algorithms are all around 87% according to the total and balanced accuracy criteria. In addition, Shapley Values of PSD, Variance of PSD and MFCC feature sets are evaluated for their influence on the classification of healthy and unhealthy respiratory sounds. Results show that PSD feature set provides the highest contribution to the classification performances in all algorithms in terms of either total accuracy or balanced accuracy or both. Variance of PSD feature provides the highest contribution to in Logitboost algorithm in the terms of total accuracy. MFCC feature set is the most effective one in K-NN algorithm in terms of the balanced accuracy criterion.

1. Introduction

The prevalence of smoking and air pollution are among the most common reasons why lung diseases are one of the most common diseases in the world. When you take into consider also occupational work environments that contain harmful gases and passive smokers who are affected by secondhand smoking, it is normal that there are millions of people suffering from these diseases in the world. Undoubtedly, accurate diagnosis of lung diseases that affect so many people is very important. A pulmonologist makes this diagnosis by listening to the patient's complaints (anamnesis), by performing a medical examination and by listening to the patient's lungs with a stethoscope. The doctor may then request spirometry, chest x-ray and computed tomography to confirm the diagnosis and to see the patient's lung condition in detail. However, the doctor's listening to the patient's respiratory sounds (auscultation) with a stethoscope is the most critical step for making a diagnosis. In this study, our aim is to make healthy and unhealthy classification by using different algorithms from respiratory sounds recorded with digital stethoscope.

In the literature, there are many studies that classify patients' respiratory sounds by machine learning algorithms. When we look at these studies, it is seen that the algorithms developed either to classify the abnormal sounds such as wheeze and crackle, which are the symptoms of lung diseases, or to classify the common lung diseases such as Asthma, Pneumonia and Chronic Obstructive Pulmonary Disease (COPD). Unhealthy respiratory sounds contain sounds with distinctive characteristics such as wheeze, crackle, rhonchi, stridor, squawks, and bronchial, depending on type of the disease. The studies in the first group focus only on the classification of these abnormal sounds. In the second group, the studies concentrate on binary classification to determine whether the person has a certain lung disease (asthma, pneumonia or COPD) or not.

In a study, it was determined from the lung sounds whether patients were healthy or asthma using random forest, random forest combined with adaboost and artificial neural networks [1]. In this study, 40 lung sounds from 20 patients were recorded at Gaziantep University Faculty of Medicine. The wavelet coefficients of these sound recordings are calculated and 4 different statistical features of the appropriate ones were extracted. When these extracted features were used as input data, accuracy of the random forest and adaboost algorithms were 90.00%, while accuracy of the artificial neural networks algorithm was 80.00%.

In another study [2], the classification of patients as COPD or not by using Forced Oscillation measurements was performed with K-NN, Linear Bayes Normal Classifier, Decision Tree, Support Vector Machine and Artificial Neural Network classifiers and their performances were compared. The forced oscillation method was used in this study consists of applying small variations of sinusoidal pressure to stimulate the respiratory system at higher frequencies than normal respiratory frequency and to measure the flow response of the respiratory system. Seven feature parameters of the measurements obtained by this method were used as input data in the classifiers. In the evaluation using all of these features, the classifier K-NN method which gave the best performance according to Accuracy (ACC) and Area Under the Curve (AUC) criteria were 97% and 100%, respectively.

In [3], Fuzzy Logic (FL) and ANNs were used together for classifying patients as COPD or asthma by using Impulse Oscillometry System (IOS) and spirometry measurements. Impulse oscillometry system is a kind of forced oscillation method that can calculate passive measurements of lung mechanics. Spirometry test is a test method that measures the intensity and velocity of air passing through a pipe-like system in unit time. The results obtained from these two methods were graded with a fuzzy logic software and used as input data of artificial neural network. In this study, Linear Feed Forward Artificial Neural Network classifier used Levenberg-Marquardt (LMA) training algorithm. The classifier correctly classified 99.41% of patients with asthma, and 99.19% of patients with COPD.

In another study, the classification of respiratory sounds as normal, wheezing or crackle was done by MLP Neural Network classifier by using Mel Frequency Cepstral Coefficient (MFCC) as the feature extraction method [4]. In this study, MFCC method was compared with Linear Estimation Cepstral Coefficient (LPCC), Perceptual Linear Estimation Cepstral Coefficient (PLPCC), Linear Frequency Cepstral Coefficient (LFCC), Inverse Mel Frequency Cepstral Coefficient (IMFCC) methods as the feature extraction method. Results showed that MFCC method was the most successful one in terms of sensitivity, specificity, and overall accuracy.

In another study, the average power spectral density (PSD) of breathing sounds was used as the feature vector, and normal or abnormal sound distinction was made by means of back propagation neural networks [5]. 1085 voices (390 abnormal) recorded from neurological intensive care units were used for training, 1042 voices (398 abnormal) were used for the test. 168 voices (119 abnormal) obtained from clinical training tapes were used for training, while 153 voices (132 abnormal) were used for the test. The performances of the neural network algorithm that used these two datasets separately and by combining them were compared, the algorithm using training tapes as the input data set showed the best performance with 91%. Neural network algorithms with different architectures were compared and the algorithm with one hidden layer having 14 neurons gave the best performance with 73%.

A study using machine learning algorithms to detect pneumonia from chest x-ray dataset examined the performance of the system using Shapley Value analysis [6]. In this study, feature vectors were extracted from x-ray images by means of a previously trained convolutional neural network (CNN). Using these vectors as input data, pneumonia was detected by logistic regression method. Then Shapley values of the features are calculated. In the prediction made by subtracting the highest 100 Shapley valued features from the data, it was seen that the performance of the model was decreased, while the performance increased when the lowest 100 Shapley valued features were removed. It was determined that 80% of 100 randomly selected chest x-ray images are correctly identified .

2. Description of Dataset

International Conference on Biomedical and Health Informatics (ICBHI) database is a public data set of lung sounds created with the contributions of the Universities of Coimbra and Aveiro from Portugal and University of Thessaloniki from Greece. This data set includes 919 lung sounds recordings from 125 people duration ranging from 10 sec to 90 sec. These recordings last 5.5 hours in total and include 6895 respiratory cycles. 1864 respirotary cycles includes crackles, 882 respirotary cycles includes wheezes and 506 respirotary cycles includes both crackles and wheezes. 125 people from whom these lung sounds were obtained, 26 of them are healthy people and 99 of them are patients with 7 different lung diseases. Half of the healthy sounds belongs to women. The average age of people with healthy pulmonary sounds is 6.20, the standard deviation is 5.18. 32.32% of unhealty sounds belongs to female patients and 66.67% of them belongs to male patients. The gender of 1.01% is unknown. The average age of people with unhealthy pulmonary sounds is 52.48, the standard deviation is 29.14. As seen in Table 1, 35 of 919 respiratory sounds are normal, while 884 are belong to 6 different lung diseases. These are: Upper Respiratory Tract Infection (URTI), Chronic Obstructive Pulmonary Disease (COPD), Lower Respiratory Tract Infection (LRTI), Bronchiectasis, Pneumonia, and Bronchiolitis.

Table 1. Distribution of sound recordings of ICBHI Database according to lung diseases

Healthy	URTI	COPD	LRTI	Bronchiectasis	Pneumonia	Bronchiolitis
35 (%3,81)	23 (%2,50)	793 (%86,29)	2 (%0,22)	16 (%1,74)	37 (%4,03)	13 (%1,41)

As seen in Table 1, the records of patients with COPD constitute the majority of the data set. This distribution makes it difficult for machine learning algorithms to learn classes other than COPD, which leads to a performance reduction. In the ICBHI database, the informations about how many respiratory cycles each lung sound record has, when the cycle begins and ends, whether it includes crackle and wheeze sounds are available as text files. With the help of this informations, in order to make the distribution more homogeneous in this data set, we augmented the data by accepting the respiratory stages of the records of other classes as if they were separate records. As seen in Table 2, our dataset is the ICBHI database with 2 classes (Healthy and Unhealthy) (1312 records were reserved for train, 595 records were reserved for testing) which is constructed with the data augmentation. The records of LRTI patients were excluded due to their very few numbers.

Table 2. Distribution of sound recordings of the dataset

Healthy	Unhealthy
322 (%16,89)	1585 (%83,11)

3. Proposed Methods

Most machine learning algorithms need features that describe the problem to solve a problem. In this study, we used two of the most commonly used features for sound data in the literature, namely Power Spectral Density (PSD) and Mel Frequency Cepstral Coefficients (MFCC).

In the study, we first obtained the PSD estimations of sound recordings with different lengths using Welch method. The number of samples of sound recordings changes from 8.821 to 882.000 and the sampling frequencies vary between 44.1 kHz and 4 kHz. One tenth of the sampling frequency is taken as a common window length for all signals. Power in different bands are calculated for each of the PSD estimates. For recordings with a sampling frequency of 4 kHz, we calculated the average power in intervals of 4 Hz up to 250 Hz., intervals of 20 Hz between 250 Hz and 1 kHz, and intervals of 240 Hz from 1 kHz to 2 kHz. For recordings with sampling frequency of 44.1 kHz, in order to extract features with the same size, the power in the intervals of 44.1 Hz up to 2.756,25 Hz., intervals of 220.5 Hz between 2.756,25 Hz and 11.135,25 Hz, and intervals of 2.646 Hz upto 21.719,25 Hz. This way, total of 105 average power values are calculated as PSD features for each record. Also, some statistical PSD-based properties (mean, median, variance, and skewness of the PSD estimates in different intervals) are calculated as features. According to the total and balanced accuracy criteria, variance of PSD feature provided the best performance.

For the calculation of MFCC, first the signal is divided into small time frames. Windowing is then used to highlight the desired frequencies. Discrete Fourier Transform (DFT) of this signal is taken and the transformed signal is passed through different band pass filters, and Mel Power Spectrum coefficients are calculated. These coefficients are finally passed through the Discrete Cosine Transform to calculate the MFCC coefficients of the signal. The features we used in this study and their dimensions are shown in Table 3.

Table 3. Features and Their Dimensions

Features used in Training Stage	Features used in Test Stage
PSD (1312x105)	PSD (595x105)
MFCC (1312x14)	MFCC (595x14)
Variance of PSD (1312x105)	Variance of PSD (595x105)

Random Forest algorithm is a supervised machine learning algorithms. The word “forest” comes from the fact that the algorithm is a decision tree-based algorithm, and the word “random” comes from the random generation of the forest from these decision trees. The randomness is achieved by the bagging method, which enables random selection of the features that form the branches of decision trees. In summary, the Random Forest algorithm combines more than one decision tree and make classification by majority voting method.

The entropy of a random variable is calculated as follows [7].

$$E\left(B\right) = -\sum_{i=1}^{n} P(B=b_i)\log_2 P(B=b_i) \tag{1}$$

High entropy decreases the predictability of that random feature. When there are two variable, conditional entropy of a random variable *B* which is conditioned on a random variable *A*, is calculated as follows [7].

$$E\left(B/A\right) = -\sum_{j=1}^{l} P(A=a_j)\sum_{i=1}^{k} P(B=b_i/A=a_j)\log_2 P(B=b_i/A=a_j) \tag{2}$$

The gain is calculated as follows according to the calculated entropy values [1].

$$G(A) = E(B) - E(B/A) \tag{3}$$

As seen in Equation (3), the random feature with low entropy value, that is, high gain, is selected as the first node in the random forest algorithm and the entropy and gain values of the next nodes are updated and recalculated. When all the nodes are determined, the first decision tree of the random forest algorithm is created. The tree structure we see in Matlab software is actually the structure of the first decision tree (Figure 1).

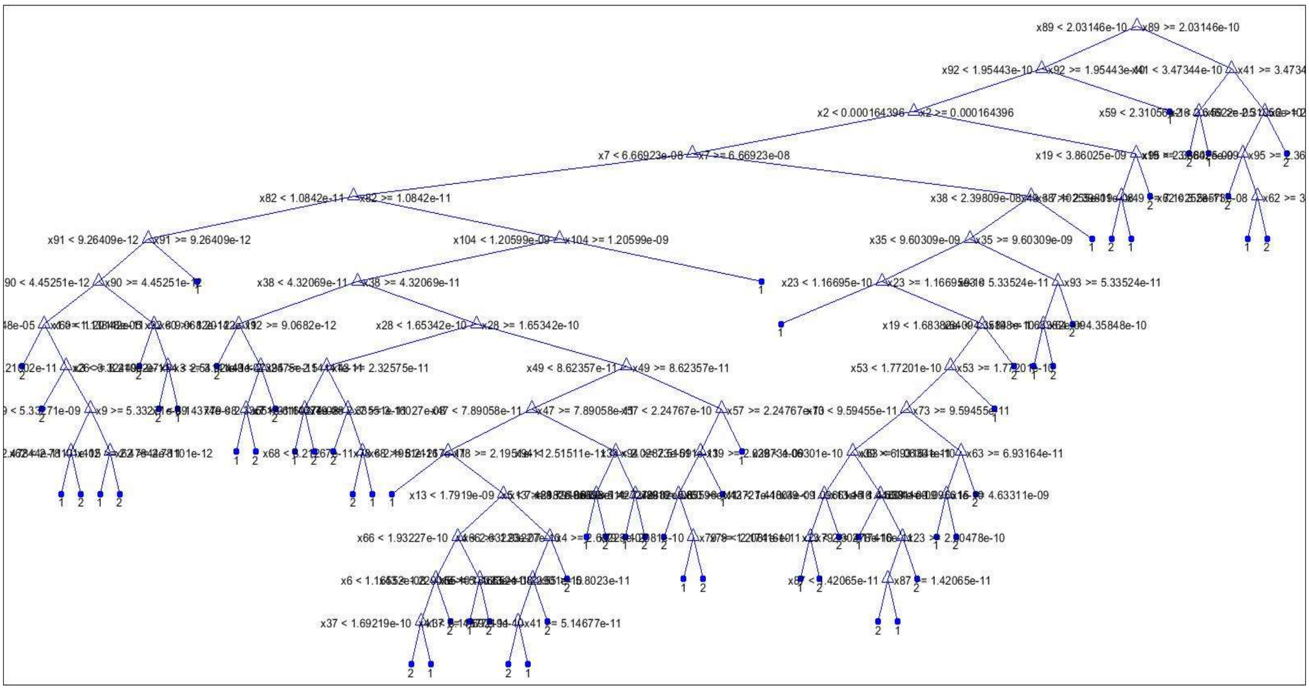


Figure 1. First Decision Tree of 2-Class Random Forest Algorithm using PSD Feature

Adaptive Logistic Regression (Logitboost) algorithm is one of the common ensemble algorithms used in binary classifications. Logitboost algorithm works similar to Adaboost algorithm, but it is different in minimizing Binomial Deviation (*BD*) value shown in Equation 4 [8].

$$BD = h_n \log\left(1 + \exp\left(-2b_n f\left(a_n\right)\right)\right) \tag{4}$$

b_n is the true class label and takes values between {-1, +1}. h_n are the observation weights that are normalized and sum of them is equal to one. $f\ (a_n)$ are the predicted classification scores and range between (-∞,+∞). Logitboost algorithm tries to make a better prediction by giving smaller values to the weights of misclassified observations (large negative values of the $b_n f\ (a_n)$ expression) in the binomial deviation calculation. Logitboost algorithm may give better results than the Adaboost algorithm when considering the total accuracy criterion for data that can be separated hardly [8].

Linear Programming Boosting (Lpboost) algorithm is an ensemble algorithm that solves classification problems by maximizing the minimum margin value in the training set. This maximization process is done with optimization algorithms called linear programming.

The margin value is the difference between the soft voting score of the algorithm when it classifies correctly and the highest score of it when it classifies incorrectly. In soft voting, the prediction probabilities of individual trees are added together and the prediction with the largest sum is selected [9]. In decision tree-based algorithms, the score for a leaf node is the posterior probability of the classification at that node. The posterior probability of the classification at a node is the ratio of the number of observations at the last branch of that node which the classification is made to the total number of observations of that node.

The reason Lpboost algorithm tries to maximize the minimum margin is to reduce the generalization error. The generalization error is equal to the probability of obtaining a negative margin [8]. Schapire and Singer [10] used the inequality 5 in their work considering the possibility of obtaining a negative margin.

$$P_{test}\left(m \leq 0\right) \leq P_{train}\left(m \leq 0\right) + O\left(\frac{1}{\sqrt{S}}\sqrt{\frac{d\log^2\left(S/d\right)}{Q^2} + \log\left(1/\delta\right)}\right) \tag{5}$$

m is the margin, Q is any positive number, d is the size of the classification space, S is the size of the training set, and δ is a small positive number. In Lpboost algorithm, ensemble members are sorted from the highest weight to the smallest in order to increase performance, so that unimportant ensemble members can be easily removed.

Totally Corrective Boosting (Totalboost) algorithm is an ensemble algorithm that is similar to Lpboost algorithm, with properties such as maximizing the minimum margin value and removing unimportant ensemble members, and is often used in multi-class separation problems.

Totalboost algorithm obeys the constraint that the weighted margin is below a certain value, and minimizes the proxy of the Kullback-Leibler divergence between the current weight distribution and the initial weight distribution. The proxy here is the quadratic extension of the divergence and is calculated as in the Equation 6.

$$P\left(W, W_0\right) = \sum_{k=1}^{K}\log\frac{W\left(k\right)}{W_0\left(k\right)} \approx \sum_{k=1}^{K}\left(1 + \frac{W\left(k\right)}{W_0\left(k\right)}\right)\Delta + \frac{1}{2W\left(k\right)}\Delta^2 \tag{6}$$

In this equation, Δ represents the difference of the weights in the present and the next iteration, and W_0 represents the initial weights of which distribution is uniform. This optimization process prevents the weights from being equal to zero. However, Totalboost algorithm solves the problem slowly due to the constraints of the optimization process in large iteration problems.

K-Nearest Neighbor (K-NN) algorithm is one of the most used supervised machine learning algorithms. In K-NN, classification is made by looking at the distance of a sample whose class is not certain, to the samples with specific class (labeled) [11]. This classification consists of 3 stages. In the first stage, all samples, including the new sample, are placed in n-dimensional space according to their coordinates. In the second stage, the k (k = positive integer) nearest samples to the new sample are determined. This determination is made with distance calculations commonly used in the literature. We used Euclidean distance calculation in this study. In the third stage, the nearest k samples determined are counted for each class and new sample is assigned to that class from which there is a maximum number of neighbors [11]. The software we used in this study and their properties are shown in Table 4.

Table 4. Algorithms and their properties

Algorithm	Property
Random Forest	Number of Grown Trees=200
Logitboost	Number of Learning Cycles=200
Lpboost	Number of Learning Cycles=200
Totalboost	Number of Learning Cycles=200
K-NN	Number of Nearest Neighbour (k=7)

4. Performance Evaluations

In this study, the performances of applied algorithms for healthy/unhealthy classification were evaluated according to total and balanced accuracy criteria.

Total Accuracy (*Tacc*) is one of the most used performance criteria for classification problems. Tacc is calculated as in Equation 7 as the ratio of the number of correctly classified samples to the total number of samples [11],

$$Tacc = \frac{k_{corr}}{N} \tag{7}$$

where k_{corr} is the number of correctly classified samples and N represents the total number of samples.

Balanced Accuracy (*Bacc*) is another performance criterion used for classification problems where all class accuracies are averaged. It is calculated as in Equation 8.

$$Bacc=\frac{1}{m}\sum_{i=1}^{m}\frac{k_i}{N_i} \tag{8}$$

where m denotes the total number of classes, k_i is the number of correct decisions for class i and N_i represents the total number of samples for that class.

The performances of our softwares using different features are shown in Tables 5 to 9. The best performances in the tables are emphasized by employing boldface characters.

Table 5. Performance values of Random Forest Algorithm using three different features.

Feature	Total Accuracy	Balanced Accuracy
PSD (595x105)	% 86,39	% 86,28
MFCC (595x14)	% 85,71	% 74,34
Variance of PSD (595x105)	% 81,68	% 67,57
PSD+MFCC (595x119)	% 84,03	% 83,40
PSD+Variance (595x210)	**% 87,06**	**% 86,33**
MFCC+Variance (595x119)	% 82,35	% 71,57
PSD+MFCC+Variance (595x224)	% 85,88	% 83,81

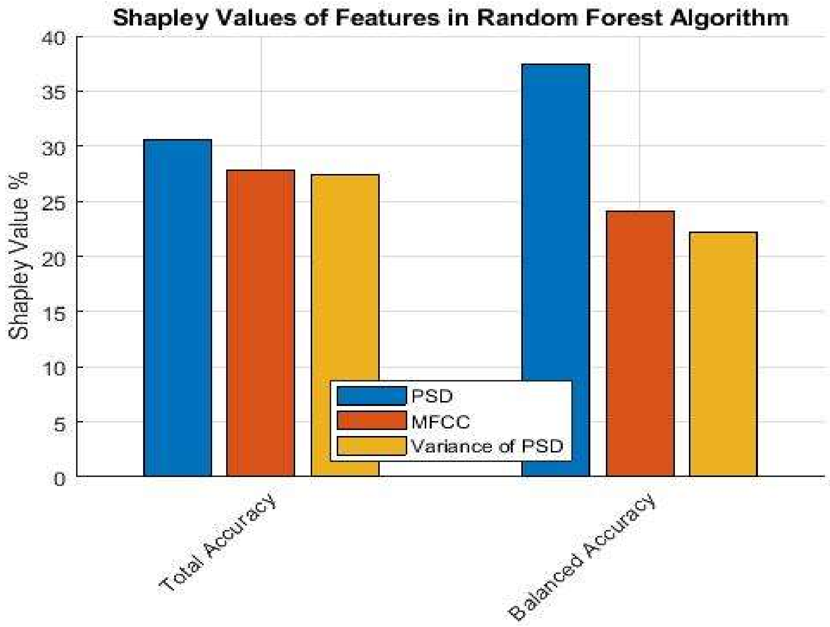


Figure 2. Shapley Values of Features in Random Forest Algorithm

Table 6. Performance values of Logit Boost Algorithm using three different features.

Feature	Total Accuracy	Balanced Accuracy
PSD (595x105)	**% 85,04**	% 87,62
MFCC (595x14)	% 83,03	% 75,94
Variance of PSD (595x105)	% 83,70	% 80,31
PSD+MFCC (595x119)	% 81,85	% 86,03
PSD+Variance (595x210)	% 84,54	**% 87,67**
MFCC+Variance (595x119)	% 83,36	% 85,51
PSD+MFCC+Variance (595x224)	% 83,70	% 87,52

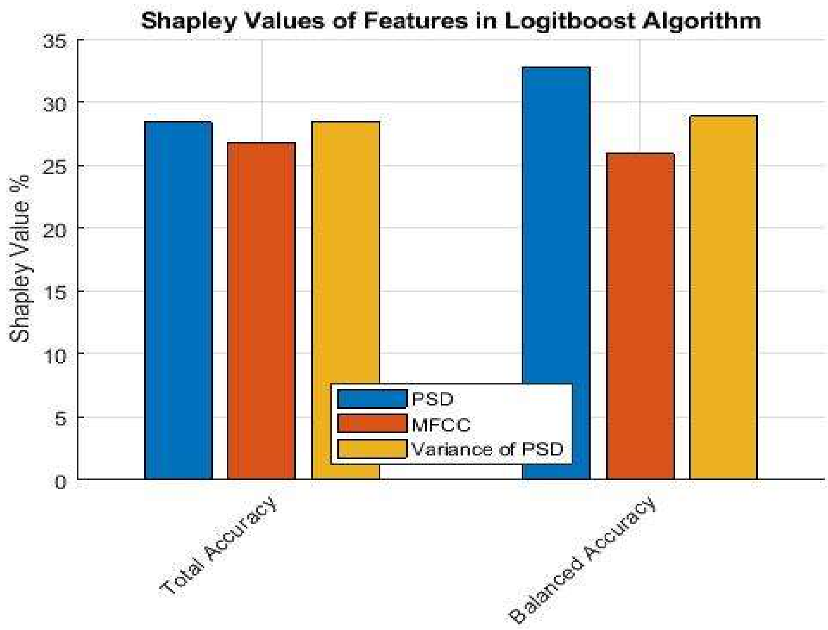


Figure 3. Shapley Values of Features in Logitboost Algorithm

Table 7. Performance values of LPBoost Algorithm using three different features.

Feature	Total Accuracy	Balanced Accuracy
PSD (595x105)	% 84,03	% 86,28
MFCC (595x14)	% 83,87	% 75,01
Variance of PSD (595x105)	% 80,34	% 73,22
PSD+MFCC (595x119)	% 84,03	% 85,92
PSD+Variance (595x210)	**% 85,71**	**% 87,67**
MFCC+Variance (595x119)	% 82,18	% 79,75
PSD+MFCC+Variance (595x224)	% 83,87	% 85,82

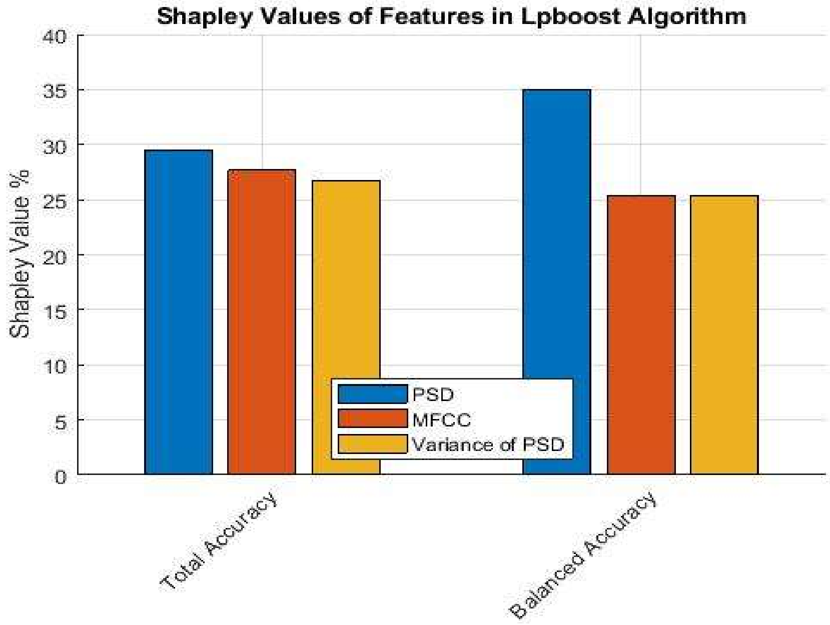


Figure 4. Shapley Values of Features in Lpboost Algorithm

Table 8. Performance values of Total Boost Algorithm using three different features.

Feature	Total Accuracy	Balanced Accuracy
PSD (595x105)	**% 84,54**	**% 86,95**
MFCC (595x14)	% 84,20	% 75,22
Variance of PSD (595x105)	% 81,85	% 75,58
PSD+MFCC (595x119)	% 80,84	% 84,33
PSD+Variance (595x210)	% 84,20	% 86,75
MFCC+Variance (595x119)	% 81,85	% 81,35
PSD+MFCC+Variance (595x224)	% 83,19	% 86,13

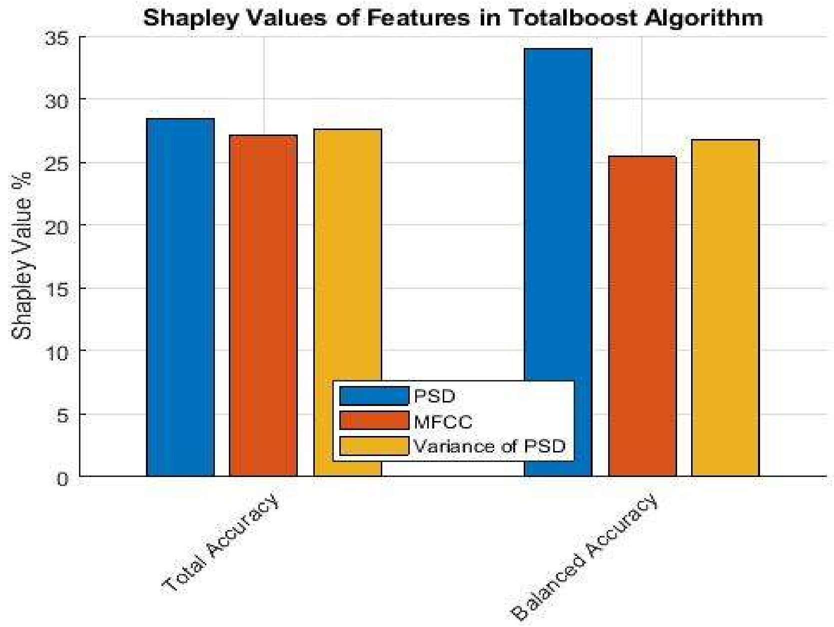


Figure 5. Shapley Values of Features in Totalboost Algorithm

Table 9. Performance values of K-NN Algorithm using three different features.

Feature	Total Accuracy	Balanced Accuracy
PSD (595x105)	% 79,33	% 72,24
MFCC (595x14)	% 78,15	% 74,76
Variance of PSD (595x105)	% 77,48	% 57,42
PSD+MFCC (595x119)	% 78,15	% 75,12
PSD+Variance (595x210)	**% 79,50**	% 71,98
MFCC+Variance (595x119)	% 78,32	**% 75,23**
PSD+MFCC+Variance (595x224)	% 78,15	% 75,12

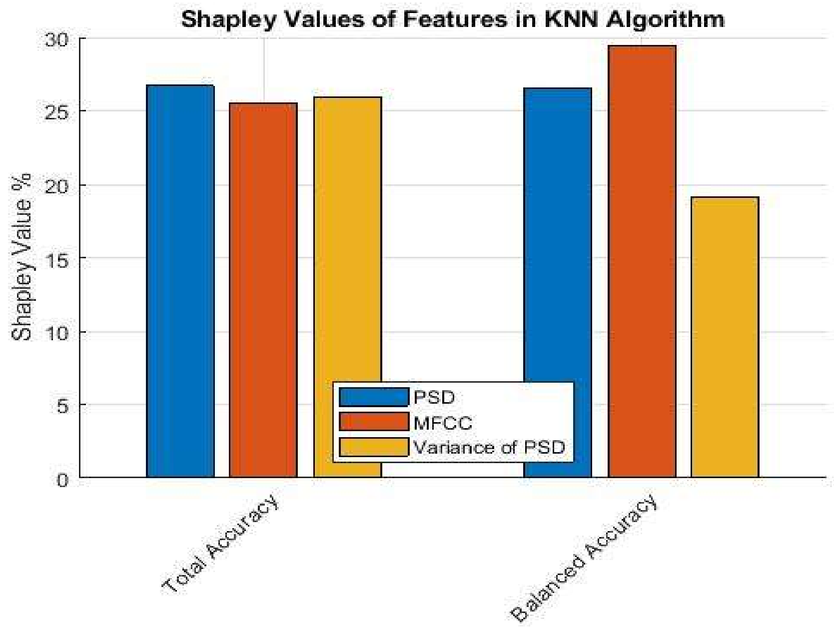


Figure 6. Shapley Values of Features in KNN Algorithm

Random Forest algorithm is the most successful one with total accuracy of 87.06% when it uses the combination of PSD and Variance of PSD features. According to this criterion, the Random Forest algorithm is followed by Lpboost, Logitboost, Totalboost, and K-NN algorithms, respectively.

Lpboost and Logitboost algorithms using the combination of PSD and Variance of PSD features, are our most successful algorithms with 87.67% performance according to the balanced accuracy criterion. According to this criterion, these algorithms are followed by Totalboost, Random Forest and K-NN algorithms, respectively.

To see how much the features contribute to the performances of algorithms, we calculated the Shapley Values of the features. For total accuracy criterion, PSD is the most effective feature with a contribution of nearly 30.00% at all algorithms except Logitboost. Variance of PSD feature is the most effective one at Logitboost algorithm with 28.48% contribution with respect to the same criterion.

For balanced accuracy criterion, PSD is the most effective feature with a contribution of nearly 35.00% at all algorithms except K-NN. On the other hand, MFCC feature is the most effective one at K-NN algorithm with 29.415% contribution for the same criterion.

5. Conclusions

In this study we try to classify lung sounds as healthy and unhealty using different classifiers and different feature set. We evaluated and comparedvthe results. Even with the unbalanced data set, (Healthy 16.89% - Unhealthy 83.11%), we were able to achive 87.00% succes rate. It is probable to have better results with a data set that have a more balanced distribution. In feature studies, additional features and different algotirthms might be examined for the purpose of classification of certain lung diseases.

We also examined the contributions of features to the classification performances of different algorithms by calculating Shapley Values of them. This analysis does not only provides interpretibility of the features in classification process but also increase the classification performance as a feature selection toool. A similar analysis would be conducted as a future study with introducing other features and for the classification of lung diseases rather than healty/unhealty classification problem.

References

1. N. Emanet, H. R. Öz, N. Bayram and D. Delen, " A comparative analysis of machine learning methods for classification type decision problems in healthcare," in Decision Analytics, vol. 1, pp. 6, 2014.

2. J. L. Amaral, A. J. Lopes, J. M. Jansen, A. C. Faria, and P. L.Melo, "Machine learning algorithm and forced oscillation measurements applied to the automatic identification of chronic obstructive pulmonary disease," in Comput. Methods Programs Biomedicine, vol. 105, no. 3, pp. 183-193, 2012.

3. A. Badnjevic, M. Cifrek, D. Koruga, and D. Osmankovic, "Neuro-fuzzy classification of asthma and chronic obstructive pulmonary disease," in BMC Med. Inform. Decis. Making, vol. 15, no. 3, p. S1, 2015.

4. N. Sengupta, Md Sahidullah and S. Goutam, "Lung sound classification using cepstral-based statistical features," in Computers in Biology and Medicine, vol. 75, pp. 118-129, 2016.

5. L. R. Waitman, K. P. Clarkson, J. A. Barwise, P. H. King, "Representation and Classification of Breath Sounds Recorded in an Intensive Care Setting Using Neural Networks," in Journal of Clinical Monitoring and Computing, vol. 16, pp. 95-105, 2000.

6. S. Tang and et. al., "Data Valuation for Medical Imaging Using Shapley Value: Application on A Large-scale Chest X-ray Dataset," in arXiv:2010.08006, 2020.

7. L. Breiman, " Random Forests," in Machine Learning, vol. 45, pp. 5-32, 2001.

8. MatlabR2019a, "Ensemble Algorithms," Statistics and Machine Learning Toolbox Documentation.

9. R. E. Schapire, Y. Singer, "Improved Boosting Algorithms Using Confidence-rated Predictions," in Machine Learning, vol. 37, pp. 297-336, 1999.

10. https://medium.com/@wvsharber/soft-voting-classifier-as-a-consensus-method-for-machine-learning-classification-24ebd4d49943 (April 2021).

11. G. Çelebi, Sayısal Stetoskop ile Elde Edilen Kalp Ses (Fonokardiyogram) Sinyallerinin Bölütlenmesi ve Sınıflandırılması, Yüksek Lisans Tezi, Ankara: Elektrik Elektronik Mühendisliği Anabilim Dalı, Hacettepe Üniversitesi, 2017.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || ISBN : 978-605-69730-2-4

More information available at aita.bakircay.edu.tr

Case and Inventory Management with Rfid Technology in Hospitals During the Covid-19 Pandemic Process

Murat KOCAPINAR [1,*] Mesut YILDIZ [1], Nebahat ÖNCEL [1], Orhan RAHMİ FESÇEKOĞLU [1], Selçuk GÖRÜCÜ [2], Yağmur BİRGİ ŞENTÜRK [3] Gencer YILMAZ [4], Fatih KARAKAYA [4]

[1]İzmir Provincial Health Directorat
[2]İzmir Provincial Health Directorat Hsu (Health Sciences University) Dr Suat Seren Chest Diseases And Chest Surgery Training And Research Hospital
[3]İzmir Provincial Health Directorat Izmir Kâtip Celebi University Atatürk Education And Research Hospital
[4]İzmir Provincial Health Directorat Izmir University of Health Sciences Tepecik Training And Research Hospital

* Corresponding Author: İzmir Provincial Health Directorat, Turkey
Tel .: +90444 35 01 E-Posta: murat.kocapinar@saglik.gov.tr

Publication Information

Keywords :
- Healthcare management,
- RFID,
- Patient and inventory tracking,
- Artificial intelligence,
- RTLS

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Today, the use of information technologies and artificial intelligence in health system management is increasing. During pandemic periods such as Covid19, it is evaluated that large capacity health institutions (such as city hospitals) that provide healthcare services may be at a disadvantage in terms of data management, analysis and reporting capabilities, functioning and speed of decision mechanisms and management. Like many developing information technologies, RFID (Radio Frequency Identification) technologies have started to find a place in health management. With this technology, it is predicted that it will provide an advantage in the effective use of time and cost in health institutions, medical equipment, and patient follow-up. With RFID technology, preventing possible contamination risks by ensuring that patients who need to be followed under isolation in hospitals during the pandemic process stay in the isolation rooms defined on the wristband, With RTLS (real-time location tracking) systems, it is aimed to provide patients with quality, fast and effective health care by reaching vital medical devices (ventilators, high flow oxygen therapy devices) in a timely manner through location signals.

1. Introduction

The Covid 19 virus outbreak occurred at the end of 2019 in Wuhan, China, and spread rapidly all over the world, causing nearly two million casualties. After the epidemic spread all over the world, the World Health Organization (WHO) declared this situation as a 'Pandemic' in March 2020, emphasizing that the situation is a major public health problem and emphasized that the effect of the measures to be taken by drawing attention to the 'epidemic' on Morbidity and Mortality will become very valuable [1,2]. For this reason, it is important to closely monitor Covid-19 (+) cases that need to be followed up under isolation in healthcare institutions in order to prevent the risk of uncontrolled transmission by contact.

2. Covid 19 Pandemic

Pandemic; In its simplest definition, it appears as the name given to infectious diseases that threaten a large number of people simultaneously in the world [3]. COVID-19 was also declared as a Pandemic by the World Health Organization (WHO) on March 11, 2020, when the first case was seen in our country. Within the scope of combating Covid-19, the Ministry of Health has started to share data such as the number of cases, the number of severe patients, the number of recovered patients, and the number of deaths from Covid-19 by the Ministry of Health. In this table, in accordance with the international definition for patients in need of intensive care, the number of Severe Patients has started to take place in the table [4]. Hence, intensive care bed capacities have gained serious importance in combating the epidemic.

3. Health System Management During Pandemic Process

Today, the use of artificial intelligence in healthcare areas is increasing. It is thought that data management, analysis and reporting, accurate and fast decision-making, and also tracking vital medical devices may be difficult for huge institutions providing healthcare services. For this reason, it is vital to be able to move quickly. In terms of manageability in large healthcare facilities (Training and Research Hospitals, City Hospitals, etc.) failure to ensure that patients remain stable, Inability to instantly access medical device and equipment data for patients in intensive care units (on the basis of health institutions and / or throughout the province to ensure patient and device coordination), Patients' relatives carry the risk of contamination through more frequent contact with healthcare personnel, as they cannot get enough instant information about their patients [5]. Ongoing pink code lawsuits (baby safety). Problems with device failure or effective use cases all over the world.

3.1 What is RFID?

Tag Structure, RFID is an automatic identification system consisting of a reader and a tag. Inside the label is a microchip and an antenna surrounding the microchip. RFID technology is a technology that identifies living and non-living things with radio waves [6]. RFID is a technology that performs data transfer wirelessly [7]. However, RFID is not a simple technology. From RFID tags, readers and computer networks, database and it consists of a complete system of special software. The use of RFID technology in healthcare fields as in every field It will provide great benefits [8].

3.2 Working Principle

The electromagnetic waves emitted by the reader activate the chip and data transfer takes place from the tag to the reader. All this happens at a distance, without any contact, and wirelessly. The reader transforms the data it receives into digital waves and transfers it to the computer [9].

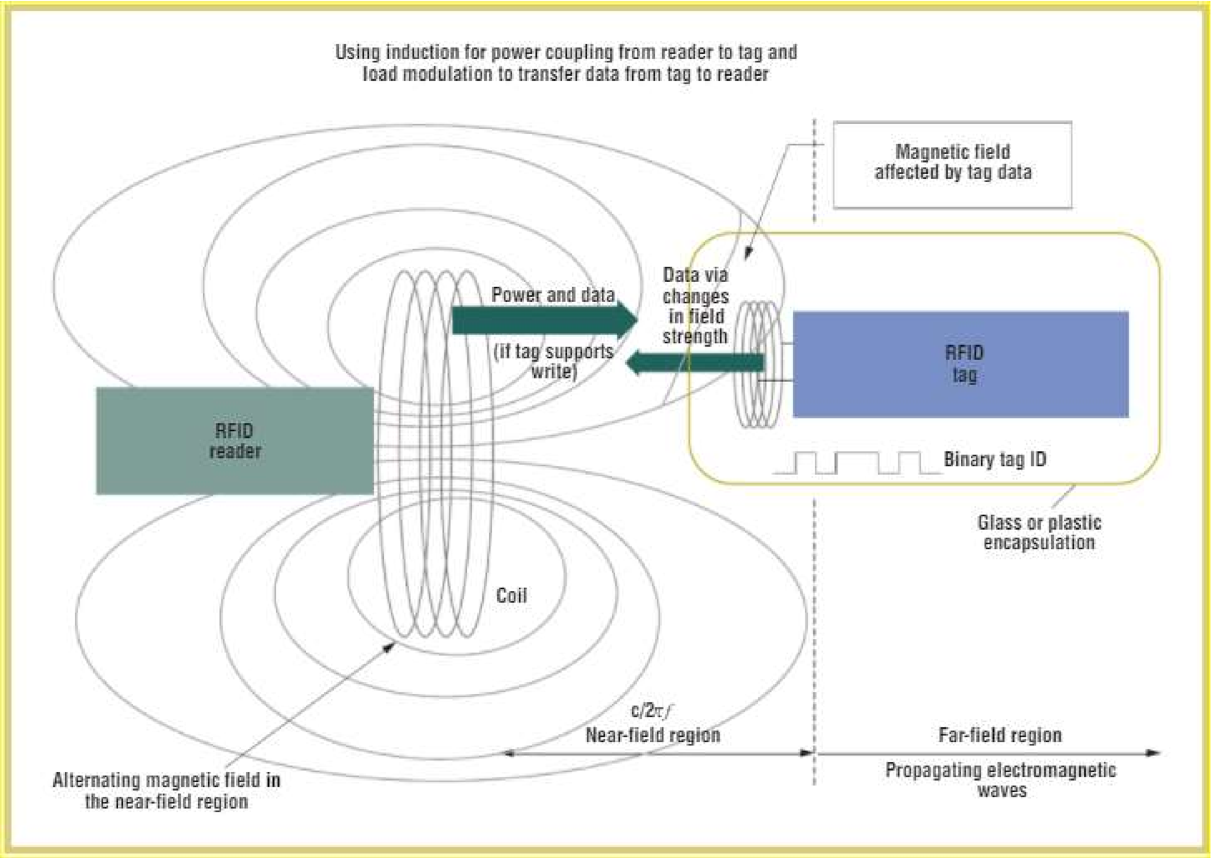


Figure 1. Near-field power/communication mechanism for RFID tags operating at less than 100 MHz. [10].

3.3 RFID usage areas

RFID identification systems today; Smart cards (MIFARE, ISO / IES 1443), credit cards, object tagging, ID cards, baggage tracking at airports, building entrance controls, OGS (active RFID), HGS cards and tags (passive RFID), Akbil (passive RFID), parking It is used in many areas such as automation, stock counting systems [9].

3.4 RFID Application Areas in Health

-Medical Devices and Medical Equipment Tracking
-Surgical Hand Tools Warehouse management
-Dry cleaner
-Patient Location Tracking
-Archive

3.5 Medical Device Tracking with RFID

Searching and finding mobile or specific medical devices and materials used in hospitals when needed causes serious time and labor loss. Real-time location tracking systems (RTLS) with RFID technology reduce the call time losses of hospitals. Being able to reach and deliver mobile devices with specific features (Ventilator, High Flow Oxygen Therapy Devices (HFOT) etc.) in a timely manner has saved lives. There are many different types of ventilator devices and respiratory support systems in our hospitals and in the market. However, there is a possibility that the ventilator you send in an area called need for a ventilator (which can sometimes be in another service and sometimes in another hospital) may not comply with the conditions of that environment. In such a case, it may result in loss of material and manpower due to the time-transportation process, as well as the loss of a patient. Likewise, it is vital to know / determine the location of High Flow Oxygen Therapy Devices or Ventilator devices with HFO module and function, which have increased in number and importance in hospitals due to the Covid 19 pandemic. Therefore, the data of where the devices with various features or mobile devices are at all times will enable the necessary decision mechanisms to work quickly and effectively in hospital management. Devices tagged with RFID technology can be tracked at any time thanks to the radiofrequency reader / sensors in the areas. This system will provide an effective and efficient management model in the use of a wide variety of specific devices and medical supplies found in hospitals during and after the pandemic.

4. Result and Evaluation

In this study, it is aimed that the problems that may be experienced with RFID technologies can be prevented. It is thought that accessing the medical device inventory instantaneously will reduce patient referrals both on the basis of central administration and on the basis of healthcare facilities, and accelerate the device transfer that can be made based on the need between institutions. At the same time, the active wires of the mother and the baby will be matched within the healthcare facilities, thereby reducing the risks of possible 'baby confusion' or 'infant abduction'. In this context, by defining the areas where babies should be located (neonatal clinics, audiometry, ophthalmology clinics, etc.), when they go out of these areas, they instantly inform the officers and give them the chance to intervene quickly. For this reason, it was aimed to end the 'code pink' events. Safe surgery is also very important in healthcare facilities that are large in square meters and have many operating theaters. However, it has become extremely important that the right patient is operated in the right operating room by the right physician. With the same wristbands, it is planned for the relatives of the patients to follow their patients by providing instant accurate information about the patient's status to the patient monitoring screens (patient; in the operating room, wake-up, M.R ... etc). Considering that RFID tags, whose costs are much lower than when they first appeared, facilitate our lives in many areas in daily life, it is predicted that more widespread use in healthcare areas will bring preactive intervention opportunities in managerial problems.

References

1. Outbreak of acute respiratory syndrome associated with a novel coronavirus, Wuhan, China; first update 22 January 2020. https://www.ecdc.europa.eu/sites/default/files/documents/ Risk-assessment-pneumonia-Wuhan -China-22-Jan2020.pdf. date of access 17.02.2021.
2. https://www.who.int/emergencies/diseases/novelcoronavirus-2019/technical-guidance/ naming-thecoronavirus-disease-(covid-2019)-and-the-virus-thatcauses-it). date of access 17.02.2021
3. https://www.bbc.com/turkce/haberler-dunya-51614548 date of access; 19.02.2021
4. https://covid19.saglik.gov.tr/ date of access; 19.03.2021
5. https://ankarasehir.saglik.gov.tr/TR,495580/ankara-sehir-hastanemizde--yenilikci-rfid-uygulamasi.html date of access; 12.03.2021
6. Chen, J., W. A., 2005. Ubiquitous Information Technology Framework Using RFID to Support Students' Learning,icalt, pp. 95-97, Fifth IEEE International Conference on Advanced Learning Technologies (ICALT'05).
7. Dowla, F., 2004. Handbook of RF & wireless technology. Elsevier, USA. Reconfigurable Architecture Workshop.
8. Pala, Z., Inanc, N., 2007. Automation with RFID Technology as an application: Parking lot circulation control (MSc, unpublished). Yuzuncu Yil University, Institute of Sciences, Van, Turkey.

9. Maraşlı, F., 2015. RFID Technology and Application Areas. BEU Journal of Science, 4(2), 249-275.
10. Want R., 2006. An Introduction to RFID Technology. IEEE Pervasive Computing. Intel Research. Santa Clara.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Investigation of Deep Learning Algorithms for COVID-19 Detection Based on Chest X-ray Images

Gökalp ÇINARER [1, *], Kazım KILIÇ [2]

[1] *Yozgat Bozok University, Dept. of Computer Technology, Turkey*
[2] *Yozgat Bozok University, Dept. of Computer Technology, Turkey Turkey*

* Corresponding Author: Yozgat Bozok University, Department of Computer Technology, Turkey
Tel.: +90 354 2175064. E-Mail: gokalp.cinarer@yobu.edu.tr

Publication Information

Keywords :

- Deep learning,
- Covid-19,
- DenseNet,
- SqueezeNet

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

In the last report of World Health Organization 2021, it has stated that 290,000 to 650,000 people may die each year with respiratory diseases caused by seasonal influenza. Additionally, it predicts that influenza will result in more deaths than other illnesses such as flu-related cardiovascular diseases. Sars-Cov-2 virus is also the deadly respiratory disease virus and has different mutations.

In 2020, about 1.8 million people died with the Covid-19 virus. The fastest detection and treatment of the disease should be initiated in the fight against COVID-19. The most important indicator that can be used in this regard is radiological data.

From this point of view, artificial intelligence (AI) systems based on deep learning will make it easier for radiologists to diagnose the disease in this process. Therefore, in this study, deep convolutional neural networks were used to detect COVID-19 cases from up to date chest radiography images with open source access.

DenseNet and SqueezeNet algorithms were used in data set for classification and feature extraction. X-ray images of normal and COVID-19 cases are scaled to 224x224 and the data set is divided into 80% training and 20% testing. The data augmentation process was applied to the images by making angular change, brightness change, horizontal and vertical shifts.

In classification with DenseNet and SqueezeNet algorithms, high accuracy values of 99.09% and 97.7%, respectively, were obtained by applying 30 epochs.

The results obtained have shown that artificial intelligence algorithms give very high accuracy results in detecting COVID-19 patients using chest X-ray radiography images.

1. Introduction

The coronavirus epidemic that occurred in Wuhan, China in 2019 affected the whole world. The disease caused by this virus was referred to in the literature as COVID-19. COVID-19, a highly contagious infection, spreads rapidly, especially through droplets and direct contact. The most common symptoms in symptomatic cases are fever, fatigue, muscle pain, sore throat and dry cough. According to the latest data of the World Health Organization (WHO) in April 2021, 3 million people worldwide died from the Covid-19 epidemic.

In COVID-19 pneumonia, early diagnosis and isolation are the main parameters in preventing the spread of the disease. It is also very important for the early treatment of the patient. It is essential to know the treatment methods well to prevent contamination especially during the incubation period. Real-time polymerase chain reaction (RT-PCR) test is used in the diagnosis of Covid-19 patients. This test is a very important parameter in detecting the virus. Although it is a very important test for diagnosis, obtaining the clinical results of Covid-19 patients with this method is quite time-consuming. In cases where RT-PCR results are negative and show symptoms, radiological data are usually guiding. In contrast, RT-PCR tests have also been found to produce false negative findings or fluctuating results in the diagnosis of COVID-19 cases [1].

Chest (computed tomography) CT examination is a very important method used in the follow-up of hospitalized COVID-19 patients [2]. In PCR positive patients, it may be necessary to examine CT images for close follow-up in terms of the course of the disease. On the other hand, when CT scans of covid-19 patients are examined, unilateral or bilateral unclear images can occur in the lung. In addition, the most common radiological finding is the ground glass appearance. Images may not be examined in detail in CT scans due to patient density and limited time. When the radiological images obtained from some patients were examined, chest x-rays of the patients were examined before the symptoms of COVID-19 and differences were observed in their CT images [3]. Therefore, there is a need for a rapid classification tool based on deep learning (DL) using CT images for the detection of COVID-19 infection.

Different artificial intelligence (AI) systems based on deep learning have been proposed for faster interpretation of COVID-19 radiographic images [4,5,6,7,8]. In the literature, it has been observed that the findings are very promising in the detection of patients infected with COVID-19 by radiographic imaging [9,10,11]. Wang and Wong proposed a deep learning model for the classification of normal, non-COVID pneumonia and COVID-19 patients in their study. They achieved 92.4% accuracy with the model recommended for COVID-19 detection [12]. In another study using the COVID-19 image, accuracy rates of 98.75% and 93.48% were reached for two and three classes with the deep learning model [13].

In this study, a deep learning-based classification system has been developed for the detection of COVID-19 disease from open source and publicly available chest radiography CT images. In the proposed model, an end-to-end architecture was designed with two different algorithms. In order to achieve a higher accuracy rate, data increase has been carried out. Classification model was trained with SqueezeNet and DenseNet-121 architectures. Using chest X-ray images with the proposed model, a higher detection rate was obtained in the diagnosis of COVID-19.

2. Material And Method

2.1 Data Set

In this study, the data set named Covid-19 radiography database [14] located in the kaggle was used to detect covid-19 from x-ray images. In this data set, there are four classes named Covid, Normal, lung opacity and viral pneumonia. In this data set, 3616 images from the covid class and 3600 images from the normal class were used in the study for the detection of COVID- 19. The file format of the images is PNG and the original size is 299x299. Covid-19 radiopraphy database continues to be updated by researchers.

2.2 Data Augmentatıon

The classification performance of deep learning models is directly related to the amount of data. Using large amounts of images during the training phase can improve performance. Data augmentation is a technique of artificially generating new training data from existing training data. In data augmentation technique, methods such as angular changes, horizontal and vertical shifts, zooms, brightness change are widely applied to existing data. The purpose of these processes is to duplicate the training data and enable the model to learn different versions of the existing image. In this study, data augmentation was carried out by applying brightness changes and angular changes and horizontal and vertical shifts to x-ray images in covid and normal class. Figure 1 shows a randomly selected group of images from class instances with data augmentation applied.

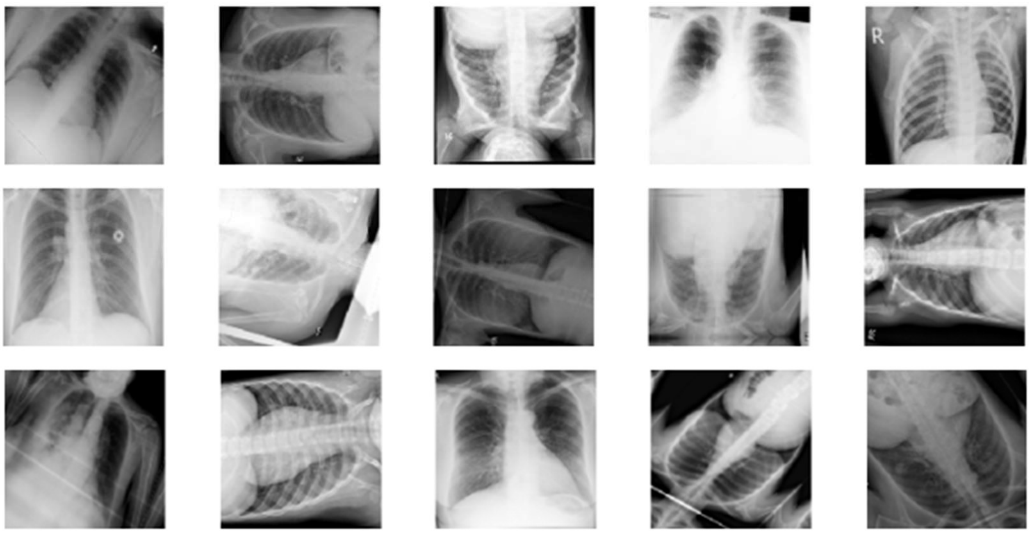


Figure 1. Data augmented COVID-19 X-ray images

2.3 Convolutıonal Neural Network

Deep learning architectures perform the process of learning from the representation of data, unlike classical machine learning techniques. Convolutional Neural Networks (CNN) are the most popular architecture among deep learning models. Due to its success in image classification in the Imagenet competition in 2012, CNN architectures are widely used in image analysis [15]. This architecture obtains features from the entrance image with convolution layers and realizes the processes of learning and predicting these properties with the artificial neural network model it has in the classification layer. In this study, current CNN architectures DenseNet and SqueezeNet architectures are used.

2.4 DenseNet-121

This architecture was introduced in 2016 by Gao Huang et al. [16]. DenseNet architecture, which has been widely used in recent years, has emerged as a result of trying to deepen convolutional neural network architectures. Traditional CNN architectures proceed by linking the information from each convolution layer to the next convolution layer. In densenet architecture, the outputs of each layer are directly linked to the next layers. This process allows the outputs of each layer to be combined in later layers. Combining feature maps learned by different layers increases the variety and efficiency in the input of the next layers. DenseNet's important advantages; it alleviates the gradient disappearing problem, improves feature propagation, allows feature reuse and significantly reduces the number of parameters. DenseNet architecture has widely used 121-169-201 layered architectures. The input image size of the network is 224x224. Besides 1x1 and 3x3 convolution filters are used in dense blocks. While 3x3 maximum pooling was used for pooling in the first layer, an average pooling size of 2x2 was used in transition layers. The number of steps is fixed as 2 in all layers.

2.5 SqueezeNet

Forrest N. Iandola et al. [17] introduced the Squeezenet architecture in 2016. CNN architectures that have emerged in recent years have often focused on improving accuracy. The aim of the SqueezeNet architecture is to reach the accuracy achieved by its competitors with less parameters and less memory consumption. For this purpose, the strategy implemented in SqueezeNet architecture consists of 3 steps. In the first step, the number of parameters is reduced by 9 times by replacing 3x3 filters with 1x1 filters. In the second step, the number of input channels is converted into convolution layers made up of 3x3 size filters. These processes take place in layers called fire modules. In the third step, late sampling in the network is provided. This ensures that the convolution layers have larger activation maps. Accuracy is tried to be increased with fewer parameters. SqueezeNet architecture starts with an independent convolution layer and then continues with 8 fire modules. The number of filters used in fire modules is gradually increased from the beginning to the end of the network. Maximum pooling is used for pooling and ReLu is used for activation.

2.6 Transfer Learning

Transfer learning is the process of using the successful learning information of the model used and trained in other tasks. In deep learning, pre-trained models are widely used to improve the performance of many tasks without further tagging data. An enormous amount of imagery is required to train deep learning models from scratch. The transfer learning method speeds up the classification task, allowing us to achieve high accuracy with a small amount of images. In this study, pre-trained ImageNet weights were used

3. Results

In order to detect the Covid-19 status from x-ray images, 5773 of 6016 images in total were reserved for the training process and 1443 for the verification process. Original size 299x299 X-ray images have been rescaled to 224x224. All experiments were carried out in cloud environment on Nvidia K80 Tesla graphics card using fast.ai open source python library [18]. The training cycle number is set to 30. The accuracy, AUC score, precision and recall values obtained as a result of 30 epochs are shown in Figure 2.

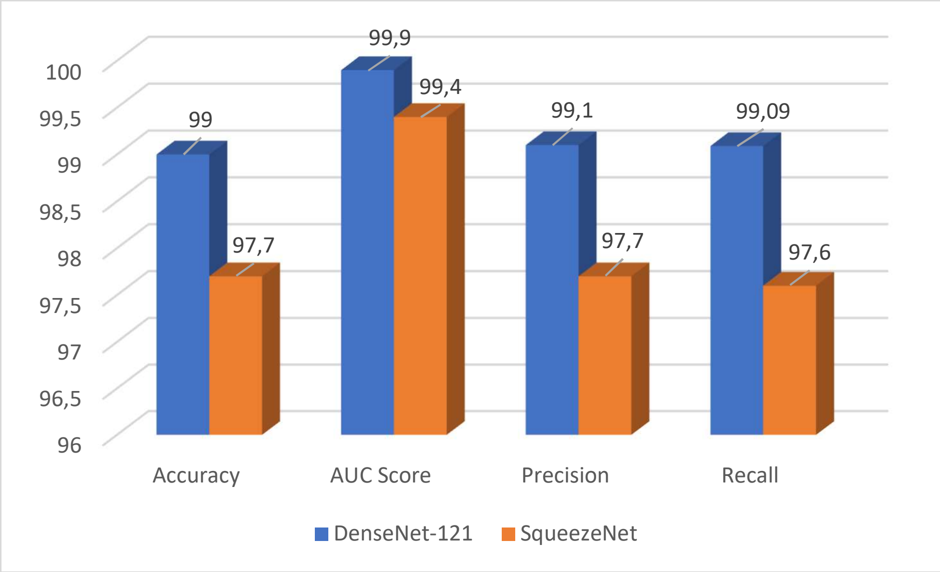


Figure 2. Performance comparison of the DenseNet-121 and SqueezeNet

As a result of the experiment, 99% accuracy was achieved by using DenseNet-121 architecture. SqueezeNet architecture reached 97.7% accuracy. The number of correct and incorrect predictions obtained with the two deep learning architectures used is shown in Table 1.

Table 1. DenseNet-121 and Squeezenet comlexity matrix

Actual	**DenseNet-121**	**Normal**	**719**	**2**
		Covid	**11**	**711**
	SqueezeNet	**Normal**	**732**	**8**
		Covid	**25**	**678**
			Normal	**Covid**
			Predicted	

Looking at the confusion matrix, it is seen that the DenseNet-121 architecture made 1430 correct predictions within 1443 images. It is seen that the SqueezeNet architecture classifies 1410 images correctly. The roc curves showing the auc score of DenseNet-121 and SqueezeNet architectures are shown in Figure 3.

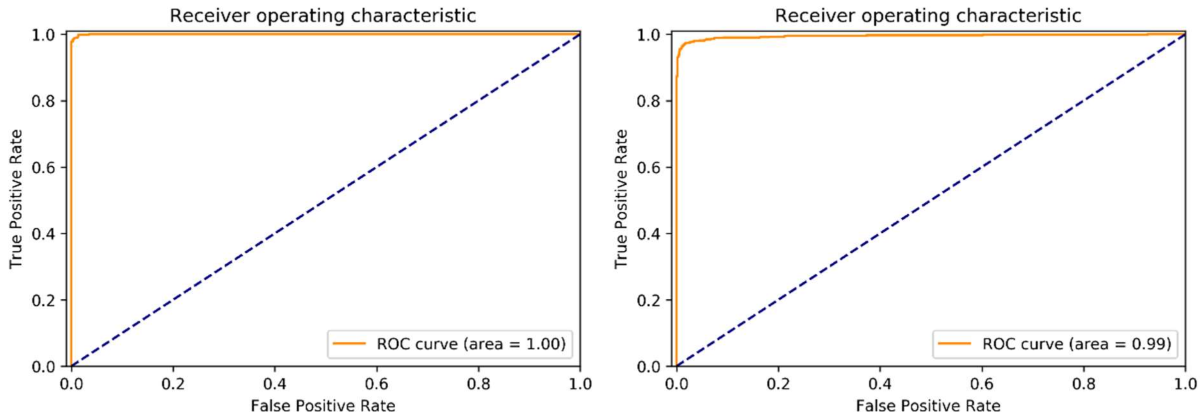


Figure 3. DenseNet-121 (on left) and Squeezenet (on right) roc curve

4. Discussion

The diagnostic accuracy produced by the detailed interpretation of the COVID-19 chest CT scans under the supervision of the radiologist is very important. On the contrary, in the current pandemic environment, it is necessary to benefit from technological artificial intelligence applications in order to use resources efficiently and to prevent the collapse of the world-wide healthcare systems and the deterioration of the economies in the organization of the disease. For this reason, the number of studies conducted with deep learning and artificial intelligence applications worldwide has increased recently. In this section, the comparison of the general performance of our study with other methods is given to evaluate the success of the algorithms used in the proposed CNN model. The proposed model was compared with the classification success of other studies obtained from chest X-ray images with various artificial intelligence techniques. Narin et al. Used three different CNN models in their study, ResNet50, InceptionV3 and Inception-ResNetV2 [19]. Li and Zhu classified three different classes of chest X-ray images with a DenseNet-based model and achieved an overall accuracy of 0.889 [20]. Farooq and Hafeez [21] presented a ResNet-based method in a dataset consisting of four different classes. The accuracy of the model was found to be 0.962. Kumar et al. Proposed a convolutional network-based model in their study. For the proposed model, they used data from platforms such as kaggle and github and obtained 95.38 accuracy from X-ray images. [22]. Zhang et al. [23] used X-ray images of 1008 undiagnosed patients with coronavirus and 70 patients diagnosed with coronavirus. Wang et al. Made a dual classification on a total of 99 CT images, including 55 viral pneumonia and 44 covid patients. In their studies using the deep CNN model, they obtained an accuracy of 95.2 AUC and 73.1 [24].

It is seen that different algorithms are used in the classification of COVID-19 with artificial intelligence algorithms. The proposed model in the study was quite successful in classifying X-ray images as normal and Covid, achieving 99% accuracy and 99.9% AUC with DenseNet architecture. Considering artificial intelligence algorithms, DenseNet CNN method gave better and faster results in binary classification compared to traditional diagnostic methods. The proposed model has a big advantage with fewer parameters and higher accuracy. When we examine the studies using COVID-19 image data, it is seen that some classification algorithms used are very successful. In addition, it is seen that the model applied with the algorithms we propose has an important and high performance value.

5. Conclusion

In this study, the capabilities of artificial intelligence have been demonstrated with different algorithms to prevent the progression of Coronavirus and to assist efforts to accurately detect and monitor its prevalence. Artificial intelligence-based CT image analysis tools, which have been developed rapidly with the spread of Coronavirus, have shown high accuracy in detecting Coronavirus patients and measuring the disease burden.

Using the deep learning image analysis system developed within the scope of this study, a value of 99.9% AUC with the DenseNet-121 algorithm and a 99.4% AUC value with the SqueezeNet algorithm were obtained in data sets of normal and infected patients. In the classification of coronavirus and non-coronavirus cases, 99% accuracy was achieved with the DenseNet-121 algorithm and 97.7% accuracy with the SquuzeNet algorithm.

Earlier and faster detection of positive cases using deep learning algorithms on CT images can reduce the time to screen for COVID-19 patients. In addition, CT images of individual patients with the virus and associated pulmonary abnormalities can be analyzed with different artificial intelligence algorithms. The performance of the model developed to evaluate the progress of the disease more accurately and to guide the patient in the treatment to be applied, can be evaluated by expert radiologists and tested with a larger database. A general limitation of the study is that more COVID-19 X-ray images can be used. We aim to make our model more effective and successful by using more image in future studies.

References

1. Li Y, Yao L, Li J, Chen L, Song Y, Cai Z, Yang C. Stability issues of RT-PCR testing of SARS-CoV-2 for hospitalized patients clinically diagnosed with COVID-19: Journal of medical virology, 92(7), 903-908 , (2020).
2. Ng MY, Lee EY, Yang J, Yang F, Li X, Wang H, Kuo MD. Imaging profile of the COVID-19 infection: radiologic findings and literature review: Radiology: Cardiothoracic Imaging, 2(1), e200034, (2020).
3. Chan JFW, Yuan S, Kok KH, To KKW, Chu H, Yang J, Yuen KY. A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: a study of a family cluster: The lancet, 395(10223), 514-523, (2020).
4. Xu X, Jiang X, Ma C, Du P, Li X, Lv S, Li L. A deep learning system to screen novel coronavirus disease 2019 pneumonia: Engineering, 6(10), 1122-1129, (2020).
5. El Asnaoui K, Chawki Y. Using X-ray images and deep learning for automated detection of coronavirus disease: Journal of Biomolecular Structure and Dynamics, 1-12, (2020).
6. Brunese L, Mercaldo F, Reginelli A, Santone A. Explainable deep learning for pulmonary disease and coronavirus COVID-19 detection from X-rays: Computer Methods and Programs in Biomedicine, 196, 105608, (2020).
7. Chowdhury ME, Rahman T, Khandakar A, Mazhar R, Kadir MA, Mahbub ZB, Islam MT. Can AI help in screening viral and COVID-19 pneumonia: IEEE Access, 8, 132665-132676, (2020).
8. Rahman T, Khandakar A, Qiblawey Y, Tahir A, Kiranyaz S, Kashem SBA, Chowdhury ME. Exploring the effect of image enhancement techniques on COVID-19 detection using chest X-ray images. Computers in biology and medicine: 132, 104319, (2021).
9. Zebin T, Rezvy S. COVID-19 detection and disease progression visualization: Deep learning on chest X-rays for classification and coarse localization : Applied Intelligence, 51(2), 1010-1021, (2021).
10. Ozturk T, Talo M, Yildirim EA, Baloglu UB, Yildirim O, Acharya UR. Automated detection of COVID-19 cases using deep neural networks with X-ray images: Computers in biology and medicine, 121, 103792, (2020).
11. Bai HX, Wang R, Xiong Z, Hsieh B, Chang K, Halsey K, Liao WH. Artificial intelligence augmentation of radiologist performance in distinguishing COVID-19 from pneumonia of other origin at chest CT: Radiology, 296(3), (2020).
12. Wang L, Lin Z Q, Wong A. Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images: Scientific Reports, 10(1), 1-12, (2020).
13. Apostolopoulos ID, Mpesiana TA. Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks: Physical and Engineering Sciences in Medicine, 43(2), 635-640, (2020).
14. Rahman T, Chowdhury MEH, Khandakar A, Mazhar R, Kadir MA, Mahbub ZB, Islam KR, Khan MS, Iqbal A, Al-Emadi N, Ibne Reaz MB. COVID-19 chest radiography database, https://www.kaggle.com/tawsifurrahman/covid19-radiography-database (March 2021).
15. Krizhevsky, A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks: Advances in neural information processing systems, 25, 1097-1105, (2012).

16. Huang G, Liu Z, Van Der Maaten L, Weinberger KQ. Densely connected convolutional networks: In Proceedings of the IEEE conference on computer vision and pattern recognition, 4700-4708, (2017).
17. Iandola FN, Han S, Moskewicz MW, Ashraf K, Dally WJ, Keutzer K. SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and< 0.5 MB model size:arXiv preprint arXiv:1602.07360, (2016).
18. Fast.ai,https://www.fast.ai/ (March 2021).
19. Narin A, Kaya C, Pamuk Z. Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks: arXiv preprint arXiv:2003.10849, (2020).
20. Li X, Zhu D. Covid-xpert: An ai powered population screening of covid-19 cases using chest radiography images: arXiv preprint arXiv:2004.03042, (2020).
21. Farooq M, Hafeez A. Covid-resnet: A deep learning framework for screening of covid19 from radiographs: arXiv preprint arXiv:2003.14395, (2020).
22. Kumar P, Kumari S. Detection of coronavirus disease (COVID-19) based on deep features: preprints.org, no. March, p. 9,(2020).
23. Zhang J, Xie Y, Li Y, Shen C, Xia Y. COVID-19 screening on Chest X-ray images using deep learning based anomaly detection: arXiv: 2003.12338 , (2020).
24. Wang S, Kang B, Ma J, Zeng X, Xiao M, Guo J, Xu B. A deep learning algorithm using CT images to screen for Corona Virus Disease (COVID-19): MedRxiv, (2020).

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || ISBN : 978-605-69730-2-4

More information available at aita.bakircay.edu.tr

Evaluation of the Performance of Feature Selection and Classification Methods for Microarray Gene Expression Data of Two Different Cancer Types

Özlem ARIK [1,*], Erdem KARABULUT [2]

[1] *Kutahya Health Sciences University, Faculty of Medicine, Dept. of Biostatistics, Turkey*
[2] *Hacettepe University, Faculty of Medicine, Dept. of Biostatistics, Turkey*

* Corresponding Author: Kutahya Health Sciences University, Faculty of Medicine, Turkey
Tel.: 05064731873. E-Mail: ozlem.arik@ksbu.edu.tr

Publication Information

Keywords :

- Microarray,
- Gene,
- Cancer,
- Feature,
- Classification

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

High feature number, low sample number parameters in microarray data obtained by microarray technology used in gene analysis negatively affect the performance of machine learning algorithms. Feature selection is important in modeling microarray data. Data mining methods such as classification are also used in analyzing data. To obtain classification models and evaluate their performance by making feature selection on two different cancer data sets taken from the NCBI-GEO database. The feature selection was performed on the microarray gene expression data of lymphoma and breast cancers with varFilter, random forest (rf) and lasso. Classification models were created using naive bayes, support vector machines, k-nearest neighbor and deep learning methods in the data sets where feature selection was made. The performances of the models were obtained by measuring the accuracy, sensitivity, specificity, area under the curve. Conducted with the R, deep learning classification method has higher performance in data setes. The success of classification models obtained by using lasso and rf feature selection methods are higher.

1. Introduction

Biostatistics is used in collecting and analyzing relevant data in research in the field of health and making the right decisions through the results (1, 2). Besides biostatistics, bioinformatics, whose importance is increasing day by day; It includes the fields of biology, computer, mathematics, statistics and genetics. One of the most important research topics of bioinformatics, which is an interdisciplinary science that develops in order to understand genetic-based data, which is the most complex and most important data type, is gene analysis (3). Thanks to the DNA microarray technology used in this field, known and unknown functions of genes are determined. Thus, the simultaneous expressions of all genes are determined to reveal gene differences and similarities in the patient and healthy tissues (4, 5). Thanks to the developments in genome sequencing and bioinformatics, better diagnosis, treatment and prevention studies are carried out by understanding the genome structure of cancer cells and the changes in the internal dynamics of cancer (6). Finding genes directly related to the disease with microarray gene expression data is important in diagnosing and classifying diseases such as cancer.

In the analysis of genetic data, since it is difficult to obtain meaningful results with classical statistical methods due to the large size of the data, analysis can be performed with various data mining methods and computer programming (7, 8).

In this study, oversized microarray gene expression data of lymphoma and breast cancer were used, including individuals in the row, and the features (genes) and response variable (tumor structure) in the column. After the data preprocessing steps, important and meaningful features were selected with the feature selection methods of varFilter, rf (random forest) and lasso (least absolute shrinkage and selection operator). Then, with the selected data, naive bayes, support vector machines and k-nearest neighbor classification methods, which are frequently used in data mining, were preferred along with deep learning to create models of patient-healthy classification. Model performance measures such as accuracy, sensitivity, specificity and under the ROC curve were used to evaluate the performance of classification models obtained by using feature selection methods and classification methods on microarray gene expression data of two different cancer types.

2. Data Mining and Bioinformatics

Revealing meaningful, valuable and useful information from raw data sets that have accumulated in the databases of public and private organizations in recent years is called data mining. Data mining, which first entered the literature in the 1980s, is widely used today (9-11). Data mining, which is an interdisciplinary field, is getting more and more accepted with the combination of concepts such as statistics, machine learning and artificial intelligence, together with the fact that classical statistical methods cannot provide valid and reliable results for large amounts of data (12, 13).

Data mining that helps to achieve successful results on large data sets; It includes a certain process flow such as determining the problem, understanding the data, preparing the data, establishing the model, evaluating the model, using the model-application and monitoring the model (14). Methods used in data mining are generally divided into two as predictive and descriptive (15, 16). Predictive methods are used to obtain the results of new situations related to the problem, thanks to the model created through data with known results of any event. Classification; are among the predictive methods. Thanks to the classification methods, a classification model is obtained with the data known to which class it belongs, and it is decided to decide which class the newly added data will be included in (13).

In the second half of the 20th century, bioinformatics, an interdisciplinary branch of science, with the increase in biological knowledge, large size biological data are organized, analyzed and made more understandable. The term bioinformatics started to be used after the mid-1980s and the need for bioinformatics for the processing of genetic information resulting from the Human Genome Project has increased. Therefore, the type of data that bioinformatics science mostly works on is genetic data and therefore gene expression data (4, 17-19).

There are three institutions in bioinformatics, which are open to the use of researchers and cooperatively work to store, organize and use nucleotide sequence information. These are GenBank (GenBank; USA-Maryland), EMBL (European Molecular Biology Laboratory; England-Hinxton) and DDBJ (DNA Data Bank of Japan; Japan-Mishima). NCBI (National Center for Biotechnology Information), which was established in Maryland in 1988 and is a branch of NLM (National Library of Medicine), is the most important biological database based on the web. NCBI includes Pubmed articles, books such as Genetics and Biochemistry, EMolecular Biology of the Cell (4, 20).

2.1. Microarray Technology and Gene Expression Data

The main material of the genetic studies, which started with Mendel's work in the 1800s, is DNA (Deoxyribo Nucleic Acid), which is found in all cellular organisms and carries the biological information needed for the development of the living thing (21-23). DNA with a spiral structure; It consists of four types of nucleotides: Guanine (G), Cytosine (C), Thymine (T) and Adenine (A). Each of the nucleotides; consists of a phosphate group, an organic base and a five-carbon sugar. Only T and A can be connected to each other, while G and C can be connected to each other (24). These nucleotides that are linked together are called nucleotide pairs (base pairs) (22). The gene, which forms the root of the word genetics, is the DNA regions located in the chromosomes in the cell nucleus, which have genetic functions such as defining physical characteristics, and have starting and ending points. There are approximately 25000 gene regions in each human cell and each has different characteristics (25). The location information of the genes on the chromosome is called locus and the locus of each gene is different (23).

Gene expression (gene expression), which indicates whether the genes are active or not, and how active they are, is the stage of transformation of genes from DNA to RNA structures and protein. There is a positive linear relationship between overproduction of protein and high gene expression (26). All of our organs contain the same genetic material. However, due to the different expression of genes in different cells, cells such as breast, lung and brain do not have the same functions (27, 28).

With DNA officially discovered sixty-seven years ago by James Watson and Francis Crick on February 21, 1953, it has become an important issue to investigate the effects of the genetic code on the life of living things. Thanks to the microarray technology, which is one of the steps taken with the advancing technology, the expressions of the genome of an organism can be examined in one go (29, 30). While features such as being fast, examining the efficacy of genes in sick and healthy cells, being able to categorize diseases are the advantages of microarray technology; The disadvantages of microarray technology are that it is expensive, it takes a long time to analyze all data at the same time and can be complex to interpret. Due to the size and complexity of the data obtained, the need for computational genomic approaches for analysis and interpretation has increased. Biostatistical analysis and bioinformatics also have a great place in meeting these needs (5, 31).

Using the gene expression data obtained by gene expression analysis made by microarray technology, it is shown where and when the genes are active, thus how much they express themselves (5, 32). Microarrays are also referred to as chips consisting of thousands of spots (spots) into which thousands of different DNA fragments are synthesized or placed. A solid surface made of glass, plastic or silicon is called a chip. Probe is every point on the surface of the chip (30, 33). If the gene could not be expressed or read, the probe will appear in black. Green, healthy individuals; red indicates sick individuals. It is shown in yellow if the patient or health status is close to each other. With computer analysis, these colors are converted into numerical values and made suitable for analysis (34, 35). The most important of the public microarray databases; It is GEO (Gene Expression Omnibus), originated in America and located under NCBI, the world's most comprehensive biological database. The other is ArrayExpress under EBI, a large and comprehensive biological database of European origin (36). Real data sets used in this study belongs to the well-NCBI GEO database.

Genes in the row and samples in the column, the mxn size gene expression data matrix is in the form of a row data structure (8, 37). In order to apply analysis such as feature selection and classification, the gene expression data matrix is transposed and samples are placed in rows and genes are placed in columns. The number of classes may be more than two and the number of individuals in each class may be different from each other. When there are different scenarios, the methods to be used for analysis will also differ. With the application of data mining and statistical methods on the obtained gene expression data matrix, genes effective on diseases such as cancer can be determined, genes with common functions can be clustered, and patient-healthy classification of individuals can be made (26). Some changes in genes that control how cells grow and divide, that is, how they function, cause cancer (23). Early diagnosis is very important in cancer, and working with gene expression data during the diagnosis and classification phase is of great importance (32).

3. Feature Selection and Classification Methods

Feature; it has a similar definition to the concept of variable, which refers to properties or situations that take different values from sample to sample. In microarray gene expression data, which are generally among high-dimensional data, the number of features (genes) is very high and the number of samples is very low. Therefore, working with microarray gene expression data that has undesirable data structure is a problem (38). For the purpose of the application planned to be made on a large data set such as microarray gene expression data, instead of using all of the features, the process of determining the best feature subset that can represent the original data set by selecting the most useful and important features is called feature selection. Thanks to the feature selection, better models are obtained in terms of speed and success performance (39, 40).

There are different methods used to perform feature selection. Generally, these methods are divided into three as statistical methods, spiral methods and embedded methods (41). Statistical methods that make choices using only statistical information are also called filtering methods. Methods such as heuristic search, genetic algorithm, particle swarm optimization are among the spiral methods. In these methods, data mining methods are used as a tool for feature selection. The methods in which the feature selection method and the data mining method are applied at the same time are called embedded methods (39, 42). In particular, the use of embedded methods in microarray gene expression data is more ideal (43). Since there are many features in the data sets used in this study, three different feature selection methods in the R program were used in order to find important and meaningful features that will affect the classification result more.

There are usable R packages created for applications such as feature selection, classification, clustering when the computer memory does not allow analysis in high-dimensional data sets such as microarray gene expression data. The R program is suitable for integration with the Bioconductor environment, which includes genomic data sources, especially a large number of microarray data sets, and open source analysis tools (44). Gene expression data of microarray studies are located in the Bioconductor ExpressionSet object. The ExpressionSet object stores data of GxN size when the number of genes on a chip is represented by G and the number of samples is N. The ExpressionSet object contains metadata information, which includes various information such as the description of the experiment that constitutes the subject of the data set, the number of features, information about the examples in the experiment. The ExpressionSet object was created to make different information sources more useful by converting them into a single structure (44, 45).

In this study, microarray gene expression data of cancer types taken from NCBI-GEO database were transformed into ExpressionSet object by Bioconductor and made ready for application. ***Genefilter*** and ***CMA*** packages are used to perform the feature selection process in microarray gene expression data using the ExpressionSet object (46).

Classification methods are used to obtain a meaningful model in order to make predictions for the future using the data containing the independent variables and the categorical response variable (9). In this study, while the features express the independent variables, the response variable consists of two classes as patient-healthy. The classification of the samples is known in the microarray gene expression data, which include samples, features and categorical response variables. With the classification models created using this information, when a new sample arrives, the class of this sample is predicted (13, 47).

There is a process followed for the classification process. After the data preprocessing step, not all of the available data set are used in model creation. A model with classification rules is created with examples whose class is known in the education dataset. In the test data set, the obtained model is tested and its accuracy is measured (48). In this study, 75% of the data set was used as training and 25% as a test data set, and 5-fold cross validation was used for model generalization. In the cross validation method, the data set is divided into k subsets. k-1 cluster is used in education, one is used in testing. The process is repeated k times and the accuracy values obtained each time are averaged and the accuracy performance of the model is calculated (12, 44).

When working with large data sets such as microarray gene expression data, classification methods, one of the most frequently used methods of data mining, are applied after selecting effective and meaningful features in order to reduce computation time and obtain models with better performance. Looking at the studies involving gene expression data, it was seen that the most preferred classification methods were naive bayes, support vector machines and k-nearest neighbor (41). In this study, in addition to these three classification methods, the deep learning method was also used.

3.1. varFilter, rf (Random Forest) and Lasso (Least Absolute Shrinkage and Selection Operator)

The `varFilter()` function in the ***genefilter*** package, one of the R packages created to eliminate computer-related problems such as speed and memory, is used to select features on high-dimensional data sets. In the varFilter method; variance values are obtained for each of the features in the data set. Among the variance values listed in descending order, those that come before a certain limit are determined. Features with determined variance values are selected for use in later stages (44). In other words, as a result of the selection with varFilter, features that vary widely between instances are selected, while features with little change are discarded. The `var.cutoff` value in the `varFilter()` function is used to express how many of the total features in the data set want to work with. For example, `var.cutoff=0.80` to select 20% of the features, and `var.cutoff=0.90` to select 10% (46).

Random forest (rf), which is a classification method widely used in data mining and has a high success rate, is also used for feature selection (39). This method, which is based on decision trees, was proposed by Breiman in 2001 and includes many decision trees applied in different subsets of the data set (49). In the rf method, trees come together to form a forest. Since the CART (Classification and Regression Trees) algorithm is applied to create a decision tree in this method, the gini coefficient is used as a criterion. The feature with the least Gini coefficient is the feature with the best partitioning. The Gini coefficient is calculated as in Equation 1.

$$Gini = 1 - \sum_{i=1}^{n} (p_i)^2 \qquad (1)$$

Here, n is the selected data, and p_i is the sum of squares of each data in the row of data from the division of all the values in that row. One of the embedded feature selection methods, the rf method works with a certain process flow. First, all feature states are checked and importance values are calculated for each feature according to the decision tree criterion to be used. Then, the features are listed according to the calculated importance value and the highest importance value is determined as the root value of the feature. Finally, the tree structure is expanded by returning to the previous step until the success rate and the number of iterations determined and the algorithm is terminated when the criterion is met (41). For the application of the rf method used in the study, ***randomForest*** package was also used in addition to the ***CMA*** package.

In order to create a model with good performance for the data set, a search algorithm is used when choosing the features that will affect the model the most. One of these embedded methods is lasso (least absolute shrinkage and selection operator) (42). Lasso was first developed by Tibshirani in 1996 as a method that can make coefficient estimation and variable selection in regression analysis at the same time (50,51). With the regression analysis, the dependent (response) variable value is estimated by using the value of the independent variable (s). In the case of a linear relationship between the independent variable (s) and the response variable, the least squares method is used to create the linear regression model. In the method, the coefficients of the independent variables, namely the parameters, are estimated. However, when the number of independent variables is too large, some problems arise, such as multicollinearity where a linear or close to linear relationship is observed between variables (52). With multicollinearity, the coefficient estimates become uncertain and the variances and standard errors of the estimates grow, R^2 becomes greater than it should. Different methods are used by making some changes in the regression model to be created to estimate the value of the response variable. Lasso is one of these methods (42). In gene expression data, independent variables are features and there are many features. In the model created by using the features in the data set with the lasso method, problems such as overfitting and multiple connections are eliminated, and the coefficients of less important features are calculated as zero. Thus, the feature selection is made automatically with lasso (53). For the application of lasso method, ***glmnet*** package was used together with ***CMA*** package.

3.2. Naive Bayes, Support Vector Machines, k-Nearest Neighbor and Deep Learning

Naive Bayes (NB) classification method, which shows high performance in terms of speed and accuracy when applied in large data sets, is a statistical method (47, 54, 55). The classification method based on the bayes theorem that emerged in the 1760s and named after the English mathematician Thomas Bayes; It is based on the assumption that the features in each class are independent from each other and are of equal importance. It is an effective method that is based on probability and has a simple algorithm structure with applicability (13, 56, 57). There are opinions that the NB classification method, which has applications in many fields, gives better results in gene expression data compared to other classification methods (41, 56). Bayes theorem, which includes a priori and conditional probabilities, is used to predict which class the new incoming data belongs to using pre-classified data (58, 38).

The following equations are used to estimate the class of the data belonging to the test data set with the NB classification method (58, 15).

$X = \{x_1, x_2, \dots, x_n\}$: a data set that belongs to an unknown class

$C = \{C_1, C_2, \dots, C_m\}$: if there are m classes in the data set, the probability of $P(C_j|X)$ according to the bayes theorem Equation 3 it is obtained with.

$$P(X) = \sum_{i=1}^{k} P(x_i|C_j).P(C_j) \tag{2}$$

with

$$P\left(C_j\middle|X\right) = \frac{P\left(x_i\middle|C_j\right)P(C_j)}{P(x_i)}$$

(3)

The probability $P\left(x_i\middle|C_j\right)$ is simplified, reducing the processing load on the calculations. For this, Equation 4 is used by assuming that the x_i values of the sample are independent from each other.

$$P(X|C_j) = \prod_{k=1}^{n} P(X_k|\,C_j) \tag{4}$$

In order to estimate the class of the sample X whose class will be determined, since the denominator values in Equation 3 are the same, the largest one is selected by comparing the numerator values and it is decided that the sample whose class is unknown is in this class (58, 15). In the study, `train()` function of the ***caret*** package of R is used to obtain the NB classification model.

The use of Support Vector Machines (SVM) classification method, which was first introduced by Vladimir Vapnik and Alexey Chervoenkis in the 1960s, became widespread in the 1990s with the first successful applications (59, 60). Although it was developed for cases where the number of classes is two, it has become applicable by expanding over time for data sets where the number of classes is more than two and that cannot be separated linearly (61). It is a highly preferred method because it gives classification results with a high performance level in large data sets such as gene expression data with a large number of features and in many other areas (60, 61). In the SVM classification method, the plane that will make the correct classification is determined by using the feature sets of different classes while distinguishing between the instances of the classes and is called the hyperplane. Points that limit the width of the boundary are also called support vectors. The farther the boundaries are from each other, the more suitable (41, 47, 62). In this study, `train()` function of the ***caret*** package of R is used to obtain the SVM classification model.

The k-Nearest Neighbor (kNN) classification method was first introduced by Fix and Hodges in the early 1950s, and it was developed and popularized by Cover and Hart towards the end of the 1960s (63-65). In the kNN classification method, which is the most basic of sample or memory-based methods, the class of the unknown sample is determined by pre-classification through the training data set (57, 66, 67). The nearest neighbors of the sample to be classified are determined in the training set and the new sample is included in the class in which most of these neighbors are. For the classification process, using distance measures, the similarity of the new sample between the samples in the training data set is checked and the class is estimated for the sample by determining the closest training data set (57, 65). For this, distance measures such as Minkowski, Euclid, and Manhattan are used. In previous studies, Euclidean distance measure was generally used (68). To obtain the Euclidean distance measure, take the square root of the sum of squares of the distance difference between features. There are different values for each of the classes, and the class with the highest value is assigned the newcomer, that is, the tested sample (41,69). Therefore, it is important that the features of the classes are determined (68). In the study, `knnCMA()` function of R`s ***CMA*** package is used to obtain the kNN classification model.

How multi-layer artificial neural networks work was shown with the article by Geoffrey Hinton and Ruslan Salakhutdinas in the 2000s. In the Deep Belief Network study in 2006, the way the multi-layer deep structures work and the self-complementing of the missing features were expressed and this was called Deep Learning (DL) (70). Later, many methods were introduced, and DL was used by scientists for the first time in 2012, and has gained widespread use over time (71). In the DL method, which is an advanced extended approach of artificial neural networks consisting of three layers as input, hidden and output, the hidden layer is more than one, so that the data can be represented comprehensively (70). Thanks to the hidden layers, the result in the output layer is achieved. DL methods generally cover the deep structures of successive layers. By consecutive layer, the exit of each layer forms the entrance of the next layer. Thus, learning is provided in a hierarchical way. Using the neurons in the input layer, the neurons in the hidden layers are calculated with the linear function $y = f(x, w)$. Neurons in the output layer are obtained by applying activation functions on the calculated neurons. The output layer obtained as a result of the processes is a non-linear form of the input layer. Generally, nonlinear problems are tried to be solved with DL methods because these types of problems have given better results than other methods (61). In RNA sequencing and microarray gene expression data, there are fewer studies in which the DL method is used for classification than the studies using classical data mining classification methods (72, 61, 71). As in other classification methods, the data set in DL is divided into two as training and test data sets. Then, the ***h2o*** package developed by the H2O.ai team (2017) is used to create the classification model. Data sets are converted into h2o objects by executing this package with the `h2o.init()` function. Through the `h2o.deeplearning()` function, the DL model is obtained from the h2o data object (44). In this study, in order to show the effect of feature selection methods on the performance of classification methods and to make comparisons, the results are in a certain standard, as in other classification methods, the application of feature selection methods and the application of DL classification models (72). Especially in the field of health, in cancer diagnosis and classification, drug development, medical image and signal data, DL methods are frequently used. It is increasingly preferred as a result of its high performance in terms of accuracy in solving questions (73).

3.3. Model Performance Metrics

Various model performance measures are used to evaluate and interpret the performance of classification methods regarding how accurately they classify. Since there is no imbalance in the distribution of class numbers in the data sets discussed in this study, the highly preferred measures such as accuracy, sensitivity, specificity and the area under the ROC curve were used among the model performance measures. The classification table is used for the calculation of these measures. There are four possible outcomes in a dataset where the number of classes is two. These results are as in the classification table given in Table 1 (61, 74).

Table 1. Classification table of real and predicted results.

	Real Class	
Predicted Class	Positive	Negative
Positive	A (True Positive- TP)	B (False Positive - FP)
Negative	C (False Negative - FN)	D (True Negative - TN)

Performance measures used in the study can also be calculated with the values in the classification table.

Accuracy, It is a highly preferred simple method in determining the performance of the classification method and is a general measure of success. It is the ratio of the number of correctly classified samples (TP + TN) to the total number of samples (TP + FP + FN + TN).

Sensitivity, it is the proportion of the samples with positive class estimated among the samples actually classified as positive. It is the performance of the classification method in determining the samples with positive value.

Specificity, it is the ratio of the samples with negative class predicted among the samples actually in the negative class. It is the performance of the classification method in determining samples with negative values.

Area Under the ROC Curve (AUC), The ROC curve, which was first used in signal detection in the 1950s, is widely used in biomedical studies. The main purpose of the ROC curve is to examine the result obtained from the classification method in terms of accuracy values. Therefore, sensitivity and specificity values are calculated first. The area under the curve (AUC) obtained on the ROC graph consisting of 1-specificity on the horizontal axis and sensitivity values on the vertical axis takes values varying between 0.5 and 1. The closer the AUC value is to 1, the better the classification performance of the method used; The method with an AUC value of 0.5 is quite unsuccessful in classification (61,75). The response variable of the data used in this study consists of two classes as patient-healthy. The power of the classification method used to distinguish between patients and healthy people is shown by AUC (76).

4. Results

In this section, the findings regarding the application of the mentioned feature selection and classification methods in microarray gene expression data of lymphoma and breast cancers are given in Table 2, Table 3, Figure 1 and Figure 2.

Table 2. Comparison of the performances of classification models created by using features determined by feature selection methods in the lymphoma data set.

Feature Selection Method	Classification Method	Accuracy	Sensitivity	Specificity	AUC
varFilter	NB	0,750	0,500	1,000	0,750
	DVM	0,750	0,500	1,000	0,750
	kNN	0,750	0,667	1,000	0,800
	DÖ	0,975	0,970	0,980	0,985
rf	NB	1,000	1,000	1,000	1,000
	DVM	0,933	0,900	1,000	0,980
	kNN	0,900	0,800	1,000	0,960
	DÖ	0,949	1,000	0,900	0,960
lasso	NB	0,933	0,900	1,000	0,980
	DVM	0,933	0,900	1,000	0,980
	kNN	0,870	0,750	0,950	0,930
	DÖ	1,000	1,000	1,000	1,000

When Table 2, which contains the results of the lymphoma data set, is examined, the performance of the model obtained by DL classification method after applying the varFilter feature selection method is quite higher than the others. The performance of the model created with the kNN classification method is slightly better than NB and SVM. The performance values of the models obtained by NB and SVM methods are the same. The best performance was achieved with the NB method among the classification models created with the features selected with rf. NB classification method is followed by performances of DL, SVM and kNN methods, respectively. In the lasso feature selection method, the classification model obtained by DL method has the best performance. Performance values of NB and SVM are the same and come after DL. Performance values of kNN are lower than the classification methods of DL, NB and SVM. The results obtained are given in Figure 1.

Figure 1 is here.

Overall, the performance of the DL method in the lymphoma data set is the best. In the rf feature selection method, NB, and in lasso feature selection, DL classification models showed almost 100% performance in terms of accuracy, sensitivity, specificity and AUC. In general, the success of the classification models obtained by using the rf and lasso feature selection methods is higher.

Table 3. Comparison of the performances of classification models created by using features determined by feature selection methods in the breast cancer data set.

Feature Selection Method	Classification Method	Accuracy	Sensitivity	Specificity	AUC
varFilter	NB	0,636	0,666	0,625	0,645
	DVM	0,540	0,333	0,750	0,541
	kNN	0,727	0,875	0,673	0,691
	DÖ	0,797	0,840	0,790	0,800
rf	NB	0,752	0,590	0,850	0,803
	DVM	0,714	0,740	0,683	0,710
	kNN	0,689	0,740	0,633	0,685
	DÖ	0,900	1,000	0,890	0,910
lasso	NB	0,693	0,750	0,617	0,780
	DVM	0,648	0,790	0,450	0,640
	kNN	0,639	0,740	0,500	0,632
	DÖ	0,909	1,000	0,850	0,933

When Table 3, which includes the results of the breast cancer data set, is examined, after applying the varFilter feature selection method, the performance of the model obtained by DL classification method is better than other methods. The performance of the classification model obtained with NB is lower than the performance of classification models created with kNN. Performance values of the classification model obtained with SVM, where the sensitivity value is low, is generally the lowest among the classification models obtained by other methods. As in varFilter, the best performance among the classification models created with the features selected with rf was achieved with the DL method. The classification method of DL is followed by the performance of NB, SVM and kNN methods, respectively. In the lasso feature selection method, the classification model obtained with the DL method has the best performance. Performance values of NB are much lower than DL. However, it is better than other classification methods. Performance values of classification models obtained by DVM and kNN methods are close to each other. The obtained results are given in Figure 2 via graphics.

Figure 2 is here.

In the breast cancer data set, DL has higher performance among the models obtained by classification methods. Classification models, which are mostly obtained by using lasso and rf feature selection methods, have higher success.

5. Conclusion and Evaluation

In this study, it is aimed to show the effect of feature selection methods on the performance level of classification methods commonly used in data mining in order to reduce the number of features in microarray gene expression data where the number of features is high and the number of samples is low. For this purpose, data sets belonging to two different types of cancer were studied. Classification models were created by applying NB, SVM, kNN and DL classification methods to the data sets containing important features obtained by applying varFilter, rf and lasso feature selection methods on the microarray gene expression data related to cancer types. Model performance measurement values in the form of accuracy, sensitivity, specificity and AUC were obtained for these models.

When the results of the lymphoma data set are examined, the performance of the NB classification method in the rf feature selection method is better than the other classification methods. Performance of NB and DVM classification methods are the same in both varFilter and lasso feature selection methods. In general, feature selection methods with better performance of classification methods are lasso and rf, respectively. The very high sensitivity value of the models obtained by the DL classification method in the lasso feature selection method and the rf feature selection method with the DL and NB classification methods indicates that their performance in determining the patient individuals is very good. The high specificity values of NB, SVM and kNN classification methods in varFilter and rf feature selection methods, and high specificity values of NB, SVM and DL classification methods in lasso feature selection method indicates that the performance of classification models in determining healthy individuals is very good. When looking at the accuracy and AUC measures, which express that the patients and healthy individuals are classified correctly, DL classification method is very successful in the lasso feature selection method.

In the breast cancer data set, the classification method with the highest performance measure values in feature selection methods is DL. Performance measure values of NB, SVM and kNN classification methods are mostly close to each other and come after DL. Considering the sensitivity values of the models created with DL classification method in rf and lasso feature selection methods, it is understood that their performance in determining patient individuals is very good. Considering the accuracy and AUC measures, which express that the sick and healthy individuals are classified correctly, the classification method of DL is very successful in the limite feature selection method.

In general, it may be preferable to use the lasso feature selection method in microarray gene expression data with a large number of features. The DL method has yielded more successful results than classical data mining methods in classifying large-scale data such as microarray gene expression data, and its use is recommended. For future studies, it is planned to use DL method in different areas such as the recognition of data obtained by medical imaging devices, especially in the field of genetics. Clustering and association rules, which are other frequently used data mining methods, can also be applied on microarray gene expression data.

References

1. Öğüş E. To Be Together Medicine And Biostatistics İn History: Review. Turkiye Klinikleri J Biostat. 9(1):74-83,2017.
2. Öner TÖ, Can Ş. Sağlıkta Biyoistatistiksel Uygulamalar. İzmir Kâtip Çelebi Üniversitesi Sağlık Bilimleri Fakültesi Dergisi. 3(1):39-45,2018.
3. Karabulut E, Karaağaoğlu E. Biyoinformatik ve Biyoistatistik. Hacettepe Tıp Dergisi. 2010;41:162-170.
4. Polat M, Karahan AG. Multidisipliner Yeni Bir Bilim Dalı: Biyoinformatik ve Tıpta Uygulamaları. S.D.Ü. Tıp Fak. Derg. 16(3):41-50,2009.
5. Yoldaş A, Karaboz İ. DNA Mikroarray Teknolojisi ve Uygulama Alanları. Elektronik Mikrobiyoloji Dergisi TR. 8(1):1-19,2010.
6. Baykara O. Kanser Tedavisinde Güncel Yaklaşımlar. Balıkesir Sağlık Bilimleri Dergisi. 2016;5(3):154-165.
7. Demircioğlu HZ, Bilge HŞ. Yumurtalık Kanseri Veri Kümesindeki Gen İfadelerinin Veri Madenciliği İle Analizi. Marmara Fen Bilimleri Dergisi. 4:125-134,2015.
8. Coşkun E, Karaağaoğlu E. Veri Madenciliği Yöntemleri ile Mikrodizilim Gen İfade Analizi. Hacettepe Tıp Dergisi. 42:180-189,2011.
9. Dolgun MÖ. Veri Madenciliği Sınıflama Yöntemlerinin Başarılarının; Bağımlı Değişken Prevelansı, Örneklem Büyüklüğü ve Bağımsız Değişkenler Arası İlişki Yapısına Göre Karşılaştırılması [Doktora tezi]. Ankara: Hacettepe Üniversitesi; 2014.
10. Çelik N. Amiyotrofik Lateral Skleroz (ALS) Hastalığının Genetik ve Klinik Veri İlişkisinin Veri Madenciliği Yöntemleri ile İncelenmesi [Yüksek Lisans Tezi]. Antalya: Akdeniz Üniversitesi; 2017.
11. Çataloluk H. Gerçek Tıbbi Veriler Üzerinde Veri Madenciliği Yöntemlerini Kullanarak Hastalık Teşhisi [Yüksek Lisans Tezi]. Bilecik: Bilecik Üniversitesi; 2012.
12. Han J, Kamber M, Pei J. Data Mining Concepts and Techniques. 3.Baskı. ABD: Elsevier; 2012.
13. Poyraz O. Tıp`Da Veri Madenciliği Uygulamaları: Meme Kanseri Veri Seti Analizi [Yüksek Lisans Tezi]. Edirne: Trakya Üniversitesi; 2012.
14. Toprak U. Karsinogenezde Mutasyonlar Arası İlişkilerin Veri Madenciliği Metotları İle Tespiti [Yüksek Lisans Tezi]. Trabzon: Karadeniz Teknik Üniversitesi; 2015.
15. Göker H. Üniversite Giriş Sınavında Öğrencilerin Başarılarının Veri Madenciliği Yöntemleri İle Tahmin Edilmesi. [Yüksek Lisans Tezi]. Ankara: Gazi Üniversitesi; 2012.
16. Ergün K. Veri Madenciliğine Giriş. Balıkesir Üniversitesi MF Endüstri Mühendisliği Bölümü Veri Madenciliği Ders Notu.
17. Luscombe NM, Greenbaum D, Gerstein M. What İs Bioinformatics? An İntroduction And Overview. Yearbook Of Medical Informatics. 10(01):83-100,2001.
18. Tanır D. Genomik Veri Tabanlarında İndeksleme ve Arama Yöntemleri Üzerine [Doktora Tezi]. İzmir: Ege Üniversitesi; 2017.
19. Gentleman RC, Carey VJ, Bates DM, Bolstad B, Dettling M, Dudoit S, ve ark. Bioconductor: Open Software Development For Computational Biology And Bioinformatics. Genome Biol.5(10):R80,2004.

20. Hopkins MM, Ibarreta D, Gaisser S, Enzing CM, Ryan J, Martin PA, ve ark. Putting Pharmacogenetics into Practice. Nature Biotechnology. 24(4): 403-410,2006.
21. Roberts HF. Plant Hybridization before Mendel. Princeton: Princeton University Press, 1929.
22. Tisdall J. Beginning Perl for Bioinformatics. ABD: O'Reilly; 2001.
23. Özdoğan A. Gen Kümeleme İşleminin Özdüzenleyici Haritalar Kullanılarak Gen Ekspresyonu, Motif Sıklık Ve Gen Konum Verilerinden Faydalanılarak Gerçekleştirimi. [Yüksek Lisans Tezi]. İstanbul: Yıldız Teknik Üniversitesi; 2009.
24. DNA'nın Keşfi [İnternet]. Ocak, Erişim adresi: https://www.biyologlar.com/dnanin-kesfi, 2019.
25. Bakırcı ÇM. Temel Genetik Kavramlar: Nükleotit, DNA, Gen, Kromozom Nedir?. [İnternet]. Erişim adresi: https://evrimagaci.org/temel-genetik-kavramlar-nukleotit-dna-gen-kromozom-nedir-7566, 2019.
26. Zararsız G. Gen Ekspresyon Verilerinde Kümelemeye Dayalı Yeni Bir Sınıflandırma Yaklaşımı. [Yüksek Lisans Tezi]. Kayseri: Erciyes Üniversitesi; 2012.
27. Haznedar B, Arslan MT, Kalınlı A. Karaciğer Mikrodizi Kanser Verisinin Sınıflandırılması için Genetik Algoritma Kullanarak ANFIS'in Eğitilmesi. Sakarya Üniversitesi Fen Bilimleri Enstitüsü Dergisi. 21(1):54-62,2017.
28. Lüleyap HÜ. Moleküler Genetiğin Esasları. İzmir: Nobel Kitabevi; 2008.
29. Watson JD, Crick FH. Molecular Structure of Nucleic Acids: A Structure for Deoxyribose Nucleic Acid. Nature. 171:737-738, 1953.
30. Sarıkaş A, Odabaşıoğlu N, Altay G. Gen İfade Verilerinde Eksik Değerleri Düzelten Kestirim Yöntemlerinin Karşılaştırılması Comparison of Estimation Methods for Missing Value Imputation of Gene Expression Data. Tıp Teknolojileri Kongresi; 27-29 Ekim; Antalya. s.114-117,2016.
31. Sassanfar S, Walker G. DNA Microarray Technology. What Is It and How Is It Useful, MIT, Biology Science Outreach. 2003.
32. İdil NB. Gen İfade Verileri ile İşlemsel Kanser Sınıflandırılması [Yüksek Lisans Tezi]. Ankara: Başkent Üniversitesi; 2009.
33. Gershon D. Microarray Technology: An Array of Opportunities. Nature. 885-891,2002.
34. Özkan Y, Selçukcan Erol Ç. Biyoenformatik DNA Mikrodizi Veri Madenciliği. 2. Baskı. İstanbul: Papatya Yayıncılık; 2017.
35. George GVS and Raj VC. Review on Feature Selection Techniques and The İmpact Of SVM For Cancer Classification Using Gene Expression Profile. International Journal Of Computer Science & Engineering Survey. 16-27,2011.
36. Öztemur Y, Aydos A, Gür-Dedeoğlu B. Meme Kanseri Mikrodizin Verilerinin Biyoinformatik Yöntemler ile Bir Araya Getirilmesi - Meta-Analiz Yaklaşımları. Turk Hij Den Biyol Derg, 72(2):155-162, 2015.
37. Jagota A. Microarray Data Analysis and Visualization. Bioinformatics by the Bay Press: Santa Cruz; 2001.
38. Kaya A. Bilgisayar Destekli Tanı Sistemi ile Akciğer Nodüllerinin Nitelendirilmesi [Doktora Tezi]. Ankara: Hacettepe Üniversitesi; 2015.
39. Budak H. Özellik Seçim Yöntemleri ve Yeni Bir Yaklaşım. Süleyman Demirel University Journal of Natural and Applied Sciences. 22 (Special Issue):21-31, 2018.
40. Yazıcı B, Yaslı F, Yıldız Gürleyik H, Turgut UO, Aktas MS, Kalıpsız O. Veri Madenciliğinde Özellik Seçim Tekniklerinin Bankacılık Verisine Uygulanması Üzerine Araştırma ve Karşılaştırmalı Uygulama. 9. Ulusal Yazılım Mühendisliği Sempozyumu; 15 - 17 Eylül; İzmir. UYMS-15. s.72-83, 2015.
41. Kaya M. Gen İfade Verilerinde Öznitelik Seçimi ve Sınıflandırma [Yüksek Lisans Tezi].Ankara: Gazi Üniversitesi; 2014.
42. Var E, İnan A. Sınıflandırma İçin Diferansiyel Mahremiyete Dayalı Öznitelik Seçimi. Journal of the Faculty of Engineering and Architecture of Gazi University. 33(1):323-336,2018.
43. Zengin HY. Sosyal Ağ Analizinin Hastalık Biyobelirteçlerinin Belirlenmesinde Kullanımı [Doktora Tezi]. Ankara: Hacettepe Üniversitesi; 2018.

44. Özkan Y, Selçukcan Erol Ç. Kanser Biyoenformatiğinde Yapay Zeka. 2. Baskı. İstanbul: Papatya Yayıncılık; 2019.
45. Falcon S, Morgan M, Gentleman R. An Introduction to Bioconductor's ExpressionSet Class [İnternet]. Temmuz. Erişim adresi: https://www.bioconductor.org/packages/release/bioc/vignettes/Biobase/inst/doc/ExpressionSetIntroduction.pdf.,2019.
46. Gentleman R, Carey V, Huber W, Hahne F. Genefilter: Genefilter: Methods For Filtering Genes From High-Throughput Experiments [İnternet]. Erişim adresi: https://bioconductor.org/packages/devel/bioc/manuals/genefilter/man/genefilter.pdf, 2019.
47. Pala T. Tıbbi Karar Destek Sisteminin Veri Madenciliği Yöntemleriyle Gerçekleştirilmesi [Yüksek Lisans Tezi]. İstanbul: Marmara Üniversitesi; 2013.
48. Akman M, Genç Y, Ankaralı H. Random Forests Yöntemi ve Sağlık Alanında Bir Uygulama. Turkiye Klinikleri J Biostat. 3(1):36-48,2011.
49. Daş B, Türkoğlu İ. DNA Dizilimlerinin Sınıflandırılmasında Karar Ağacı Algoritmalarının Karşılaştırılması. Elektrik – Elektronik – Bilgisayar ve Biyomedikal Mühendisliği Sempozyumu; 27 – 29 Kasım; Bursa. Eleco, s.381-383,2014.
50. Tibshirani R. Regression shrinkage and selection via the lasso. Journal of the Royal Statistical Society. Series B (Methodological). 58(1):267-288,1996.
51. Fontı V. Feature Selection using LASSO. Vrije Universiteit Amsterdam; s.26,2017.
52. Ludwig N, Feuerriegel S, Neumann D. Putting Big Data Analytics to Work: Feature Selection for Forecasting Electricity Prices Using the LASSO and Random Forests. Journal Of Decision Systems.;24(1):19-36, 2015.
53. Muthukrishnan R, Rohini R. LASSO: A Feature Selection Technique in Predictive Modeling for Machine Learning. IEEE International Conference on Advances in Computer Applications; 2016; Coimbatore. ICACA, s.18-20,2016.
54. Wibawa AP, Kurniawan AC, Murti DM, Adiperkasa RP, Putra SM, Kurniawan SA ve ark. Nugraha YR. Naive Bayes Classifier for Journal Quartile Classification. iJES. 7(2):91-99,2019.
55. Onan A, Korukoğlu S. Metin Sınıflandırmada Öznitelik Seçim Yöntemlerinin Değerlendirilmesi. XVIII. Akademik Bilişim Konferansı; 30 Ocak-5 Şubat; Adnan Menderes Üniversitesi, Aydın, 2016.
56. Korkem E. Mikroarray Gen Ekspresyon Veri Setlerinde Random Forest ve Naive Bayes Sınıflama Yöntemleri Yaklaşımı [Yüksek Lisans Tezi]. Ankara: Hacettepe Üniversitesi; 2013.
57. Kayaalp F, Başarslan MS, Polat K. Kronik Böbrek Hastalığını Tanımlamada Bir Hibrit Sınıflandırma Örneği. Electric Electronics, Computer Science, Biomedical Engineerings Meeting;18-19 Nisan; İstanbul Arel Üniversitesi, İstanbul, 2018.
58. Karaibrahimoğlu A. Veri Madenciliğinden Birliktelik Kuralı ile Onkoloji Verilerinin Analiz Edilmesi: Meram Tıp Fakültesi Onkoloji Örneği [Doktora Tezi]. Konya: Selçuk Üniversitesi; 2014.
59. Vapnik VN. An Overview of Statistical Learning Theory. IEEE Transactıons on Neural Networks. 10(5):988-999,1999.
60. Aydın Haklı D. Sınıf Dengesizliği Sorununu Çözmek için Kullanılan Algoritmaların Farklı Sınıflandırma Yöntemlerinde Performanslarının Karşılaştırılması. Ankara: Hacettepe Üniversitesi; 2018.
61. Kaşıkçı M. Transkriptom Veri Seti Üzerinde Derin Öğrenme Yöntemi ile Klasik Veri Madenciliği Yöntemlerinin Sınıflama Performanslarının Karşılaştırılması [Yüksek Lisans Tezi]. Ankara: Hacettepe Üniversitesi; 2019.
62. Gümüş E. Makina Öğrenme Yöntemleriyle Genom Dizilim Verilerinin Analizi [Doktora Tezi]. İstanbul: İstanbul Üniversitesi; 2013.
63. Fix E, Hodges JL. Discriminatory Analysis, Nonparametric Discrimination: Consistency Properties. Technical Report 4. USAF School of Aviation Medicine, Randolph Field, Texas;1951. Report No:4.
64. Cover MT, Hart P. Nearest Neighbor Pattern Classification. IEEE Transactions on Information Theory. 13(1):21-27, 1967.

65. Elasan S. Veri Madenciliğinde Farklı Karar Ağaçları ve K-En Yakın Komşuluk Yöntemlerinin İncelenmesi: Kadın Hastalıkları ve Doğum Verisinde Bir Uygulama [Doktora Tezi]. Van: Van Yüzüncü Yıl Üniversitesi; 2019.
66. Taşcı E, Onan E. K-En Yakın Komşu Algoritması Parametrelerinin Sınıflandırma Performansı Üzerine Etkisinin İncelenmesi. XVIII. Akademik Bilişim Konferansı; 30 Ocak-5 Şubat; Adnan Menderes Üniversitesi, Aydın, 2016.
67. Öğüş E, Can MB, Çamur E, Koru M, Özkan Ö, Rzayeva Z. Veri Kümelerinden Bilgi Keşfi: Veri Madenciliği; 15. Ulusal Biyoistatistik Kongresi, Uluslararası Katılımlı; 20-23 Ağustos; Aydın, 2013.
68. Daş B, Türkoğlu İ. DNA Dizilimlerindeki Nükleotit Çiftlerinin Frekans Değerlerine Göre Farklı Sınıflandırma Yöntemleri ile Karşılaştırılması. Tıp Teknolojileri Ulusal Kongresi; 25 – 27 Eylül; Kapadokya. TıpTekno`14. s.191 -194, 2014.
69. Demircioğlu HZ. Biyoinformatikte Çok Boyutlu Verilerin Boyut İndirgenerek Sınıflandırılması [Yüksek Lisans Tezi]. Ankara: Gazi Üniversitesi; 2015.
70. Hinton GE, Salakhutdinov RR. Reducing the Dimensionality of Data with Neural Networks. Science. 313(5786):504-507,2006.
71. Türkçetin AÖ. Akciğer Kanserinin Tespit Edilmesinde Derin Öğrenme Algoritmalarının Kullanılması [Yüksek Lisans Tezi]. Isparta: Isparta Uygulamalı Bilimler Üniversitesi; 2019.
72. Çiftçi F, Kaleli C, Günal S. Öznitelik Seçme ve Makine Öğrenmesi Yöntemleriyle Eğitmen Performansının Tahmin Edilmesi. Anadolu Journal of Educational Sciences International. 8(2): 419-440,2018.
73. Doğan F, Türkoğlu İ. Derin Öğrenme Algoritmalarının Yaprak Sınıflandırma Başarımlarının Karşılaştırılması. Sakarya University Journal of Computer and Information Sciences. 1:10-21, 2018.
74. Çoşkun C, Baykal A. Veri Madenciliğinde Sınıflandırma Algoritmalarının Bir Örnek Üzerinde Karşılaştırılması. XIII. Akademik Bilişim Konferansı. 2-4 Şubat 2011.
75. Kılıçkap M. Bilgi Kuramı Yaklaşımı ile Bilgisayarlı Tomografik Koroner Anjiyografinin Tanısal Değerinin Değerlendirilmesi [Yüksek Lisans Tezi]. Ankara: Hacettepe Üniversitesi; 2012.
76. Dişçi R. Tanı Testlerinin Değerlendirilmesi ROC Analizi. İstanbul Üniversitesi, Onkoloji Enstitüsü; 2013.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Artificial Intelligence in Physiotherapy and Rehabilitation

Sema GULTURK [1], Yagmur CAM [2,*]

[1] *Department of Physiotherapy and Rehabilitation, Faculty of Health Sciences, On Dokuz Mayıs University, Samsun, Turkey*
[2] *Department of Physiotherapy and Rehabilitation, Faculty of Health Sciences, Hatay Mustafa Kemal University, Hatay, Turkey*

* Corresponding Author: Yagmur CAM, Department of Physiotherapy and Rehabilitation, Faculty of Health Sciences, Hatay Mustafa Kemal University, Hatay, Turkey
E-Mail: yyagmurcam@gmail.com

Publication Information

Keywords :

- Artificial neural networks,
- Machine learning,
- Physiotherapist,
- Telerehabilitation

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

The concept of artificial intelligence (AI) has been an important application in intensive care units, inpatient services, and outpatient clinics, as well as providing the destruction of many taboos in physiotherapy and rehabilitation related to musculoskeletal, cardiovascular, neurological, pediatric, geriatric and many problems. AI applications can be used to evaluate and analyze the patient in physiotherapy and rehabilitation, and to determine the effectiveness of the treatment applied to the patient, and offer practical solutions in the clinic. AI can range from determining the risk of injury in athletes to determining the level of exposure to the physical capacity of the patient hospitalized in the intensive care unit. In babies born with any risk factor, the use of AI applications to determine the effectiveness of the treatment, to evaluate the changes in babies in the process objectively, and to process the movement patterns that are accepted as early diagnosis indicators, provides a different perspective to the field of pediatric rehabilitation. AI training in the field of physiotherapy and rehabilitation; data model creation, video collection, and labeling, preprocessing (noise reduction, orientation, FPS, and size adjustment), data set expansion, skeletal data extraction, data set creation, deep learning model training and finally implementation stages. In this field, images and videos are used in AI training, especially to evaluate the effectiveness of treatment. AI applications provide a different perspective to physiotherapists by determining the patient evaluation, treatment and the effects of the treatment on the patient. It is thought that developments in this field will increase the efficiency of physiotherapists in the clinic and their integration in the multidisciplinary field.

1. Introduction

With the latest advances in information technology and the widespread accessibility of the internet, a large accumulation of data has been achieved in many areas, including health [1]. It is thought that better inferences can be made about the clinical prediction, management, and outcomes of the disease if the increasing data about the patient in the health system are analyzed and interpreted. In the future, it is thought that complex medical data analysis will go beyond the cognitive level of the human, and the cooperation of artificial intelligence (AI) systems will be needed to analyze the patient's condition exactly [2,3].

2. Artificial Intelligence

AI is an interdisciplinary research area that understands, models, and copies human intelligence and cognitive processes by applying to devices in line with computational, mathematical, logical, mechanical, and biological principles [4], which are used to perform technology operations that require the participation of human intelligence [5]. More specifically, it is the study of the synthesis and analysis of computational factors that exhibit intelligent behavior. The agent can adapt to changing environments and goals, learn from experience, and make appropriate choices within the framework of perceptual and computational limitations [6]. In this way, expert systems can cover a wide variety of sub-units, including information representation, robotics, natural language processing, intelligent tools, predictive analytics, and planning [5], and play a major role in the development of technology [4].

By 2026, the value of artificial intelligence in the healthcare market is expected to reach 45.2 billion dollars, and machine learning technology is expected to cover a large part of the artificial intelligence market. With the COVID-19 pandemic, the use of artificial intelligence in many applications in healthcare is expected to increase [7].

3. Machine Learning

Artificial intelligence has a subfield called machine learning, which uses strategies capable of learning with or without being modified by an external user [8]. Machine learning, a branch of artificial intelligence, includes several algorithms or methods to create automatic models from data [9]. Computers, which can learn and act like humans, observe data and information and improve learning in the process by feeding on real data interaction [10].

Machine learning is divided into three parts as supervised, unsupervised, and reinforced learning [8]. Supervised learning includes characterization and repetition strategies in which the prediction model is created based on information obtained from information and efficiency sources; unsupervised learning collects information based on input and groups by deciphering it [11].

Another area of machine learning is deep learning using AI neuronal networks, which have many hidden layers apart from the input and output layers [11]. Deep learning imitates human learning in a situation that can not be formulated or standardized [12], and it allows complex problems to be tackled in any case [11].

The human nervous system consists of neurons that connect at a synapse to send information between two points in the body. In the deep learning mechanism, with repetitive learning, each synapse connection strengthens or weakens with repetitive learning [12]. The more deep learning algorithms learn, the better they perform [11].

4. Artificial Neural Networks

Tasks and processes associated with high mental activities specific to human intelligence, such as information acquisition, perception, thinking, reasoning, generalization, learning, and decision making, can be provided by a computer-controlled machine or computer system with AI method [13,14]. Some of the artificial intelligence techniques are expert systems that create solutions to the problems determined by establishing a link between information like an expert, intelligent agents working independently using various artificial intelligence techniques, fuzzy propositions that facilitate decision-making by processing imprecise information, and artificial neural networks, which are a learning-based system [13].

The most basic feature of artificial intelligence applications is that they can make a decision about a problem or a situation while searching for a solution [15]. Artificial neural networks are one of these decision mechanisms [16].

Artificial neural networks are formed by imitating the human brain and transferring biological neural networks to computer programs with a mathematical model [15,17]. In artificial neural networks, many simple processing units located in parallel to each other work at the same time [14]. Artificial neural networks based on the learning mechanism establish connections and relationships between samples, and in line with the information learned, they become capable of making decisions about new examples that they have never experienced before [13]. Artificial neural networks can extract the necessary features from the connected images and mimic object perception by establishing connections between artificial neuron layers [18]. The power of neural computing depends on the intensity of the connection between processing units that constitutes the total processing load [14,19]. The more samples in which artificial neural networks are trained, the easier and clearer the diagnosis of the problem is [15].

Artificial neural networks are advantageous due to their speed, ability to learn, and their ability to solve complex problems simply. At the same time, analysis success in artificial neural networks is not seriously affected in case of possible damage in separate processing elements [14,19].

5. Artificial Intelligence in Health

It is known that technology has important benefits in the field of medicine. Many life-facilitating applications have been discovered for both physicians and patients. The most common of these applications are virtual reality, artificial intelligence, and machine learning technologies. Exoskeletons are one of the technological methods that motivate the patient to move and develop using various video games [4].

AI is a technology that aims to provide automatic adaptation of the system with minimal clinician input [20]. AI offers many systems that help diagnose faster and give basic medical feedback in the field of health [21]. Artificial intelligence-based technologies achieve success in many clinical application areas, including decision support systems, diagnosis, prediction, image recognition, and natural language processing.

Today, artificial intelligence research offers the development of expert systems that guide clinical decision making, better diagnosis with computer algorithms in the analysis of CT and MRI imaging, prediction of patient results, improved management and planning in health systems [22]. Artificial neural network learning utilizes in voice analysis in patients with hearing problems, in surgical imaging systems, in determining the side effects of drugs, in understanding the cause of epileptic seizures, in examining the markers detected in imaging methods such as electrocardiography and electroencephalography, in determining the best time in organ transplantation applications [14,19] in the diagnosis of orthodontic extractions in dentistry [23]. As a result of these developments in the field of health, it is predicted that future healthcare professionals will need to change some basic concepts in clinical practice [24].

6. Artificial Intelligence in Physiotherapy and Rehabilitation

Along with the health integration of technology, there have been some developments in the field of physiotherapy. The main purpose of using technology in physiotherapy and rehabilitation is to ensure that patients can exercise correctly and to evaluate the effectiveness of exercise on the patient. Especially with the COVID-19 pandemic, it is aimed to continue physiotherapy and rehabilitation services with telerehabilitation applications [25].

Recent advances in medical AI are largely the result of advances in the subfield of machine learning. Therefore, learning depends on the quality of the data used to train and validate the algorithms [26]. Technological advances such as machine learning algorithms used to improve the understanding, diagnosis, and management of acute and chronic diseases have increased the capacity to define patterns in data sets and have been widely used to classify individuals with liver disease and heart failure [27,28], and in pain research [29].

AI research provides significant advances in the areas of information retrieval and storage, problem-solving and reasoning, image recognition, planning, and physical manipulation [30]. These developments also constitute the basic aspects of physiotherapy applications. Therefore, most traditional physiotherapy applications will become increasingly sensitive to AI-based systems in the process [31]. Machine learning is generally preferred because it has the potential to support physiotherapy applications through diagnosis, decision-making, and measurement [4].

In addition to machine learning, artificial neural networks are also used in performance modeling and determination of skill level in many sports such as swimming [32], the effect of 20-meter speed shuttle run test performance, gender, age, body weight, and height results on the prediction of maximum oxygen intake in young individuals [33]. In a team sport, it was used to classify the game position of a player according to the defined skill sets and to define the performance characteristics according to the game position [34]. These developments in medical technology provide the necessary materials for the care and support that the therapist will provide in line with the needs of the patients. In this way, the workload of the therapist is reduced and more patients can be treated [4].

7. Conclusion

Artificial intelligence applications have given physiotherapists a different perspective by determining the patient evaluation, treatment, and the effects of the applied treatment on the patient. It is thought that developments related to artificial intelligence in the field of physiotherapy and rehabilitation will increase the efficiency of physiotherapists in the clinic and their integration in the multidisciplinary field.

References

1. Zhou, X., Wu, Z., Yin, A., Wu, L., Fan, W., & Zhang, R. (2004). Ontology development for unified traditional Chinese medical language system. *Artificial intelligence in medicine*, *32*(1), 15-27.
2. Wartman, S. A., & Combs, C. D. (2018). Medical education must move from the information age to the age of artificial intelligence. *Academic Medicine*, *93*(8), 1107-1109.
3. Obermeyer, Z., & Lee, T. H. (2017). Lost in thought: the limits of the human mind and the future of medicine. *The New England journal of medicine*, *377*(13), 1209-1211.
4. Godse, S. P., Singh, S., Khule, S., Yadav, V., & Wakhare, S. (2019). Musculoskeletal physiotherapy using artificial intelligence and machine learning. *Int. J. Innov. Sci. Res. Technol*, *4*(11), 592-598.
5. Frankish, K., Ramsey, W.M. The Cambridge Handbook of Artificial Intelligence. Cambridge, UK: Cambridge University Press; 2017.
6. Poole, D. L., & Mackworth, A. K. (2010). *Artificial Intelligence: foundations of computational agents*. Cambridge University Press.
7. Hassabis, D., Kumaran, D., Summerfield, C., & Botvinick, M. (2017). Neuroscience-inspired artificial intelligence. *Neuron*, *95*(2), 245-258.
8. Mak, K. K., & Pichika, M. R. (2019). Artificial intelligence in drug development: present status and future prospects. *Drug discovery today*, *24*(3), 773-780.
9. Heller, M., 2019, *What is machine learning? Intelligence derived from data,* https://www.infoworld.com/article/3214424/what-is-machine-learning-intelligence-derived- from-data.html, Available date: 5 May 2020]
10. Faggella, D. (2020). *What is machine learning?,* https://emerj.com/ai-glossary-terms/what- is-machine-learning/, Available date: 5 May 2020.
11. Mohanty, S., Rashid, M. H. A., Mridul, M., Mohanty, C., & Swayamsiddha, S. (2020). Application of Artificial Intelligence in COVID-19 drug repurposing. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews*.
12. Jung, S. K., & Kim, T. W. (2016). New approach for the diagnosis of extractions with neural network machine learning. *American Journal of Orthodontics and Dentofacial Orthopedics*, *149*(1), 127-133.
13. Oztemel E. Yapay Sinir Ağları, Papatya Yayıncılık, Ağustos, 2003.
14. Yasav M. Yapay Sinir Ağlarıyla Yüz Mimiklerinin Tanınması.Yüksek lisans tezi. Yıldız Teknik Üniversitesi Elektronik Haberleşme Mühendisliği Anabilim Dalı, 2008.
15. Elmas, Ç. Yapay Sinir Ağları (Kuram, Mimari, Eğitim, Uygulama). Seçkin Yayıncılık. Ankara, 2003.
16. Yeloğlu, Ö., Uğur, A. Modern Programlama Platformlarında Yapay Sinir Ağı Yazılımlarının Geliştirilmesi. Bilgi Teknolojileri Kongresi III (Bilgitek 2004), Denizli, 1-8, 2004.
17. Arslan, A., & İnce, R. (1993). Geriye Yayılma Yapay Sinir Ağı Kullanılarak Betonarme Kolonların Tasarımı. *Turkish Journal of Engineering and Enviromental Sciences*, *2*, 127-135.
18. Cao, C., Liu, F., Tan, H., Song, D., Shu, W., Li, W., Zhou, Y., Bo, X., & Xie, Z. (2018). Deep learning and its applications in biomedicine. *Genomics, proteomics & bioinformatics*, *16*(1), 17-32.
19. Bozuyuk, T. Yapay Zeka Teknolojilerinin Endüstrideki Uygulamaları, Yüksek Lisans Tezi Marmara Üniversitesi Fen Bilimleri Enstitüsü, Istanbul, 2005.
20. Massalha, S., Clarkin, O., Thornhill, R., Wells, G., & Chow, B. J. (2018). Decision support tools, systems, and artificial intelligence in cardiac imaging. *Canadian Journal of Cardiology*, *34*(7), 827-838.
21. Rouse, M. AI (artificial intelligence) definition in Essential Guide: Special report: Artificial intelligence apps come of age. Contributors: Ed Burns and Nicole Laskowski. Available from: https://searchenterpriseai.techtarget.com/definition/AI-Artificial- Intelligence (2019 Jan 4).
22. Harwich, E., & Laycock, K. (2018). Thinking on its own: AI in the NHS. *Reform Research Trust*.

23. Jung, S. K., & Kim, T. W. (2016). New approach for the diagnosis of extractions with neural network machine learning. *American Journal of Orthodontics and Dentofacial Orthopedics*, *149*(1), 127-133.
24. Wartman, S. A., & Combs, C. D. (2018). Medical education must move from the information age to the age of artificial intelligence. *Academic Medicine*, *93*(8), 1107-1109.
25. Russell, T. G. (2007). Physical rehabilitation using telemedicine. *Journal of telemedicine and telecare*, *13*(5), 217-220.
26. Rowe, M. (2019). An introduction to machine learning for clinicians. *Academic Medicine*, *94*(10), 1433-1436.
27. Diller, G. P., Kempny, A., Babu-Narayan, S. V., Henrichs, M., Brida, M., Uebing, A., Lammers, A.E., Baumgartner, H., Li, W., Wort, S.J., Dimopoulos, K. & Gatzoulis, M. A. (2019). Machine learning algorithms estimating prognosis and guiding therapy in adult congenital heart disease: data from a single tertiary centre including 10 019 patients. *European heart journal*, *40*(13), 1069-1077.
28. Wu, C. C., Yeh, W. C., Hsu, W. D., Islam, M. M., Nguyen, P. A. A., Poly, T. N., Wang, Y.C., & Li, Y. C. J. (2019). Prediction of fatty liver disease using machine learning algorithms. *Computer methods and programs in biomedicine*, *170*, 23-29.
29. Lötsch, J., & Ultsch, A. (2018). Machine learning in pain research. *Pain*, *159*(4), 623-630.
30. Frankish, K., & Ramsey, W. M. (Eds.). (2014). *The Cambridge handbook of artificial intelligence*. Cambridge University Press.
31. Rowe, M., Nicholls, D., & Masters, K. (2019). Artificial intelligence in clinical practice: Implications for physiotherapy education. OpenPhysio, 1-6.
32. Silva, A. J., Costa, A. M., Oliveira, P. M., Reis, V. M., Saavedra, J., Perl, J., Rouboai A. & Marinho, D. A. (2007). The use of neural network technology to model swimming performance. *Journal of sports science & medicine*, *6*(1), 117-125.
33. Ruiz, J. R., Ramirez-Lechuga, J., Ortega, F. B., Castro-Pinero, J., Benitez, J. M., Arauzo-Azofra, A., Sanchez, C., Sjöström, M., Castillo, M. J., Gutierrez, A., Zabala, M. & HELENA Study Group. (2008). Artificial neural network-based equation for estimating VO2max from the 20 m shuttle run test in adolescents. *Artificial intelligence in medicine*, *44*(3), 233-245.
34. Woods, C. T., Veale, J., Fransen, J., Robertson, S., & Collier, N. F. (2018). Classification of playing position in elite junior Australian football using technical skill indicators. *Journal of sports sciences*, *36*(1), 97-103.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Current Status and Open Problems in Bone Age Estimation

Bülent ESEN [1, *], Metin TURAN [1], Nurşen Turan YURTSEVER [2], Onur BUĞDAYCI [3]

[1] *Istanbul Commerce University, Department of Computer Engineering, Turkey*
[2] *Marmara University, School of Medicine, Department of Forensic Sciences, Turkey*
[3] *Marmara University, School of Medicine, Department of Radiology, Turkey*

* Corresponding Author: Istanbul Commerce University, Department of Computer Engineering, Turkey
Tel.: +90 5304196334. E-Mail: bulent.esen@istanbulticaret.edu.tr

Publication Information

Keywords :

- Bone age estimation,
- Artificial neural network,
- Image processing,
- Forensic informatics

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Bone age is an effective indicator for diagnosing various diseases and to determine bone ages of livings. The earliest well-known studies belong to the Greulich-Pyle and Tanner-Whitehouse, as a result bone age development atlases were published using hand and wrist radiography. Atlases works well for the younger ages between 0-18, while they have deviations at elder ages. Kazuro Anhara and Takao Suzuki emphasized the importance of changes in pubic symphysis of pubic bones belonging to 20 to 40 years old cases who were not alive for further ages. All this researches focuses on the hand intensive works. However, automation of bone age detection using artificial intelligence techniques such as image processing of radiological images is important in order to prevent human side-effects on the evaluation, they are called automated methods. Some examples are automatic bone age estimation fully automatic with carpal bone segmentation using fuzzy classification, fuzzy-based radius model for bone age estimation including image preprocessing, and neural network applications mostly seen on the literature. It is obvious, artificial intelligence promises faster bone age estimation and to minimize different evaluations between experts. However, new studies are needed for applying new techniques (deep learning) efficiently and discovering new bones to estimate elder ages accurately in the field of forensic informatics especially.

1. Introduction

In this study, important studies on bone age estimation from the past to the present are examined and open problems that have not yet achieved sufficient results are mentioned.

Skeletal maturation varies according to the geography, gender and socio-economic status of the person. Estimation of bone age shows the degree of skeletal maturation. The age calculated from the date of birth of the person is the calendar age, and the bone age is the age determined by looking at the skeletal maturity rather than the calendar age. Bone age estimation is necessary in the diagnosis of some diseases. Age estimation is also important in judicial terms, and bone age estimation is required in many issues such as competence in crime and age correction. Especially in cases where children are registered late in the population in rural areas, or if the same identity information is maintained for the unregistered child after the death of the older child, it is important to estimate the real age of the person [1-2].

Studies have been carried out on alive and dead cases in determining the bone age. Kazuro Anhara and Takao Suzuki carried out the main study on anatomically examining the bones and estimating the age according to the changes on the bones. This study was accepted especially because it explains the morphological changes on the bone in detail. Radiological method is used to estimate the bone age of living individuals. In these methods, radiographic images obtained from the wrist bones in children aged 0-18 and from the shoulder, clavicle and pelvis bones in individuals over 20 years old are compared with the measurements in certain atlases and the age of the person is determined. This approach is the method used widely in the clinic and obtaining realistic results [3]. The most well-known systematic studies are the studies of Greulich-Pyle and Tanner-Whitehouse. Hand and wrist radiography was used in these studies. Because the hand and wrist are regions that have the necessary conditions for estimating the skeletal maturation process. In addition, considering that the majority of people use their right hand in their daily work, studies have focused on the left hand and wrist, under the assumption that the right hand can develop more than the left hand.

Bone age estimation is an issue concerning Forensic Informatics. Forensic problems that are tried to be solved by manually (autopsy or comparative results obtained from atlases on radiographic images) are time-consuming. For this reason, it is important to make computer-based analysis to solve forensic problems. Computer forensics is also considered as digital forensic or forensic information technology. Forensic Informatics is based on X-ray image analysis, Computed Tomography (CT) / Magnetic Resonance Imaging (MRI) and ultrasonography analysis [4]. Radiologists are responsible for visualizing the internal structure of the human body using electronic devices. These images are examined in more detail by the attending physician for medical diagnosis. Therefore, the digitized image should be well defined.

2. Manual Methods of Bone Age Estimation

2.1. Age Estimation by Regression Analysis on Pubic Symphysis

The study conducted by Kazuro Anhara and Takao Suzuki was applied on 70 pairs of pubic bones belonging to Japanese deceased cases. 33 pairs of these bones were obtained from Tokyo University Department of Anatomy and 37 pairs from Sapporo Medical College [5]. The study demonstrated that the pubic symphysis is a reliable indicator of age for the estimation of bone age between 20 and 40 years of age [5]. As a result of their morphology and experience, they focused on the following seven morphological features for the assessment of age in symphysis. These are: horizontal ridges and furrows, pubic tubercle, lower end, dorsal margin, superior Ossific nodule, ventral beveling, and symphysial rim.

2.2. Description of Age Changes in Pubic Symphysis

2.2.1. Horizontal Ridges and Furrows

It has been determined in the study that: the situations where the protrusions on the symphysis surface are high and the grooves deep and sharp are very evident under the age of 20. By the age of 20-23, the grooves become shallow and the ridges relatively dull. This slimming continues until the age of 27. After the age of 28, with rare exceptions, this feature disappears completely and the symphysial surface becomes flat [5].

2.2.2. Pubic Tubercle

In individuals under the age of 23, there is epiphyseal cartilage between this tubercle and the pubic bone. However, after the age of 24, the tubercle completely merges with the pubic bone without exception.

2.2.3. Lower End

Before 22 or 23 years of age, the lower end of the symphysial surface is indistinguishable from the upper end of the lower pubic ramus. Between about 23 and 30 years of age, the lower part of the symphysial surface is surrounded by a narrow ridge, and after about 30 years of age, the ridge becomes wider and shows a triangular swelling in most cases.

2.2.4. Dorsal Margin

Up to the age of 19, there are no marginal ridge limiting the symphysial surface, and at around 20 years of age, a scar of the ridge appears on the dorsal border of the symphysial surface. In individuals older than 27 years of age, the formation of the ridge is almost complete, although still narrow along the entire length of the dorsal rim. In about half of the cases included in the study by Anhara and Suzuki, the back was enlarged after the age of 33 or 34. In current examples, 12 out of 22 (54.4%) show expanded margins.

2.2.5. Superior Ossific Nodule

This formation appears in the upper part of the pubic surface for a limited time. No nodules can be seen in individuals under the age of 20, but it is easily seen between the ages of 21-27 and then disappears again. Because the age changes of this nodule are relatively different, its occurrence or disappearance represents a good age indicator for the period from the early to late twenties.

2.2.6. Ventral Beveling

By age 22, the ventral border of the pubic symphysial surface joins the ventral surface of the pubic bone. In later ages, a narrow surface appears between the two surfaces. It is not defined for ages 23 to 27. Between the ages of 28 and 33, it occurs along the entire length of the pubic symphysis. In individuals older than 33 or 34 years of age, the upper part of the ventral curve disappears, but the variation of this change is relatively large.

2.2.7. Symphysial Rim

In older individuals, the surface of the symphysial is not very frequent, but is surrounded by a relatively wide and matt margin (rim). This finding can be seen in people over the age of 30, and its incidence increases after the age of 34. Therefore, the age of an individual with this phenomenon (rim) can be estimated to be in his/her mid-thirties or older, but this does not mean that the individual without the phenomenon is young.

2.3. Greulich and the Pyle Method

It is a method developed by Greulich and Pyle. These scientists obtained different radiographic images of children of different age groups, including left shoulder, elbow, hip and knee. The data collection process included approximately 1000 children's radiographs between 1931-1942. This study was published by Stanford University in 1959 under the title of Hand Bone Development Stages (Atlas of Skeletal Development of the Hand and Wrist) [4]. Since male and female mature at different speeds, two different atlases have been put forward. These atlases are the basic model used to analyze age-related changes in human bone structure. This method is called as GP method in the literature.

2.4. Tanner and Whitehouse (TW) Method

In this method developed by Tanner and Whitehouse, radiographs of the left hand and wrist were used again. In this method, bone joints were used as a determining feature in bone age estimation. The atlas of this study was published in 1962 (TW: TW1, TW2, TW3) [4]. In this method, the most accepted RUS (Radius, Ulna, Short Bone) scores are used. For the estimation of bone age, hand and wrist bones were considered as 8 main bones in total and 9 bones together with the ulna were considered. This method has been updated with studies conducted in various countries and the USA. Because the stages of bone development in the 1960s and the developmental stages of the 1990s differ [6]. The new method is named TW3.

2.5. Current Status in Turkey

The Forensic Age Estimation (Adli Yaş Tayini Kitabı - AYT) book published by the Forensic Medicine Institute is used in age estimation. The features to be used in estimating the age of cases between the ages of 1 and 50 have been estimated. The age estimation report is prepared by estimating the height, weight, number of teeth and radiological features for the relevant age and comparing it with the findings of the case for which age estimation is desired. It was observed that there was a significant difference between the age estimated by the AYT book and the real age, such as 1.21 years for boys and 2.17 years for girls [7]. In addition, research continues on new approaches and methods in estimating bone age.

2.6. Evaluation of Age Estimation in Forensic Medicine by Examination of Medial Clavicular Ossification from Thin Section Computed Tomography Images

In the study conducted by Murat Serdar Gürses et al., 1041 Thorax Computed Tomography images obtained between January 2012 and February 2014 at the radiology department of Uludağ University were used [8]. These images belong to cases between 10 and 35 years old. This study is basically based on the staging method developed by Schmeling and Kellinghaus. These stages seen on the clavicle are expressed as follows: Figure 1 for Stage 1, Figure 2 for Stage 2, Figure 3 for Stage 3, Figure 4 for Stage 4 and Figure 5 for Stage 5.

2.6.1. Stage 1: The ossification center is not followed:

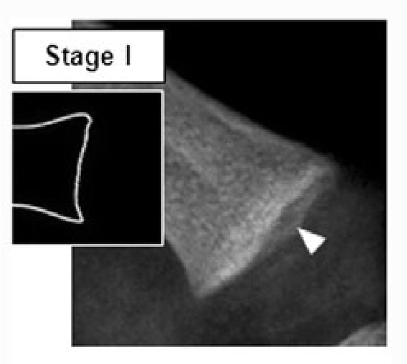


Figure 1. Clavicle at Stage I

2.6.2. Stage 2: The ossification center is ossified; the epiphyseal cartilage is not ossified.

2.6.2.1. Stage 2a: The longitudinal epiphyseal measurement is one-third or less compared to the transverse measurement of the metaphyseal tip.

2.6.2.2. Stage 2b: The longitudinal epiphyseal measurement is one-third to two-thirds greater than the transverse measurement of the end of the metaphysis.

2.6.2.3. Stage 2c: The longitudinal epiphysis measurement is more than two-thirds compared to the transverse measurement of the metaphyseal tip.

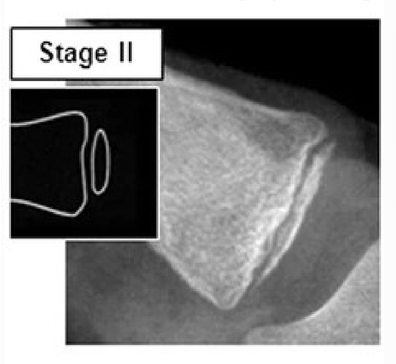


Figure 2. Clavicle at Stage II

2.6.3. Stage 3: The epiphyseal cartilage is partially ossified.

2.6.3.1. Stage 3a: Pineal-metaphyseal fusion completes one-third or less of the old space between epiphysis and metaphysis.
2.6.3.2. Stage 3b: The epiphysis-metaphysis fusion completes more than one-third to two-thirds of the old space between the pineal and metaphysis.
2.6.3.3. Stage 3c: The epiphysis-metaphysis fusion completes more than two-thirds of the old space between the pineal and metaphysis.

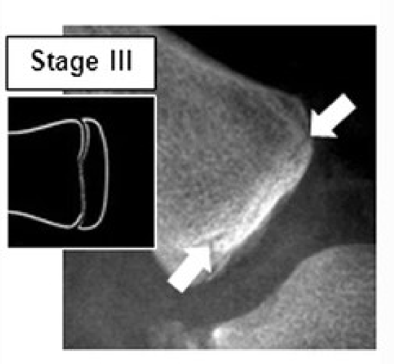


Figure 3. Clavicle at Stage III

2.6.4. Stage 4: The epiphyseal cartilage is completely ossified; the epiphysis scar is visible.

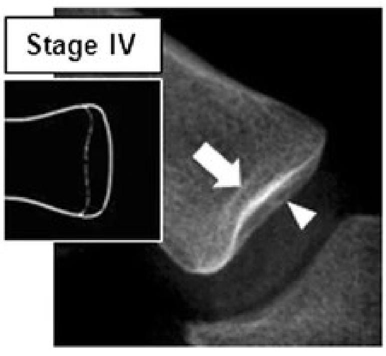


Figure 4. Clavicle at Stage IV

2.6.5. Stage 5: Pineal cartilage is completely ossified; Pineal scar is no longer visible.

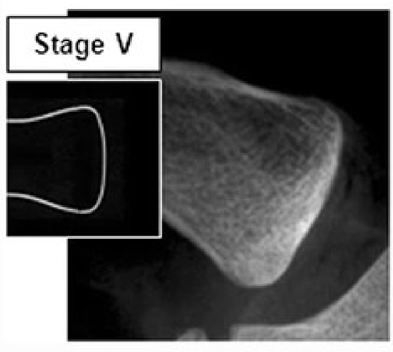


Figure 5. Clavicle at Stage V

In this study, two radiologists, one with 15 years of experience and the other with 5 years of experience, examined the CT images at 2-week intervals, and the results of which they reached a consensus were determined, and age was estimated. Located in this study, two radiologists, Turkey's estimated age than before yet on CT images, before they are given to age estimation on CT images. It was stated that the age of the cases from which the images were obtained was not previously known by either of the two radiologists. In cases where there is a developmental difference between the left and right clavicle, the side with more development is taken as a basis.

As a result, evaluation of clavicle ossification was possible in 725 cases. Comparisons between male and female data mostly revealed statistical differences in the 4th stage. However, such a difference was not observed in other stages.

3. Automatic Methods for Bone Age Estimation

3.1. Automatic Bone Age Assessment for Young Children from Newborn to 7-Year-Old Using Carpal Bones

In this study by Zhang et al, a carpal ROI (Region of Interest) analysis and bone age estimation study with fuzzy classification were performed for fully automated carpal bone segmentation. In this study, a model was developed and tested using x-ray images obtained from 205 children [9]. Figure 6 shows the stages of detecting the carpal bones through the hand x-ray image.

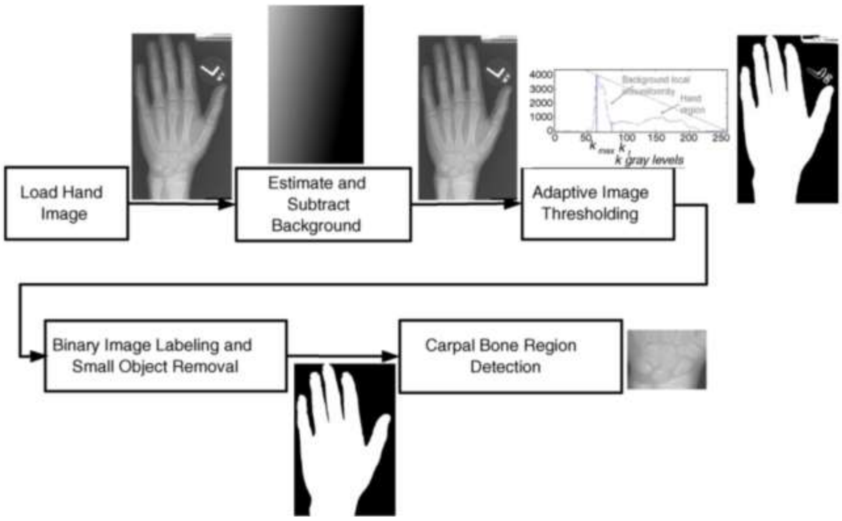


Figure 6. Procedure steps to determine the carpal bones from the X-ray image of the hand

The method applied in this study consists of 7 stages. The first step is to extract carpal bones from hand x-ray images. In the second step, filtering is applied to remove unwanted phenomena (background, shadow, etc.) on the image. In the third stage, the edges of the carpal bones are clarified with the edge detection algorithm. In the fourth stage, bones other than carpal bones are removed from the image. In the fifth stage, carpal bones are determined according to the model shown in Figure 7.

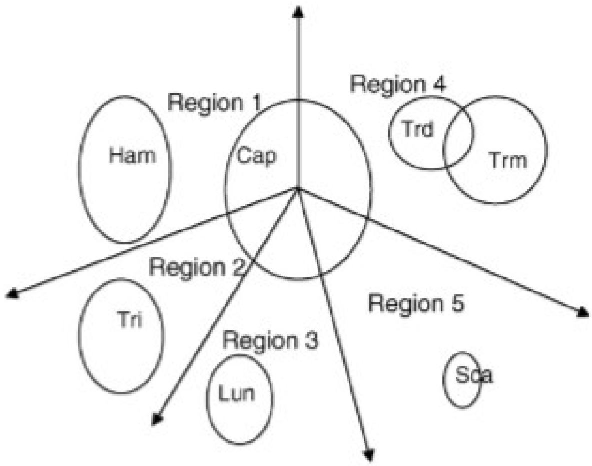


Figure 7. Carpal bone identification model

In this model, the polar coordinate system containing the center of the capitate as the starting point is divided into five regions. Based on priori anatomical information, capitate, hamatum, tricuitrum, lunatum, scaphoid, trapezium, and trapezoideum carpal bones are located in each of these five regions.

Figure 8 shows the ROI image of seven carpal bones obtained from the X-ray image of the hand.

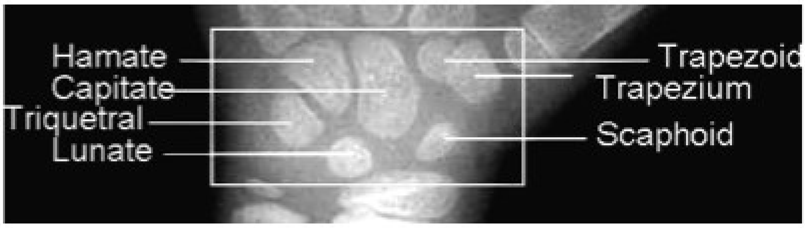


Figure 8. Identification of the carpal bones in the X-ray image of the hand

Figure 9 shows the developmental stages of the carpal bones of Asian men from newborn to 7 years old. The numbers on the images represent the age groups from which the images were acquired.

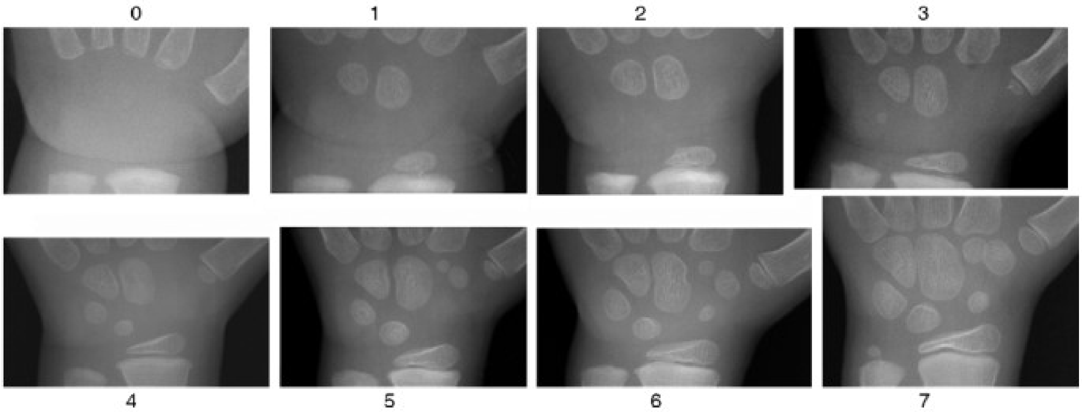


Figure 9. The developmental stage of the carpal bones in Asian males from newborn to 7 years of age

When examined chronologically, as can be seen in Figure 9, the first carpal bones detected are capitate and hamatum (seen on second image in Figure 9). Therefore, these two carpal bones were selected for analysis in this study. In the sixth stage, the extracted features were selected and in the last stage, age estimation was made by passing to the fuzzy classification stage.

3.2. Distal Radius Bone Age Estimation Based on Fuzzy Model

In the study by Sadiah Jantan et al., A fuzzy-based radius model for bone age estimation including image preprocessing and feature extraction is defined. In this study, it was aimed to estimate the bone age by using a fuzzy model based on distal radius bone features. 333 left hand digital X-ray images were included in this study. X-ray images are of 167 Asian-American boys and 167 Asian-American girls aged 0-18 [10].

The study basically consists of 5 stages. These are extraction of ROI, pre-processing of ROI (removal of background, shadow, etc. noise by applying filters), extraction of features, and estimation of age according to the classification result by inserting it into the fuzzy classifier at the last stage. The method followed is shown schematically in Figure 10.

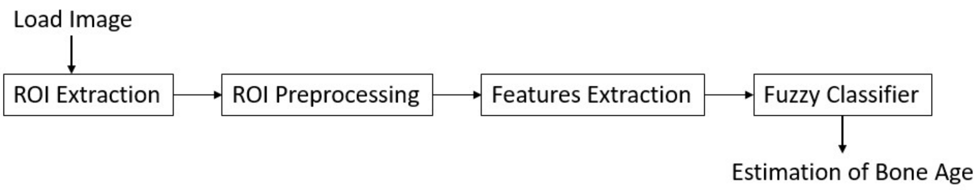


Figure 10. Flow chart of age estimation with Fuzzy Logic

Based on the results, it has been confirmed that the ratio of the radius to the distal end is an important parameter for explaining the state of bone growth before a child reaches the age of 14.

3.3. A Novel Method Using Neural Networks for Age Estimation in Children

In the study conducted by Harun Çelik and Semra İçer, it was aimed to estimate bone age from wrist x-ray images in children using Artificial Neural Network (ANN). The ANN developed in this study can automatically determine the age. 42 reference images were used for boys and girls in the study. First, the development of the elbow and forearm epiphyses in these images was examined, then ANN was trained with the features of these epiphyses and a system capable of automatic age estimation was developed [11].

In this study, the elbow and forearm epiphyses, which are considered to be more proportional to potential growth, were taken into account. While the transverse growth of these two epiphyses up to a certain age is a distinctive feature, growth occurs more towards the neck at later ages. For this reason, both transverse growth and longitudinal growth developments were taken into account in the calculations.

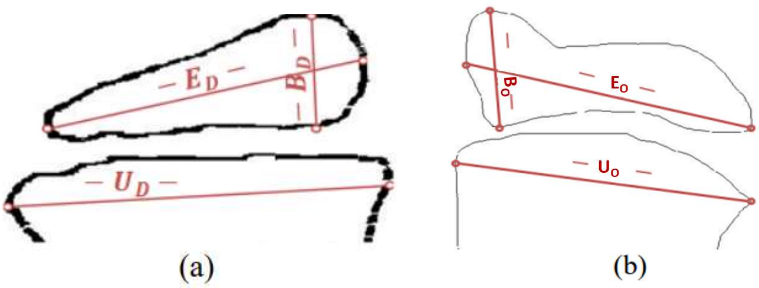


Figure 11. (a) Tip and epiphysis of the elbow bone, (b) tip and epiphysis of the forearm bone

Figure 11 shows the tip and epiphysis of the elbow bone (a) and the tip and epiphysis of the forearm bone. Where parameters are as follows:
U_D: the longest transverse end of the elbow end,
E_D: the widest length between the two transverse ends of the elbow epiphysis,
B_D: longitudinal widest length of the elbow epiphysis,
U_O: the longest transverse to the tip of the forearm bone,
E_O: the widest length between the two transverse ends of the forearm epiphysis,
B_O: the longest longitudinal length of the forearm epiphysis,

The researchers decided to look at the relationship between age and these epiphyses to determine whether it is sufficient to look at the forearm bone in age estimation. For this purpose, they calculated the change of epiphyseal development values corresponding to every age in boys and girls. They tried to reveal age estimation ability with correlation analysis. According to the result of correlation analysis, it was accepted as a perfect fit when the correlation coefficient was +1, and when it was -1, it was accepted that there was an inverse relationship between variables.

Table 1. Correlation analysis according to gender

	Boy	Girl
E_D / U_D	0.9046	0.8819
B_D / U_D	0.9422	0.9705
E_O / U_O	0.9573	0.9406
B_O / U_O	0.9793	0.9539

Analysis results showing the relationship between calculated epiphyseal growth values and bone age are given in Table 1. When the results in this table are examined, there is a relationship between the width and length of the epiphysis with a rate of over 90% in males and over 88% in females.
The ANN used in the study was designed with multiple layers. It has five neurons in input layer, two neurons in hidden layer and one neuron in output layer. In the experiments, the model with the Mean Squared Error (MSE) was preferred. The algorithm scheme of the system is as shown in Figure 13.
As a result, the system developed with this method was tested on 32 wrist images of different ages, whose bone age was estimated by two experts before, and predicted the bone age with an average error of 0.52 years. Thanks to this developed system, age estimation can be made quickly for children.

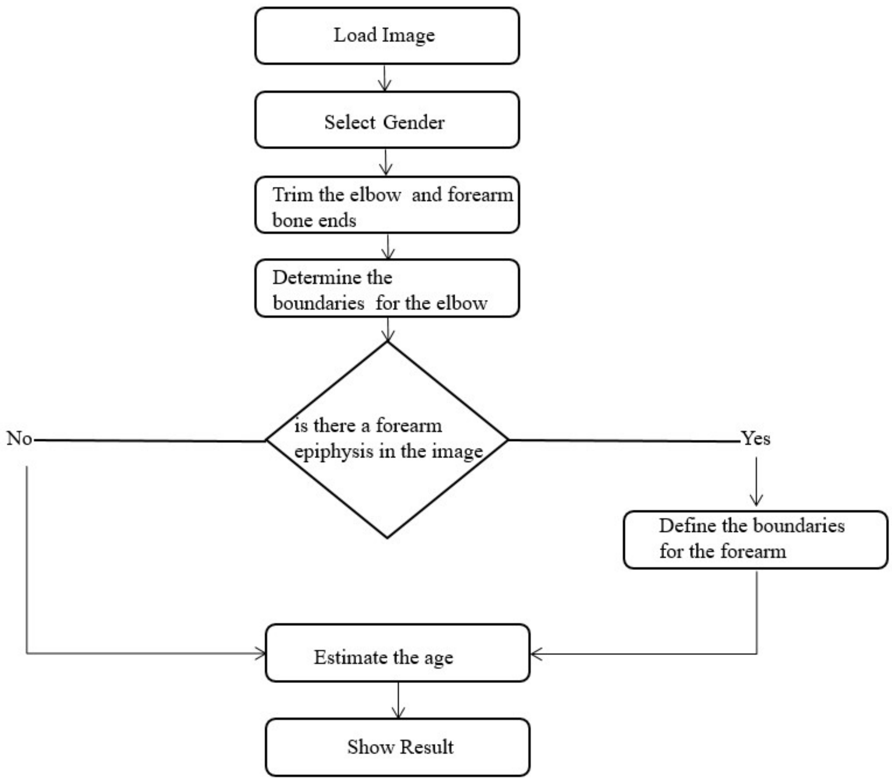


Figure 13. System operating model

3.4. Use of Artificial Neural Networks to Estimate Radiological Bone Age from Hand - Wrist X-Ray Images

Esra Hasaltın and Erkan Beşdok developed a semi-automatic system for bone age estimation using ANN. X-ray images of 307 pediatric cases without growth disorders were used in the study. 144 of these images belong to female and 163 to male cases [12]. Carpal bone areas were used in the study. In the calculation of the areas of the carpal bones, the borders of the bones were first marked by an operator and these marked points were transformed into a cubic spline curve.

5 different models have been applied in artificial neural network design.

- *Model 1*: 7 neurons in input layer (carpal bones), 5 neurons in hidden layer and 1 neuron in output layer (predicted bone age)
- *Model 2*: 8 neurons in input layer (7 carpal bones and 1 calendar age), 5 neurons in hidden layer and 1 neuron in output layer (predicted bone age)
- *Model 3*: 8 neurons in input layer (7 carpal bones and 1 gender), 5 neurons in hidden layer and 1 neuron in output layer (predicted bone age)
- *Model 4*: 7 neurons in input layer (carpal bones belonging to female cases), 5 neurons in hidden layer and 1 neuron in output layer (predicted bone age)
- *Model 5*: 7 neurons in input layer (carpal bones belonging to male cases), 5 neurons in hidden layer and 1 neuron in output layer (predicted bone age)

Performance analysis of three different learning algorithms has been performed and the performance of various learning algorithms on the data set has been evaluated. These learning algorithms are; Resilient Propagation - RP is Levenberg-Marquardt (LM) and batch gradient descent with momentum (GDM) - variable learning rate (GDX).

Different transfer functions were used in the artificial neural network structure according to the learning model. In the LM algorithm, the sigmoid transfer function in the hidden layer and output layers, tangent hyperbolic in the hidden layer in the RP algorithm, the sigmoid transfer function in the output layer, linear in the hidden layer and sigmoid transfer function in the output layer in GDX algorithm were applied. The authors stated that they also experimented with different transfer functions, but they used the ones that gave the best results in this study. Of the data set consisting of 251 cases, 150 were used for learning and 101 for testing. In studies where male and female cases were evaluated separately, 110 were used as learning and 27 test data for male cases, and 90 learning and 24 test data for female cases.

Bone age was estimated by an expert radiologist by evaluating the X-ray images according to the Greulich-Pyle atlas. The information about the learning method and other cases were given to different ANN models and the results were evaluated comparatively. According to the results obtained, LM algorithm gave the best result in all models according to MSE error criteria. Then RP algorithm took second place and GDX algorithm ranked third. In the test data, the RP algorithm gave a better result.

4. Conclusion

Artificial intelligence is promising for the future in order to estimate the age from radiological images quickly and to minimize the different evaluations between experts. However, new studies are needed for the development of this technique, which is very new in the field of forensic informatics. In the literature, it is seen that computer-aided automatic bone age estimation applications are generally carried out with X-ray images of the hand and wrist. However, the hand and wrist development is largely completed after the age of 18, which is inadequate in estimating the age of the cases between the ages of 18-50. For this reason, computer-based systems and radiological image processing techniques will fill the knowledge gap in this field in terms of the development characteristics of bones in different ages, genders and races.

References

1. Yılmazer Ö. Adli Tıp Kurumu'nda Yaş Tayininde Kullanılan Yöntemin Verimlilik Açısından Değerlendirilmesi. Uzmanlık Tezi, T.C. Adalet Bakanlığı Adli Tıp Kurumu, İstanbul, 2006.
2. Uğur Ersoy Ö. Kemik Yaşının Değerlendirilmesi.0-18 Yaş Arası Popülasyonda Kesitsel Çalışma. Uzmanlık Tezi, T.C. Adalet Bakanlığı Adli Tıp Kurumu, İstanbul, 2003.
3. Kemik Yaşı Tayininde Kullanılan Greulich-Pyle ve TannerWhitehouse Yöntem lerinin Karşılaştırılması - Adli Tıp Bülteni, 2020; 25(1): 6-15 - Atilla Kaplan*, Hakan Yılmaz)
4. Rajitha Bakthula , Suneeta Agarwal, Automated Human Bone Age Assessment using Image Processing Methods – Survey, International Journal of Computer Applications (0975 – 8887) Volume 104 – No.13, October 2014.
5. Kazuro Hanhara, Takao Suzuki, Estimation of Age from the Pubic Symphysis by Means of Multiple Regression Analysis J. PHYS. ANTHROP. (1978) 233-240.
6. Tanner-Whitehouse bone age reference values for North American children – James Tanner, Dan Oshman and others.
7. Gök Ş, Erölçer N, Özen C. Adli Tıpta yaş tayini. Adli Tıp Kurumu Yayınları, 1985.
8. Murat Serdar Gurses, Nursel Turkmen Inanir, Gokhan Gokalp, Recep Fedakar, Eren Tobcu, Gokhan Ocakoglu, Evaluation of age estimation in forensic medicine by examination of medial clavicular ossification from thin-slice computed tomography images, Int J Legal Med (2016) 130:1343–1352.
9. Zhang A, Gertych A, Liu BJ. Automatic bone age assessment for young children from newborn to 7 year old using carpal bones, Computerized Medical Imaging and Graphics.
10. Sadiah Jantan, Aini Hussain, Mohd Marzuki Mustafa, Distal Radius Bone Age Estimation Based on Fuzzy Model, 2010 IEEE EMBS Conference on Biomedical Engineering & Sciences (IECBES 2010), Kuala Lumpur, Malaysia, 30th November - 2nd December 2010.
11. Harun Çelik, Semra İçer, Çocuklarda Yaş Tayini İçin Yapay Sinir Ağlarının Kullanıldığı Yeni Bir Yöntem, Biyomedikal Mühendisliği Bölümü, Erciyes Üniversitesi, Kayseri, Türkiye.
12. Esra Hasaltın, Erkan Beşdok, El – Bilek Röntgen Görüntülerinden Radyolojik Kemik Yaşı Tespitinde Yapay Sinir Ağları Kullanımı.

AITA

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

COVID-19, Artificial Intelligence, and Wastewater-based Epidemiology

Füsun ÖZYAMAN [1*], Özlem YILMAZ [2]

[1] *Dokuz Eylül University, Faculty of Medicine, Department of Medical Microbiology, İzmir, Turkey*
[2] *Dokuz Eylül University, Faculty of Medicine, Department of Medical Microbiology, İzmir, Turkey*

* Corresponding Author: *Dokuz Eylül University, Faculty of Medicine, Department of Medical Microbiology, İzmir, Turkey*
Tel.: +90535 550 68 80. E-Mail: fusun.ozyaman@ogr.deu.edu.tr

Publication Information

Keywords : COVID-19, artificial intelligence, wastewater-based epidemiology, pandemics

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

The ongoing COVID-19 pandemic is a health emergency globally. Wastewater-based epidemiology (WBE) supported with artificial intelligence (AI) is a noninvasive, efficient, population-wide, cost-effective, complementary tool in detecting SARS-CoV-2 in wastewater and providing early warnings of ongoing and future pandemics. The combination of WBE, AI, nanotechnology, predictions, surveillance and modeling is important for early detection and prevention of pandemics. Examples of new, rapid, automated, sensitive and quantitative methods aided with AI are Droplet-Digital-PCR, Point-of -Care, biosensors, biomarkers, and combinations of biosensors, microfluidic and paper-based instruments. The combination of edge computing, AI and blockchain is used for precise results, rapid data processing and sharing. WBE computational model and simulation show the feasibility, advantages, disadvantages of WBE with the temperature, water use and travel time variables. Model predicting the fecal-oral transmission way according to the percentages of intrinsic disorder and hardness of viral shell, SARS-CoV-2 is resistant and are shed in high numbers from the body. WBE is used to monitor the new variants, community vaccination results and to detect the infected person by near-source tracking. Pandemic's effect on water cycle can be compensated by water industry digitalization such as using the data of public health and wastewater. AI is also useful in planning the post-COVID-19 cities and the treatment plants by models. WBE supported with AI is an important approach for early detection, control of the COVID-19 pandemic and protection of public health. Further studies are required to overcome the challenges and for improvement.

1. Introduction

Artificial intelligence (AI) deals with intelligent machines and computer programs [1] and solves hard problems such as making predictions and decisions by imitating the human brain [2]. Health data aided with AI help to improve our lives and informative about the different characteristics of infections and vaccine designs [3]. The burden of COVID-19 pandemic and the efforts for prediction and prevention have been experienced by the whole world, but the problem is still increasing [4]. Wastewater analysis analyzes urine and fecal samples at the population level. In wastewater-based epidemiology (WBE) observation of concentration of the virus help early detection of pandemic in real-time. Virus shedding rates, transport rates, degradation rates, and correlations are needed for accurate evaluation [5]. To control the pandemic's challenges, WBE supported by AI, surveillance, predictions, modelings, nanotechnological and new methods are important in the detection, prevention and responding to the pandemic [6].

2. Applications of AI in WBE

Hart and Halden used WBE and computational model for the feasibility, advantages and disadvantages of the investigation. It is feasible when one infected case/100-2,000,000 non-infected people are detected in wastewater. Temperature, wastewater travel time and water use are the variables in the study. In the model simulation wastewater system data, wastewater-loading rate, wastewater loads, population density were used and numerical analysis was conducted. WBE and medical tests costs were analyzed [7]. WBE's disadvantage is not being able to show the patients. Some countries do medical tests for each person, but this method is slow and expensive. It is concluded that WBE is a rapid, inexpensive and powerful tool to monitor COVID-19 [7,15,17,21,23]. WBE is a complementary tool and cannot replace clinical tests [7].

Goh et al. developed a prediction model by AI analysis of PID of SARS-CoV-2 shells for transmission ways based on shell hardness. SARS-CoV-2 is categorized in the respiratory, fecal-oral transmission intermediate level. Transmission way and virulence are closely related to viral load. Shell proteins are crucial in viral replication and disorder increases the replication. Since SARS-CoV-2 has the lowest percentages of intrinsic disorder (PID) and the hardest shells, it is resistant to antimicrobial enzymes in body fluids and outside the body. As a result, high number of viruses are shed from the body, which are active and contagious [8,9]. Besides, shell disorder shows the places possible for mutation. Disordered places are the targets in vaccine candidates, when mutating to attenuate the virus in vaccine production [9].

Granata et al. used machine learning (ML) to predict wastewater quality indicators related to the water shed. Suitable treatment methods depend on the pollutant concentrations. Two models of AI were used in the study in the prediction and it is concluded that ML helps calculate wastewater quality indicators to be used for the sizing of wastewater treatment when there is the lack of measures [10].

The paper-based instrument detects SARS-CoV-2 in wastewater and determines the asymptomatic people in the population. It is real-time and warns the government to prevent the spread of the pandemics. Asymptomatic people learn if they are infected or not, quarantined and get the COVID-19 treatment [11].

Maere et al. planned modeling for simulating of COVID-19 in wastewater to manage negative effects in treatment units. The corrections can be at the effect of wastewater dilution by precipitation, the stay-time in wastewater, the temperature, and the interactivity with particles. Observing the viral infection status of population can be upgraded and pandemic management can be better by the modeling [12].

Heijnen et al. used droplet digital RT-PCR to detect SARS-CoV-2 variants in wastewater. New variants with mutation N501Y have high transmissibility and antibody escape so they should be detected rapidly, and quantitatively with sequences involving the N501Y mutation. In this study, variants with the N501Y mutation and Wild Type501N SARS-CoV-2 RNA were detected with droplet digital RT-PCR and multiple mutations can also be detected by RT-droplet digital PCR in wastewater. Whole genome sequencing is also used to detect SARS-CoV-2 variants in wastewater, however droplet digital PCR is more quantitative than whole genome sequencing [13].

Since safe water supply and water hygiene have high importance during the pandemic, the effect of water treatments and disinfection on spread of SARS-CoV-2 was investigated. COVID-19 pandemic and digitalization of the water industry are seen simultaneously, which needs a reanalysis of the Water-Human-Data Cycle. The digitalization of the water industry can bring useful methods to help in the pandemic and multidisciplinary cooperation is needed to overcome the challenges [14].

A noninvasive detection and prediction method WBE, nanosensors and AI can be used together for detection of SARS-Cov-2 in wastewater for the whole population. Nanosensors with AI or information technology (IT) helps us in understanding transmission and infection. For a better virus remediation in wastewater, nanoparticles will be designed and AI-sensors will be used as a tool in public health. In colorimetric system using gold nanoparticles and targeting the N-gene of the virus, the virus can be detected by naked eye. Gold nanoparticles and target RNA sequences show precipitation in10 minutes. SARS-CoV-2 -contaminated water affects the organisms in water and the disease can be transmitted by food. When drinking water and wastewater accidentally mix, controlling the spread of the virus is also important [15]. Wastewater with virus going to the aquatic environment can be a reservoir to infect the animals, therefore for detection and transmission control, multidisciplinary cooperation of engineers, doctors and modelers is needed in WBE [16]. Near-source tracking (NST) is a WBE-based method for the detecting infected small group or a person [15,18]. NST and clinical testing are used together to block the outbreaks in different countries and can be used in crowded institutions such as hospitals and universities [18].

SARS-CoV-2 was detected in wastewater in many countries and it correlated with the clinical disease results. The presence of SARS-CoV-2 in wastewater has some health risks in countries with old water-wastewater system. Transmission in pools and transmission by aerosols in bathrooms is also important [17].

The models are helpful as decision support tools and some COVID-19 pandemic modeling examples are basic reproduction number (R0), social distancing, lockdown, hospital capacity, drug delivery and vaccine delivery. The accuracy of modeling should match the dynamics of real-world. Modeling by simulating the transmission and by prediction decreases the health problems which is a multidisciplinary process [6].

WEB is a good tool for population screening and rapid microfluidic methods are used to detect virus in wastewater. New Point-of-Care (POC) microfluidic instruments isolating nucleic acids are a rapid and cheap method to detect and search the transmission of COVID-19 [19].

After community vaccination, measuring the concentration of virus in wastewater to determine regions where the virus is not decreasing can be useful. Officials try increasing the vaccination in these regions. Unvaccinated people can be motivated or pop-up vaccination places can be used to solve the problem [20].

Measurements and data of viral prediction models in wastewater include viral concentration, quality and strength measurements, wastewater system data, environmental data, batch test measurements, population data, disease data and health records. These data are analyzed and predictions are made for outbreaks [21].

Edge computing, blockchain, AI, Internet of Things and intelligent devices are important in tracking and preventing the spread of SARS-CoV-2 in wastewater. Study combines the edge computing, AI, and blockchain for reliable solutions, data processing and sharing to control the pandemics and the system predicts the spread of the virus by analyzing data for early warning. Effective decisions can be taken, treatment evaluations can be made by the government by observing infection rate. In the system, sensors collect virus data in wastewater, data are processed at the edge, analyzed by AI, predictions are made about the spread, shared by blockchain and government uses the data to manage the pandemic [22].

3. Conclusion

Pandemic increases the vulnerability in all countries. Early detection is important in control and prevention of pandemic and WBE supported with AI applications is a good tool for early detection of COVID-19 in the whole population. Prevention by alert systems, surveillance with rapid results, informing the best practices, modelings, transmission simulations and predictions are important to decrease the pandemic's effects. Multidisciplinary cooperation and further studies are required to overcome the challenges and for improvement.

References

1. McCarthy J. What is artificial intelligence? [Internet]. Computer Science Department, Stanford University. Stanford, CA. 2007 Available from:94305 http:// www-formal.standforf.edu/jmc/whatisai.pdf.
2. Kaya U, Yılmaz A, Dikmen Y. Sağlık Alanında Kullanılan Derin Öğrenme Yöntemleri, Avrupa Bilim ve Teknoloji Dergisi Sayı 16, S. 792-808, (2019). [In Turkish]
3. Agrebia S, Larbib A. Use of artificial intelligence in infectious diseases, Artificial Intelligence in Precision Health. 415–438, (2020). doi: 10.1016/B978-0-12-817133-2.00018-5
4. Prüss-Üstün A, Bos R, Gore F, Bartram J. World Health Organization. Safer water, better health: costs, benefits and sustainability of interventions to protect and promote health, World Health Organization, Geneva, (2008).
5. Xagoraraki I, O'Brien E. Wastewater-Based Epidemiology for Early Detection of Viral Outbreaks, Women in Water Quality. 75–97, (2020). doi: 10.1007/978-3-030-17819-2_5
6. Bedi JS, Vijay D, Dhaka P, Gill JPS, Barbuddhe SB. Emergency preparedness for public health threats, surveillance, modelling & forecasting, Indian J Med Res 153, pp 287-298, (2021). DOI: 10.4103/ijmr.IJMR_653_21
7. Hart OE, Halden RU. Computational analysis of SARS-CoV-2/COVID-19 surveillance by wastewater-based epidemiology locally and globally: Feasibility, economy, opportunities and challenges, Science of the Total Environment, 730 138875, (2020).
8. Goh GKM, Dunker AK, Foster JA, Uversky VN. Shell disorder analysis predicts greater resilience of the SARS-CoV-2 outside the body and in body fluids, Microbial Pathogenesis Volume 144, 104177, (2020). https://doi.org/10.1016/j.micpath.2020.104177
9. Goh GKM, Dunker AK, Foster JA, Uversky VN. A novel strategy for the development of vaccines for SARS-CoV-2 (COVID-19) and other viruses using AI and viral shell disorder, J. Proteome Res., 19, 11, 4355–4363, (2020).https://doi.org/10.1021/acs.jproteome.0c00672

10. Granata F, Papirio S, Esposito G, Marinis DD. Machine Learning Algorithms for the Forecasting of Wastewater Quality Indicators,Water, 9, 105, (2017). DOI: 10.3390/w9020105
11. Mao K, Zhang H, Yang Z. Can a Paper-Based Device Trace COVID-19 Sources with Wastewater-Based Epidemiology?Environ. Sci. Technol., 54, 3733−3735, (2020).
12. Maere T, Vanrolleghem PA, Nicolaï N. COVID-19: wastewater-based epidemiology back-calculation using hybrid modelling methods, modelEAU - Peter A Vanrolleghem's Lab, Natural Sciences and Engineering Research Council of Canada,(2020).
13. Heijnen L, Elsinga G, Graaf MD, Molenkamp R, Koopmans MPG, Medema1 G. Droplet Digital RT-PCR to detect SARS-CoV-2 variants of concern in wastewater, medRxiv, (2021). doi: https://doi.org/10.1101/2021.03.25.21254324
14. Poch M, Garrido-Baserba M, Corominas L, Perelló-Moragues A, Monclús H, Cermerón-Romero M, Nikos Melitas N, Jiang SC, Rosso D. When the fourth water and digital revolution encountered COVID-19 Science of the Total Environment 744 140980, (2020).
15. Adeel M, Farooq T, Shakoor N, Ahmar S, Fiaz S, White JC, Gardea-Torresdey JL, Mora-Poblete F, Rui Y. COVID-19 and Nanoscience in the Developing World:Rapid Detection and Remediation in Wastewater, Nanomaterials, 11, 991, (2021). doi.org/10.3390/nano11040991
16. Ferri M. Covid-19 crisis management from a One Health perspective: can we do better? 8 July 2020 FVE/FEAM webinar, (2020).
17. Usman M, Ho Y. COVID-19 and the emerging research trends in environmental studies: a bibliometric evaluation, Environmental Science and Pollution Research, 28:16913–16924, (2021).
18. Hassard F , Lundy L ,Singer AC , Grimsley J , Cesare MD Innovation in wastewater near-source tracking for rapid identification of COVID-19 in schools, Lancet Microbe 2(1):e4-e5,(2021). https://doi.org/10.1016/ S2666-5247(20)30193- 2. Epub 2020 Oct 30.
19. Donia A, Hassan S, Zhang X, Al-Madboly L, Bokhari H. COVID-19 Crisis Creates Opportunity towards Global Monitoring &Surveillance. Pathogens, 10, 256, (2021). https://doi.org/10.3390/pathogens10030256
20. Smith T, Cassell G, Bhatnagar A. Wastewater Surveillance Can Have a Second Act in COVID-19 Vaccine Distribution. JAMA Health Forum, e201616, (2021). doi:10.1001/jamahealthforum.2020.1616
21. Xagoraraki I. Can We Predict Viral Outbreaks Using Wastewater Surveillance? M.ASCE Journal of Environmental Engineering, Vol. 146, Issue 11, 01820003, (2020). https://doi.org/10.1061/(ASCE)EE.1943-7870.0001831
22. Alrubei S, Ball E, Rigelsford J. A Secure Distributed Blockchain Platform for Use in AI-Enabled IoT Applications 2020 IEEE Cloud Summit, pp. 85-90, (2020). doi: 10.1109/IEEECloudSummit48914.2020.00019
23. Cao Y, Francis R. On forecasting the community-level COVID-19 cases from the concentration of SARS-CoV-2 in wastewater, Science of the Total Environment, 147451, (2021). https://doi.org/10.1016/j.scitotenv.2021.147451

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Effects of Artificial Intelligence Technologies on Nursing Practices in The Field of Health

Nezahat ÜNALDI [1,*], Berna EREN FİDANCI [2]

[1] *University of Health Sciences, Gülhane Faculty of Nursing, PhD Student, Turkey*
[2] *University of Health Sciences, Gülhane Faculty of Nursing, Faculty Member, Turkey*

* Corresponding Author: University of Health Sciences, Gülhane Faculty of Nursing, Turkey
Tel.: +903123043907. E-Mail: nez.unaldi@gmail.com

Publication Information

Keywords :

- Artificial intelligence,
- Technology,
- Nursing,
- Health

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Introduction and purpose: The societal and technological progress have brought digital reforms in the field of health. With the advancement of technology, nursing practices has been evolving and artificial intelligence technologies are being used extensively. The aim of this study is to examine the effects of artificial intelligence technologies on nursing practices and raise awareness for nursing profession.

Materials and methods: This study was conducted between 24.02.2021 and 24.03.2021 by scanning the databases with keywords such as "artificial intelligence", "technology", "nursing", "health", "nursing practices".

Findings: Usage of technology in the field of health is important for changes such as medical imaging, increase in worker efficiency, early diagnosis and treatment, acceleration of nursing period, increase in patient and relatives' satisfaction, simplification of workflow, effective usage of institution's resources, minimization of possible faults and waste.

Discussion and conclusion: Patient sensors, speech recognition systems, remote patient monitoring, robots, virtual nurses, mobile health services and many more artificial intelligence technologies are commonly used for clinical applications of nursing to provide a qualified and reliable patient care. These artificial intelligence technologies have many positive benefits for better monitoring of patients, smoothening of diagnosis and treatment processes, dispensing, positioning bed-dependent patients and transportation of patients.

It is necessary to follow and use technological advancements to provide a qualified health service to people. Nurses' knowledge of how to use artificial intelligence technologies, its' applications and following of recent advancements will make sure that medical care will be provided in an effective and reliable way.

1. Introduction

Societal and technological progress in the world created digital reforms in healthcare field. Thanks to technological progression, nursery applications changed dramatically and artificial intelligence technologies are commonly used now [1,2].

Technology usage in healthcare has significant effects such as; medical imaging, increasing worker efficiency, early diagnosis and treatment, acceleration of nursing period, increasing patient and relatives' satisfaction, improving the workflow, effective usage of institution's resources, minimizing waste and possible faults [3,4].

Artificial intelligence in nursing helps on preparation of drugs, acceleration of patient follow-up process, accelerating diagnosis and treatment, positioning bed-dependent patients and transportation of patients [4,5,6]. This study aims to examine reflections of artificial intelligence on healthcare and raise awareness for nursing profession.

2. Artificial Intelligence (Artificial Intelligence-AI)

The intelligence machines and softwares can execute is called artificial intelligence. AI is a branch of science that can do cognitive activities such as utilizing databases, learning, planning, reasoning, moving and recognizing sounds. AI tries to imitate people's thinking and decision-making ability and enables machines to provide solutions to complex problems like humans [7].

AI does what people do faster, more efficiently and at a lower cost. The advancement of technology has also affected the healthcare system, has led to many innovations and fundamentally changed traditional health care [3,7,8].

3. Artificial Intelligence Technologies in Field of Science

Artificial intelligence is used for early diagnosis, correct treatment, radiology, drug development (antibiotics), robotics, sound and face recognition (language processing), education, patient monitoring, depression diagnosis, solving clinical problems, analyzing information, making decisions and keeping patients healthy [1,2,3,4,9].

Cost and Quality Management: Cost savings can be achieved by determining drug doses and adjusting bed capacity in hospitals using machine learning methods [2].

Documentation Management: It is estimated that savings of $18 billion will be achieved in the United States by using AI-supported systems in processes such as creating patient files and prescribing [10].

Natural Language Processing (NLP): It is a system that enables nurses and doctors to recognize and transcribe their voices. "Wysa" is an NLP based application that can provide psychological counseling. This service provides support and advice on psychological disorders (stress, anxiety, etc.) [2].

Electronic Health Records (EHR): Allows access to patient information by multiple healthcare providers. Patient data can be collected and analyzed and can help understand the patient's medical needs [4,9,11,12].

Big Data Analysis: These are technologies that enable the processing and use of data for developing technologies such as the internet of things, artificial intelligence, NLP, virtual reality and blockchain in the field of health. Big data technology increases the quality of life by things like predicting epidemics, reducing costs, and protecting from diseases [4,6].

Diagnosis of Diseases, Treatment and Applications: A deep learning system which learning algorithms can be developed upon is being used in applications such as "Watson for Health" and "Deep Mind" in various parts of the world. These technologies are used in the early diagnosis of chronic diseases and diseases such as Parkinson's and cancer. Also in depression and mental health disorders; diagnosis can be made by collecting daily e-mail and social data such as sensor, SMS and phone calls [2,3,7]. The

Netherlands uses artificial intelligence for health system analysis. It detects errors in treatment and inefficiencies in the workflow and prevents unnecessary hospitalizations [7,9,12].

Drug Therapy and Drug Development: Data from various sources such as patient health records and genetic records can be analyzed with AI to help predict how a drug may affect a person's cells and tissues [7]. "Robotic Prescription Dispensing Systems" makes the distribution of drugs more accurate and safer, reducing the responsibilities of nurses in drug intake management [5,12].

Imaging and Analysis Tools: Artificial intelligence uses CT, BT and retinal scans, electrocardiograms, and X-Ray scans to detect cancer, stroke, diabetes and other diseases. According to the literature, it has been found that the cost of diagnosing using artificial intelligence is lower than traditional diagnosis [7,9].

Telehealth: It is the use of telecommunication technology in services such as patient education, patient care and counseling. It is a system that includes communication technologies such as image, speech and audio transfer; video conference, telephone line, digital wireless connection and media tools such as computers and mobile phones. It is a service that makes it easier for nurses to reach individuals, does not require contact, and enables follow-up of more than one person at the same time [4,13,14].

Remote Health Technologies: It includes a wide range of technologies such as remote patient monitoring, video conferencing and communication via computer. With this technology, nurses can process large amounts of data (vital signs, symptoms, etc.) from the system and use their clinical decision-making skills in accordance with each patient's condition. In interacting with the patient, communication skills such as active listening, questioning, rerouting, and verification are used [11,15]. "Hospital to Home" program implemented in Singapore was developed to help patients manage their transition to home care [5].

Mobile Health: Detailed patient information can be accessed that can help people with chronic illnesses to maintain a healthy life. Thanks to this technology, healthier populations and a reduction in the cost burden on health can be achieved [4,7].

Wearable Technology: Using AI technologies and the Internet of medical devices to help people stay healthy. Heartbeat, blood pressure values, sleep patterns and nutritional status of individuals are monitored with the sensors in these devices. Thanks to the data collected from patients, risks are identified before they become critical [2,7,9]. It will facilitate regular check-ups in elderly care and reduce hospital dependency [3].

Robots: With the effective use of robots, it is ensured that efficiency in production is increased, high sensitivity is reached in drug tests and medical analysis, and logistics work in the hospital is carried out quickly and safely [1]. Robot nurses assist nurses in various tasks such as helping with daily tasks, positioning, carrying, and providing emotional support. Robot "Cody" can dress patients, take bed baths and is used in the rehabilitation of patients [1,11]. In Japan, robots are used for training patients, taking blood samples from them and for nursing care. "Pepper" robots in Belgium meet the visitors, answer their questions and provide the necessary information for adherence to the hospital [1,11,12]."Paro" provides comfort and emotional support to elderly people and autistic children. "Veebot" is used for the most suitable vein selection. "RIBA" is designed to help the patient get out of bed. "Da Vinci Surgical Robot" increases surgeons' precision and accuracy. It reduces the responsibilities of nurses working in the operating room [5,9,12,16].

Virtual Nursing: Virtual nurses can direct patients to effective treatment and follow-up patients after treatment. Thus, wrong drug use and unnecessary treatments can be prevented [17]. "Molly" is a virtual nurse developed to track discharged patients, allowing doctors to focus on more urgent cases [9,10].

With the use of AI technology in the field of health, new drugs will be discovered, studies on genes will be carried out, and early diagnosis and treatment of diseases will be provided. Thus, diseases will be prevented and it will be possible to stay healthy for a longer time. Various screening and analysis will be applied quickly and accurately [3,7].

4. Nursing and Artificial Intelligence Technologies

Nursing is an information discipline and practice profession that deals with the health of the individual and society that develops itself with technological, scientific and socio-cultural changes in the world and in Turkey. Factors affecting the transition of nursing from traditional roles to contemporary roles are advances in technology and science, emphasis on ethical principles, demographic changes (increase in the elderly population, migration, etc.), human rights movements, and health promotion approach [4,5,18,19]. Nurses use the roles of educators, administrators, researchers, caregivers, supporters and decision makers to provide quality health care [5,18,19].

Today, nurses use new technologies in patient care management. Professional nurses adopting AI technologies can add value to their professional skills by combining nursing science with computing and information science to streamline their workflow. In an age driven by technological developments, nurses should take an active role in the development of technology in health care [5,6].

5. Artificial Intelligence Technologies in Nursing Applications

Nursing practices are carried out according to a routine process called "Nursing Process", which includes diagnosis, planning, application and evaluation. This process guides nurses in their nursing care practice. Artificial intelligence is important in nursing processes such as daily clinical diagnosis, care planning and evaluation of results [5,11,12].

According to the literature, AI applications reduce the workload of nurses, increase the time spent directly on patients, improve the quality of healthcare services, and ensure the safety of patients in medical treatment [4,6,20].

Nursing practices and the way nurses perform their care duties are also changing with the use of new technologies. Ex; With the use of telehealth technology that monitors the patient's condition, it enables patients to receive care where they prefer [5,19].

Challenges faced by nurses in patient care include staff shortages, inexperience, documentation burdens, lack of supplies, institutional restrictions, and physical fatigue due to repetitive actions such as lifting patients [21,22].

The use of robots in the nursing process can increase the time nurses spend for care and minimize the risk of occupational illnesses [1]. Use of artificial intelligence in nursing practices; By supporting critical thinking, it affects the nursing process positively and enables nurses to make the right decisions [23,24].

6. Effects of Artificial Intelligence Technologies on Nursing Practices

Positive effects

- Improves communication with nurses and other members of the healthcare team.
- Improves documentation in healthcare.
- It reduces medication errors and costs.
- Increases patients' ability to manage self-care.
- With smart alarm systems and wearable technology, the patient can be monitored at home.
- It reduces medical errors, lowers costs and provides the best care.
- It positively affects the quality of life and patient comfort.
- Provides patient satisfaction and participation. It improves the quality and efficiency of care.
- Provides time management. Time spent on patient care is reduced.

• It affects the nurse-patient relationship positively. Professional satisfaction increases.

• New types of connections are established with patients and an atmosphere of trust is created.

• Provides person-centered care.

• It reduces the workload on nurses [5,6,11,20,21,23,24].

Adverse effects

• Due to the inability to use time well, human contact decreases and social isolation may increase.

• Applications that imitate the companion or caregiver can be experienced by the user as being deceived.

• There are risks due to the use of technology that may compromise patient privacy.

• It can have a negative effect on individual autonomy.

• Healthcare professionals may think that their authorities are under threat if their expertise is questioned by artificial intelligence.

• Artificial intelligence can render healthcare professionals reckless, reducing the likelihood of controlling results and avoiding errors [5,25].

7. Artificial Intelligence Technologies and Ethical Dimension

According to the literature, ethical concerns have arisen with the use of AI technologies in the field of health. There can be prejudice that artificial intelligence can replace humans and anxiety that it will dominate people. Nurses who adopt this view may oppose the inclusion of artificial intelligence in healthcare services on the grounds that their jobs will expire [5,6].

The most common concern is responsibility anxiety. If artificial intelligence makes a serious mistake, the question of who should be held responsible is a matter of debate. The possibility of artificial intelligence to implement its own decisions one day also causes anxiety. Another issue is the view that privacy and confidentiality cannot be paid attention to. Private interviews with robots can be monitored by unsuitable persons [1,6,7,19,26,27].

A study by Mittelstadt et al. (2016) mentions a conceptual map based on six types of ethical concerns expressed by algorithms. These; insufficient evidence, incomprehensible evidence, false evidence, biased conclusions, transformative effect, and traceability. The map is designed as a helpful tool in resolving ethical dilemmas. Attention should be paid to ethical violations such as moral responsibility and legal obligation, the autonomy of individuals and their right to access information, fair sharing and discrimination. Ethical concerns about the algorithms indicated by the map are multidimensional and therefore require multidimensional solutions [27].

Ethical requirements are honesty, integrity, transparency, benevolence, non-malicious intent, and respect for autonomy. It should be ensured that the use of AI technologies in the field of health comply with ethical rules. Since it is very difficult to model compassion and empathy in robots, it does not seem possible to replace nurses in the future [6,12,26,27].

8. Results

In order to provide quality health service to people, technological developments in the field of health should be followed and used. It will ensure that nurses, who have a key role in the healthcare team, know how to use artificial intelligence technologies, follow them, apply them, and provide effective and safe care.

Nurses are integral elements of technological development in healthcare. Nurses should encourage innovative tools to contribute to education and care. As these virtual platforms begin to revolutionize the digital healthcare field, the goal should not be to break traditions, but simply to facilitate nursing practices through the embrace of technology.

References

[1] Eşkin Bacaksız F, Yılmaz M, Ezizi K, Alan H. Sağlık Hizmetlerinde Robotları Yönetmek. SHYD. 2020;7(3):458-465.
[2] Akalın B, Veranyurt Ü. Sağlıkta Dijitalleşme ve Yapay Zekâ, SDÜ Sağlık Yönetimi Dergisi. 2020;2(2):131-141.
[3] Büyükgöze S. Dereli E. Dijital Sağlık Uygulamalarında Yapay Zeka. VI. Uluslararası Bilimsel ve Mesleki Çalışmalar Kongresi-Fen ve Sağlık. 2019:07-10.
[4] Çetin B, Eroğlu N. Hemşirelik Bakımında Teknolojinin Yeri ve İnovasyon. Acta Media Nicomedia. 2020:3(3).
[5] Pepito JA, Locsin R. Can Nursing Drive Technological Advances in Healthcare in the Asia-Pacific? Asian Pac IsI Nurs J. 2018;3(4):190-198.
[6] Şendir M, Şimşekoğlu N, Kaya A. Sümer, K., Geleceğin Teknolojisinde Hemşirelik. SBÜ Hemşirelik Dergisi. 2019:1(3), 209-214.
[7] Uzun T. Yapay Zekâ ve Sağlık Uygulamaları. İzmir Kâtip Çelebi Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi. 2020:3(1):80-92.
[8] Liu R, Rong Y, Peng Z. A review of medical artificial intelligence, Global Health Journal. 2020;(4),2.
[9] Amisha, Malik P, Pathania M, Rathaur VK. Overview of artificial intelligence in medicine. J Family Med Prim Care. 2019;8:2328-31.
[10] Kalis B, Collier M, Fu R. 10 promising AI applications in health care. Harvard Business Review. 2018.
[11] Rouleau G, Gagnon MP, Côté J, Payne-Gagnon J, Hudson E, Dubois C. A. Impact of İnformation and Communication Technologies on Nursing Care: Results of an Overview Of Systematic Reviews. J Med Internet Res. 2017;19(4):122.
[12] Pepito JA, Locsin R. Can nurses remain relevant in a technologically advanced future?. International Journal of Nursing Sciences. 2019;6:106-110.
[13] Pazar B, Taştan S, İyigün E. Tele sağlık sisteminde hemşirenin rolü. Bakırköy Tıp Dergisi, 2015;11(1):1-4.
[14] Olson CA, Thomas JF. Telehealth: No longer an idea for the future. Advances in Pediatrics. 2017;64(1):347-370.
[15] Carroll W. Artificial Intelligence, Nurses and the Quadruple Aim. OJNI. 2018;22(2).
[16] Liu R, Rong Y, Peng Z. A reviewofmedical artificial intelligence. Global Health Journal, 2020;4(2).
[17] Thomas R. Artificial Intelligence and Nursing: The Future Is Now, JONA, 2020:50(3).
[18] Boz Yüksekdağ B. Hemşirelik eğitiminde bilgisayar teknolojisinin kullanımı. Açıköğretim Uygulamaları ve Araştırmaları Dergisi. 2015;1,103-118.
[19] Stokes F, Palmer A. Artificial Intelligence and Robotics in Nursing: Ethics of Caring as a Guide to Dividing Tasks Between AI and Humans. Nurs Philos. 2020;21:e12306.
[20] Liao PH, Hsu PT, Chu W, Chu WC. Applying artificial intelligence technology to support decisionmaking in nursing: A case study in Taiwan, Health Informatics Journal. 2015;21(2):137-148.
[21] Clipper B, Batcheller J, Thomaz AL, Rozga A. Artificial intelligence and robotics: A nurse leader's primer. Nurse Leader. 2018;16(6):379-384.
[22] McBride S, Tietze M, Robichaux C, Stokes L, Weber E. Identifying and addressing ethical issues with use of electronic health records. Online Journal of Issues in Nursing. 2018;23(1).
[23] Bini SA. Artificial intelligence, machine learning, deep learning, and cognitive computing: what do these terms mean and how will they impact health care. The Journal of Arthroplasty. 2018;33(8):2358-2361.
[24] Whende MC. Artificial Intelligence, Critical Thinking and the Nursing Process. OJNI. 2019;23(1).
[25] Nuffıeld Councıl on Bioethics, Artificial intelligence (AI) in healthcare and research, May 2018. ET. 20.03.2021.
[26] Keskinbora KH. Medical ethics considerations on artificial intelligence, Journal of Clinical Neuroscience. 2019;64:277-282.
[27] Mittelstadt BD, Allo P, Taddeo M, Wachter S, Floridi L. The ethics of algorithms: Mapping the debate, Big Data & Society. July-December 2016:1-21.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || ISBN : 978-605-69730-2-4

More information available at aita.bakircay.edu.tr

Virtual Reality Applications for Fire Safety Education in Operating Rooms: A Review Article

Büşra Nur TEMUR [1,*], Nilgün AKSOY [1]

[1]*Akdeniz University, Department of Surgical Nursing, Turkey*

* Corresponding Author: Akdeniz University, Department of Surgical Nursing, Turkey
Tel.: +90 554 879 98 12. E-Mail: nurtemur@akdeniz.edu.tr

Publication Information

Keywords :

- Artificial Intelligence,
- OR fire,
- Nursing,
- Technology,
- Virtual Reality

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Introduction-Aim: Operating room fires are devastating but preventable. Fires in the operating room environment can cause patient and staff burns, serious injury, and even death. To extinguish the fire that occurs in operating rooms, effective training under a realistic scenario that teaches safe, correct, and appropriate behavior is required. This study aims to summarize artificial intelligence-supported active virtual reality applications in operating room fire scenarios.

Material-Method: Studies were determined by scanning the last 5 years from Pubmed, Science Direct, Web of Science, and national databases. The searches were made in English and Turkish with the keywords "Artificial intelligence, Operating room fire, Virtual reality" and combinations.

Results: Nurses should be competent in the content of training on surgical devices that have the potential to cause fire and how to intervene. Virtual reality applications have become an important component of health education. It has been reported that it has an affordable cost in the long term, increases performance and recall rates of information, and decreases the error rate.

Discussion-Conclusion: Operating room fire training can be used safely and reproducibly under the guidance of artificial intelligence. It also has the potential to increase knowledge assessment and learning. Virtual reality simulators offer high accuracy simulation technology and experiential teaching-learning process to train nurses in this field. More studies involving virtual reality applications and fire safety training are needed.

1. Introduction

There are many risk factors in Operating Room (OR), especially biological, physical and infectious [1]. To reduce these risks and protect occupational health and safety, environmental safety must be provided during the surgical operation process in the OR [2]. The frequency and risk of fire in the OR are often underestimated. It is estimated that there are OR fires in the United States at least 650 times a year [3-4]. OR fires are devastating but preventable [5-7].

The most common safety measure mentioned in the literature is to increase the awareness and training of all members of the surgical team on fire hazards in the OR [4,8]. It requires training under a realistic scenario that teaches and includes how to react safely, accurately, and appropriately to extinguish a life-threatening surgical fire in an OR [9].

Virtual reality (VR) is a set of artificial sensory experiences that can create the illusion of physical existence in a computer-generated environment. VR allows the creation of an environment and simulates the physical presence in it [10]. One of the biggest advantages of the VR application is that it can create real or life-threatening fire scenarios that would not be possible in the real world due to high costs or high risks. VR simulations overcome operational barriers, enabling OR staff to be trained more frequently, effectively, and cost-effectively in clinical training. VR training improves retention, performance, and patient outcomes by increasing opportunities to apply critical skills. VR simulation;

- ✓ Easily applicable to large teams with fewer lecturers and equipment at 83% more affordable cost,
- ✓ It can be applied with a single earphone in 12 hours instead of an average of 20-25 personnel,
- ✓ Increases performance by 250%,
- ✓ It increases the rate of recall information by 80%,
- ✓ Reduces errors by 40% [9].

The Perioperative Registered Nurses Association (AORN) introduced a fire safety toolkit containing fire prevention, a risk assessment checklist, and instructions on how to extinguish the fire [11]. AORN's recommendation includes conducting a fire risk assessment before commencement of the procedure, communicating the assessment to team members during the timeout process, and documenting the assessment in the patient's record [5,11]. With the development of Artificial Intelligence (AI) technology in recent years, virtual applications play an increasingly important role in providing internship-oriented, individually adaptable training content [7].

The purpose of this review is to summarize effective VR applications for OR fire safety education.

2. Material-Method

Studies were determined by scanning the last 5 years from Pubmed, Science Direct, Web of Science, and national databases. The searches were made in English and Turkish with the keywords "Artificial Intelligence, Operating Room Fire, Virtual Reality" and combinations.

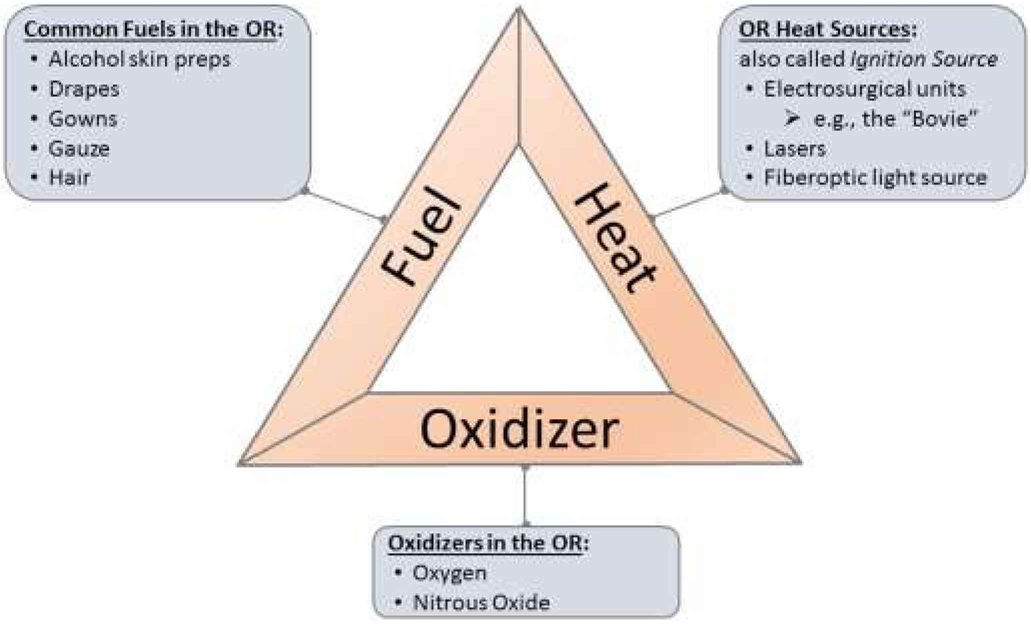
Inclusion criteria; Studies involving OR fire training and using VR modules as an initiative are included.

As a result of the screening, 5 current articles were evaluated in terms of the study year, purpose, a technology used and important results obtained from the study.

3. Results

OR fires are rare events that are underreported and continue to be a source of devastating complications [12,13]. All 3 components of the fire triangle are required to create a fire. Recognizing the materials required to start a fire, the OR team can avoid scenarios that would create fires [12].

Figure 1: OR fire triangle [12]



Fire training simulators that provide virtual experience and training that simulate fire situations provide valuable data in fire response, such as the dynamic behavior of smoke and heat, evacuation, rescue, and firefighting. An important function of these simulators is to express such data in the form of realistic graphs, allowing trainees to experience dangerous situations that they usually cannot directly experience. Because of these experiences, users faceless fear and confusion in real fire cases [14].

The alert status text remains in front of the user at all times, regardless of where he or she is currently looking and is used for critical real-time training scenario updates [13].

Study Year	Purpose of Study	Technology Used	Participants	Outcome
Di Qi et al., 2021	The purpose of this study is to investigate the validity of an AI-guided VR simulator for the OR fire scenario.	AI-powered OR fire training is developed based on an open source platform, Interactive Medical Simulation Toolkit (iMSTK)	The study was conducted with 53 participants with various clinical and educational experience.	It has been reported that the AI-powered VR simulator further increases the training efficiency, and shows the potential to improve the user's performance. AI-powered simulators have been reported to offer the potential to assess knowledge and increase learning in a safe, repeatable, immersive environment.
Kishiki et al., 2019	The study aims to examine the use of OR fire simulation scenarios as training tools to improve the confidence and competence of OR teams, in addition to traditional didactic teaching.	In this simulation, SimMan Essential High-Fidelity patient simulation model, whose changing physical characteristics and vital signs are controlled from an observation room separated by one-way glass, is used.	The study continued compartment into 2 groups with 82 participants, 35 of whom were nurses.	Simulation training has been reported to significantly improve medical staff's competence and confidence in managing OR fires. With this application, it is reported that each team member understands their role in fire prevention and management and provides a realistic application with real smoke as the most useful parts of simulation applications.
Rossler et al., 2019	This pilot study examined the effectiveness of Virtual Electrosurgical Skills Training (VEST) on OR fire safety skills among nursing students.	Virtual Electrosurgical Skill Training (VEST) module has been applied.	The study was carried out with 20 nursing students. Participants were randomized into experimental and control groups. The study was conducted with a	It has been reported that academic and clinical educators should include VR simulation to teach fire safety education and to strengthen fire safety practices. It has been reported that with the VEST module, the addition of VR applications to traditional programmed training shows a greater increase in knowledge. The authors reported the usefulness of the VEST module in teaching OR- fire safety.

			pretest-posttest design.	
Sankaran arayanan et al., 2018	The study aimed was to evaluate the effectiveness of the VEST-OR fire module by the participants..	VEST-OR module implemented.	The study was designed as a two-group control and an experiment. The study consisted of 20 participants, 10 were surgeons.	It has been reported that an engaging, interactive environment that provides rapid feedback, suitable for their own pace, provides an experiential learning environment for users that reinforces what they learn from the didactic material. It has been concluded that Interactive VR-based hands-on training is a relatively inexpensive and effective mode for teaching OR fire prevention and management scenarios.
Dorozhkin et al., 2017	The module has been developed to allow the OR team (surgeon, anesthetists and nurses) to interact with a virtual OR environment that includes a virtual patient and a fire extinguisher.	Virtual Electrosurgical Skill Trainer (VEST)- The Virtual Electrosurgical Skill Trainer module was used.	A study was conducted with 49 participants with VEST experience.	It has been reported that it can be the ideal training method for OR fire emergencies in fully immersive VR environments such as VEST training.

Sankaranarayanan et al. (2018) reported that while 70% of the participants in the simulation group performed the correct step steps in the OR fire scenario test, only 20% of the participants in the control group could choose the steps correctly [5]. Dorozhkin et al. (2017) also explained that the participants rated the usefulness of the simulator very high in learning OR fire prevention/training skills and that the combination of realistic visuals and a highly immersive interactive environment was considered a much better alternative to traditional training methods. At the same time, the participants evaluated VR training as effective and useful [13].

In two recent studies, researchers have described the use of fire VR simulation to train OR staff in the safe use of electrosurgical devices [5,13]. In the study by Di Qi et al. (2021), 79.25% of the participants reported that the overall usefulness of AI guidance was at least 6 out of 7 [7].

VR simulation, which is applied to nursing students, offers a creative teaching method for presenting skills-based education such as fire safety in an experiential way instead of traditional didactic theory and proficiency checklist formats [15]. Although approximately 40 percent of users receiving OR-VR simulator training stated that they had some confusion regarding the use of the simulator, approximately 70 percent reported that they preferred it to traditional educational approaches such as reading textbooks [13].

It has been reported that VR applications are effective in OR fire safety education [5,7,13,15].

4. Discussion-Conclusion

Prevention of surgical fires requires a clear understanding of the risks associated with many adverse events, as well as effective communication between healthcare personnel (surgeon, anesthetist, and operating room nurse) [6]. Prevention of OR-fires requires awareness of risk factors. If an OR- fire occurs, coordination of healthcare professionals is imperative to minimize secondary damage. OR all surgeons, anesthetists, and nurses should be thoroughly trained not only in fire prevention techniques but also in the rapid control of any fire that occurs [14]. Registered nurses working in the OR are exposed to fire hazards that can greatly affect personal and patient safety. Learning how to manage a potentially devastating surgical fire is AORN's priority [15,16]. Nursing and medical professionals have an even greater obligation to remain competent in the educational content of surgical devices that have the potential to ignite a fire and how to respond to it [15,17]. An OR-fire is a stressful, crisis-prone event, and therefore simulation should be a key element of OR-fire training. VR offers a valuable alternative to real OR-fire training [13].

OR- fires are a well-known problem that requires the proper training of all operating room staff [13]. The AI-powered operating room fire training system is a full range of interactive VR simulators designed to train an OR-fire to control [7]. OR team members should be aware of the risk factors for surgical fires as well as appropriate responses and actions in the event of an OR fire. According to recent research, VR could be a worth exploring option for surgical fire training [18]. Because an OR-fire event is relatively rare to occur, the simulation plays an important role in training the OR team in preparedness. Fire drills are a method that the entire surgical team can use to improve their reaction to fire [5].

Simulations allow these teams to address specific learning goals, using specific scenarios to test technical skill, communication, teamwork, and the application of medical knowledge in a specific context [6]. AI-powered simulators offer the potential to assess knowledge and increase learning in a safe, repeatable, immersive environment. The validity of the AI-powered operating room fire simulator is based on its usefulness and effectiveness specifically for OR-fire training. The simulator should be planned for use to evaluate OR personnel and to teach the appropriate response to the fire scenario [7].

VR simulators offer high accuracy simulation technology, and experiential teaching-learning processes to train nurses in this area. More studies including fire safety training are needed with the VR application.

References

1. Gezginci E, Goktas S. Air Conditioning in Operating Room. Journal of Nursing Science, 2018;1(1): 38-41.
2. Ilce A, Soysal GE. Surgical smoke, its effect on air quality and measures to be taken. In Ilce A. (Ed.), Current Issues in Surgery and Operating Room Nursing. Ankara: Hatipoğlu Publishing, 2020; pp. 153-170.
3. Roy S, & Smith LP. Preventing and managing operating room fires in otolaryngology—head and neck surgery. Otolaryngologic Clinics of North America, 2019;52(1): 163-171.
4. Thirunavu V, Gangopadhyay N, Lam S, & Alden TD. Fire Hazard Prevention and Protection in Neurosurgical Operating Rooms Revisited: A Literature Review Challenged by a Recent Incident Report. Interdisciplinary Neurosurgery, 2020; 23: 1-4. doi: 10.1016/j.inat.2020.100997.
5. Sankaranarayanan G, Wooley L, Hogg D, Dorozhkin D, Olasky J, Chauhan S, Fleshman JW, De S, Scott D, Jones DB. Immersive virtual reality-based training improves response in a simulated operating room fire scenario. Surg Endosc. 2018;32(8): 3439-3449. doi: 10.1007/s00464-018-6063-x.
6. Kishiki T, Su B, Johnson B, Lapin B, Kuchta K, Sherman L, Carbray J, Ujiki MB. Simulation training results in improvement of the management of operating room fires-A single-blinded randomized controlled trial. Am J Surg, 2019;218(2): 237-242. doi: 10.1016/j.amjsurg.2019.02.035.
7. Qi D, Ryason A, Milef N, Alfred S, Abu-Nuwar, MR, Kappus M, Jones DB. Virtual reality operating room with AI guidance: design and validation of a fire scenario. Surgical endoscopy, 2021;35(2): 779-786.
8. Chae SB, Kim WK, Yoo CJ, & Park CW. Fires and burns occurring in an electrocautery after skin preparation with alcohol during a neurosurgery. Journal of Korean Neurosurgical Society, 2014;55(4): 230-233. doi: 10.3340 / jkns.2014.55.4.230
9. https://www.aorn.org/education/facility-solutions/fire-in-the-or, Date of access: 24.03.2021.
10. Arias S, Fahy R, Ronchi E, Nilsson D, Frantzich H, & Wahlqvist J. Forensic virtual reality: Investigating individual behavior in the MGM Grand fire. Fire Safety Journal, 2019;109:1-12. doi: 10.1016/j.firesaf.2019.102861.
11. Spruce L. Back to basics: preventing surgical fires. AORN Journal, 2016;104(3): 217-224.
12. Jones EL, Overbey DM, Chapman BC, Jones TS, Hilton SA, Moore JT, Robinson TN. Operating room fires and surgical skin preparation. Journal of the American College of Surgeons, 2017;225(1): 160-165.
13. Dorozhkin D, Olasky J, Jones DB, Schwaitzberg SD, Jones SB, Cao CG, De S. OR fire virtual training simulator: design and face validity. Surgical endoscopy, 2017;31(9): 3527-3533.
14. Cha M, Han S, Lee J, & Choi B. A virtual reality based fire training simulator integrated with fire dynamics data. Fire Safety Journal, 2012;50: 12-24.
15. Rossler KL, Sankaranarayanan G, Duvall A. Acquisition of Fire Safety Knowledge and Skills With Virtual Reality Simulation. Nurse Educ. 2019;44(2): 88-92. doi: 10.1097/NNE.0000000000000551.
16. Hughes AB. Implementing AORN recommended practices for a safe environment of care. AORN Journal, 2013; 98(2): 153-166.
17. Marquessa Fisher CRNA, DNP. Prevention of surgical fires: a certification course for healthcare providers. AANA Journal, 2015;83(4): 271-274.
18. Hauk L. Virtual reality may prove useful for surgical fire education and training. AORN J, 2018;108(4): 4. doi: 10.1002/aorn.12406.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || ISBN : 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Artificial Intelligence Applications in the Field of Psychiatry

Gözde AVCI BUYUKDOGAN [1, *]

[1] *Diyarbakir Dagkapi State Hospital, Diyarbakir, Turkey*

* Corresponding Author: *Diyarbakir Dagkapi State Hospital, Diyarbakir, Turkey*
Tel: 0 (412) 228 63 55 E-Mail: fatmaavcimd@gmail.com

Publication Information

Keywords :
- Depression,
- Machine learning,
- Psychiatry,
- Mental health,
- Artificial intelligence.

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

The main diagnostic method of psychiatric disorders today is largely based on patient-physician interviews. Although great advances have been made in genetics and neuroimaging branches, the lack of reliable biomarkers in the field of psychiatry makes it difficult to distinguish between patients and healthy individuals. Electronic medical databases and evaluation of patient records with artificial intelligence applications can help us overcome these limitations. Artificial intelligence is used in the field of mental health in diagnosis, predicting disease development, predicting behavioral disorders such as suicide attempts and treatment interventions. Studies in large control groups are needed to reveal whether artificial intelligence-assisted psychiatric treatments are superior to traditional clinical interviews and their effects on early diagnosis and treatment interventions. These studies will help bring a new dimension to the field of psychiatry and play an important role in improving the quality of life of individuals with psychiatric disorders.

1. Introduction

Artificial Intelligence terminology was officially used for the first time in 1956 by McCarthy and Minsky, and today it is commonly defined as the ability of a system to interpret external data, learn from this data, and use this data for a specific goal.(1). Radiology, neurology, ophthalmology, hematology, cardiology are examples of these medical fields, and artificial intelligence applications can provide support not only in retrospective data interpretation but also in terms of prospective interpretation and early diagnosis (2).

The lifetime prevalence of one or more psychiatric disorders is estimated to be about 30%. Psychiatric disorders affect individuals from an early age, becoming one of the main causes of disability worldwide.(3). For years, psychiatry has been based on clinical evaluation and observation of the clinician and includes subjective evaluations. Artificial intelligence is seen as promising in this respect with its contributions to the field of psychiatry. Artificial intelligence can be used in diagnosis, prediction and treatment in the field of psychiatry. (4).

2. Artificial Intelligence Applications in Psychiatry

Artificial intelligence in psychiatry includes advanced computer techniques beyond clinical observation and self-report data in evaluating the mental state of the patient (4). It contributed to the development of better techniques as a pre-diagnostic assessment tool, formulation of the individual's risk in terms of psychiatric disorders, and individualization of treatment (5, 6).

2.1. Artificial Intelligence Applications in Psychiatric Diagnosis

Today, psychiatric diagnosis process is based on patient-physician interviews. The field of psychiatry lacks reliable biomarkers, laboratory techniques, neuroimaging methods or genetic markers that can be used in diagnosis and relies heavily on self-report and clinical observation data. With the developing technology, it has been shown that it is possible to contribute to the psychiatric diagnosis process through artificial intelligence-supported systems using electronic medical databases and health records. For example, by analyzing speech transcripts with the latent semantic analysis technique, the clinician can be supported in making a psychiatric diagnosis (4). In a study conducted in 2010, speech transcripts were analyzed using the Latent Semantic Analysis method, and it was successfully determined whether that speech belonged to an individual with a diagnosis of schizophrenia or a healthy individual, and even fine deviations between the healthy individuals without any relationship and first-degree relatives of individuals diagnosed with schizophrenia in a repeated study using this method. (7, 8).

In a recent study, it was possible to successfully distinguish between healthy individuals and adults with Attention Deficit and Hyperactivity Disorder with machine learning techniques based artificial intelligence applications that were used by taking electroencephalography records examining brain waves. (9).

Virtual human can support the clinician's diagnostic process by using nonverbal cues such as mimic and posture during live conversation (10). With this program, post-traumatic stress disorder symptoms were scanned by interviewing the virtual human. (11).

In another study, neurocognitive tests were applied to 35 patients in the stabilization period after the first psychotic attack, 35 individuals who were the siblings of these patients without psychiatric disease and healthy controls without any psychiatric disease. Machine learning-based artificial intelligence system was able to distinguish the healthy control group with %80 accuracy according to the responses of these tests. (12)

2.2. Artificial Intelligence Applications in Psychiatric Prediction

In a study conducted in 2015, the risk of developing psychosis was predicted by speech analysis of high-risk youth. (13). Such a system is very promising for early intervention, which is very important for the course of the disease.

An important part of psychiatric emergencies are suicidal thoughts or attempts. According to the data of the World Health Organization, approximately 800,000 people die each year due to suicide. (14). In a follow-up study conducted with adults who had attempted suicide, by applying a machine learning system based on electronic health records, the probability of a suicide attempt repetition within 7 days following the suicide attempt was found to be %92 accurate, and the probability of attempting suicide within 2 years was %80 accurate. (15). Using some algorithms, artificial intelligence evaluated the MR images of 34 participants, 17 of whom had suicidal thoughts and 17 were classified as happy individuals. As a result, he distinguished the two groups with %91 success and achieved %94 success in identifying those who had attempted suicide. (16). In a recent study by Etkin et al., the machine learning algorithm applied to the EEG recordings of patients with major depressive disorder predicted the response to a certain antidepressant at a rate of %76. (17). Using fMRI data with an artificial intelligence application consisting of 84 robots, an accuracy of %87 was achieved in schizophrenia prediction with multiple brain parcellation ensemble-learning. (18).

2.3. Artificial Intelligence Applications in Psychiatric Treatment

In the field of e-psychiatry, e-therapy applications have opened the way to reach many people. With these computer-based therapy programs, individuals who are hesitant to apply for treatment or therapy due to stigmatization, who have difficulty reaching the treatment center due to their psychiatric illness or who cannot receive therapy due to long waiting lists can also be reached. MOST, which is an internet-based initiative, that is moderated online social therapy, offers peer support and psychological support in an integrated way under the observation of the clinician. (19).

Studies have shown that a therapeutic robot that can detect and respond to tactile and auditory stimuli supported by artificial intelligence has positive psychological effects on dementia patients, patients treated for recurrent ovarian tumors, and has positive effects such as increased social interaction in children with autism. (20-22).

3. Ethics and Limitations

The use of artificial intelligence in the field of mental health brings some ethical problems with it. In order not to harm the patient, it is necessary to pay attention to bias during the data collection phase in artificial intelligence algorithms used in diagnosis and predictive estimation. (6). Since artificial intelligence creates an algorithm over the available data, the effect of data quality on the result is also seen as an important limitation.

4. Conclusion and Evaluation

Although there are promising developments in the use of artificial intelligence in the field of mental health, it does not yet have the capacity to make a diagnosis with %100 accuracy and this is not expected in the future, it can always be in a position to support the clinician and a hybrid system with the clinician (23).

References

1. Haenlein M, Kaplan A. A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. California management review. 2019;61(4):5-14.
2. Alsuliman T, Humaidan D, Sliman L. Machine learning and artificial intelligence in the service of medicine: Necessity or potentiality? Current Research in Translational Medicine. 2020;68(4):245-51.
3. Kessler RC, Angermeyer M, Anthony JC, De Graaf R, Demyttenaere K, Gasquet I, et al. Lifetime prevalence and age-of-onset distributions of mental disorders in the World Health Organization's World Mental Health Survey Initiative. World Psychiatry. 2007;6(3):168-76.
4. Fakhoury M. Artificial Intelligence in Psychiatry. In: Kim Y-K, editor. Frontiers in Psychiatry: Springer Nature Singapore Pte Ltd; 2019. p. 119-25.
5. Shatte AB, Hutchinson DM, Teague SJ. Machine learning in mental health: a scoping review of methods and applications. Psychological medicine. 2019;49(9):1426-48.
6. Graham S, Depp C, Lee EE, Nebeker C, Tu X, Kim H-C, et al. Artificial intelligence for mental health and mental illnesses: an overview. Current psychiatry reports. 2019;21(11):1-18.
7. Elvevåg B, Foltz PW, Weinberger DR, Goldberg TE. Quantifying incoherence in speech: an automated methodology and novel application to schizophrenia. Schizophrenia research. 2007;93(1-3):304-16.
8. Elvevåg B, Foltz PW, Rosenstein M, DeLisi LE. An automated method to analyze language use in patients with schizophrenia and their first-degree relatives. Journal of neurolinguistics. 2010;23(3):270-84.
9. Tenev A, Markovska-Simoska S, Kocarev L, Pop-Jordanov J, Müller A, Candrian G. Machine learning approach for classification of ADHD adults. International Journal of Psychophysiology. 2014;93(1):162-6.

10. DeVault D, Artstein R, Benn G, Dey T, Fast E, Gainer A, et al., editors. SimSensei Kiosk: A virtual human interviewer for healthcare decision support. Proceedings of the 2014 international conference on Autonomous agents and multi-agent systems; 2014.
11. Wörtwein T, Scherer S, editors. What really matters—an information gain analysis of questions and reactions in automated PTSD screenings. 2017 Seventh International Conference on Affective Computing and Intelligent Interaction (ACII); 2017: IEEE.
12. Guliyev Eİ, Kalmady SV, Greiner R, Dursun S, Üçok A. P. 630 Neurocognition for the classification of first episode schizophrenia patients, unaffected family members and healthy controls: A machine learning study.
13. Bedi G, Carrillo F, Cecchi GA, Slezak DF, Sigman M, Mota NB, et al. Automated analysis of free speech predicts psychosis onset in high-risk youths. npj Schizophrenia. 2015;1(1):1-7.
14. Organization WH. Suicide in the World - Global Health Estimates. 2019.
15. Walsh CG, Ribeiro JD, Franklin JC. Predicting Risk of Suicide Attempts Over Time Through Machine Learning. Clinical Psychological Science. 2017;5(3):457-69.
16. Just MA, Pan L, Cherkassky VL, McMakin DL, Cha C, Nock MK, et al. Machine learning of neural representations of suicide and emotion concepts identifies suicidal youth. Nature Human Behaviour. 2017;1(12):911-9.
17. Wu W, Zhang Y, Jiang J, Lucas MV, Fonzo GA, Rolle CE, et al. An electroencephalographic signature predicts antidepressant response in major depression. Nature Biotechnology. 2020;38(4):439-47.
18. Kalmady SV, Greiner R, Agrawal R, Shivakumar V, Narayanaswamy JC, Brown MRG, et al. Towards artificial intelligence in mental health by improving schizophrenia prediction with multiple brain parcellation ensemble-learning. npj Schizophrenia. 2019;5(1):2.
19. Gleeson J, Lederman R, Koval P, Wadley G, Bendall S, Cotton S, et al. Moderated Online Social Therapy: A Model for Reducing Stress in Carers of Young People Diagnosed with Mental Health Disorders. Frontiers in Psychology. 2017;8(485).
20. Kim Y-D, Hong J-W, Kang W-S, Baek S-S, Lee H-S, An J, editors. Design of robot assisted observation system for therapy and education of children with autism. International Conference on Social Robotics; 2010: Springer.
21. Robins B, Dautenhahn K, Te Boekhorst R, Billard A. Robotic assistants in therapy and education of children with autism: can a small humanoid robot help encourage social interaction skills? Universal access in the information society. 2005;4(2):105-20.
22. Chang W-L, Šabanović S, Huber L, editors. Situated Analysis of Interactions between Cognitively Impaired Older Adults and the Therapeutic Robot PARO. Social Robotics; 2013 2013//; Cham: Springer International Publishing.
23. Miller DD, Brown EW. Artificial intelligence in medical practice: the question to the answer? The American journal of medicine. 2018;131(2):129-33.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Performance Comparison of Polyp Segmentation Model Using Imbalance-Aware Losses in Deep Neural Networks

Ozan GÖKKAN [1,*], Mehmet KUNTALP [2]

[1] *Ege University, Graduate School of Natural and Applied Science, Dept. of Biomedical Technologies, Turkey*
[2] *Dokuz Eylül University, Graduate School of Natural and Applied Science, Dept. of Biomedical Technologies, Turkey*

* Corresponding Author: Ege University, Graduate School of Natural and Applied Science, Turkey
E-Mail: ozangokkan@gmail.com

Publication Information

Keywords :

- Polyp segmentation,
- Deep neural networks,
- Class imbalance,
- Loss function

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Late detection of polyps could lead to colon cancer. The development of a polyp segmentation model to determine how they spread on the mucosal layer has a critical importance. Colonoscopists often use the colonoscopy device to view the entire colon in their routine practice to remove polyps with excisional biopsy. The aim of this study is to develop a polyp segmentation model to identify precise region of a polyp by combining 34-layered ResNet, using pre-trained weights on ImageNet, as an encoder and UNet as a decoder neural network. In doing so, augmented versions of publicly available datasets were used during the training and 5-fold cross validation steps. Also, to overcome the class imbalance problem, we produced performance comparative results using the imbalance-aware loss functions such as focal loss, tversky loss, and focal tversky loss. As a result of the use of focal loss that produced the best results, we achieved validation scores of 0.8433 as dice and 0.7711 as intersection over union (IoU).

1. Introduction

Colorectal polyps may occur in human colon region and may eventually develop into cancerous tissue types. For both monitoring and removing the polyps, colonoscopy is the gold standard. Colonoscopists often use this procedure for viewing the entire colon in their routine practice to remove polyps by excisional biopsy. However, colonoscopic examinations may require special training and experience. Furthermore, even among experts, different evaluation results may occur. For these reasons, computer vision applications and deep neural networks are developed using multiple colonoscopic images for the purpose of classification and segmentation in recent years. For example, Jha et al. improved ResUnet++ for polyp segmentation and they achieved dice scores of 81.33% for Kvasir-SEG dataset and of 79.55% dice score for CVC-clinic DB [1]. In this sudy, we developed a polyp segmentation model to identify precise region of a polyp using 34-layered ResNet as an encoder and UNet as a decoder network using pre-trained imagenet weights in transfer learning. While developing a polyp segmentation model, we used different class-imbalance aware loss functions and compared the model performances of them. Data acquisiton and preparation has two critical points at first step for deep neural networks. First, the performance of a loss function is directly related to highly resoluted images; the better the image, the better the performance. Next, a loss function should be aware of the unbalanced distribution among both intra-class distribution of images and inter-class distribution of pixel-wise levels in an image. For this situation, objective of this study is to perform and evaluate three different loss functions that are very popular in literature such as focal loss, tversky loss and focal tversky loss. The purpose of using these losses is to fine-tune some hyperparameters that are adaptive to balance the class-imbalance issue. For example, it is possible to optimize tunable parameters, such as α and γ, in focal loss which is an extended version of cross-entropy as shown in equation 1. In both tversky and focal tversky loss functions, we can adjust the impact of both false positives and false negatives to create better learning model.

2. Datasets & Preparation

Spatial pattern information and sufficient data play an important role when feeding to deep neural networks. Polyps can be classified by KUDO (pit pattern) classification [2] and Paris classification [3]. KUDO classification is based on the surface textural pattern of polyps such as hyperplastic polyp, tubular adenoma or tubulo-villous adenoma. For the case of Paris classification, polyps can be categorized into morphological structure such as pedunculated, flat or sessile type. We used four different publicly available datasets that are CVC Clinic DB, CVC Colon DB, Etis-Larib and Kvasir-Seg DB. At this point, CVC clinic DB consists of 612 polyp white light (WL) images extracted from 31 video sequences with 31 different polyps. There are six different polyp classes according to Paris criteria: Ip (protruded, pedunculated), Is (protruded, sessile), IIa (superficial, elevated), IIb (flat), IIc (superficial shallow, depressed) and III (excavated). Two of them, IIc and III, have a low prevalence and they were not found in the clinical interventions with colonoscopic imaging when creating the database. Hence, types of clinic DB polyps have been categorized into two groups: Adenomatous (488 images) and Hyperplastic (124 images) under histological examinations after biopsy [4]. CVC Colon DB has 380 sequential WL images with polyps extracted from 15 videos with annotated masks performed by clinicians. Kvasir-SEG database has 1000 polyp images with different spatial resolutions. ETIS-Larib DB 196 WL images with polyps extracted from 34 sequences with 44 different polyps [5].

3. Feeding neural networks

We fed data to neural networks after applying preprocessing steps such as data augmentation and normalization. Then, we performed 5-fold stratified cross-validation to optimize the learning model during training. To do so, we firstly generated augmented images using these techniques: rotation, scaling, flipping and contrast-limited adaptive histogram equalization. For example, we applied randomly selection of horizontal flipping, vertical flipping or both, scaling, rotating with randomly selection of rotation angle among 0, 10, 45, 90, 180, 270 and clahe (contrast-limited adaptive histogram equalization) by adjusting clip limit as 0.01 and tile grid size as 8 by 8. In scaling, we rescale image sizes with a multiplier factor of 0.1, so we added a little zoom-in effect to each image. For flipping, we flipped the rows and columns symmetrically depending on horizontal and vertical case, respectively. In clahe, each image divided by 8x8 grids and then histogram equalization is applied for each local subimage or grid. Contrast limiting or thresholding value as clip limit is applied to the each local subimage's histogram to enhance the contrast. Then bilinear interpolation is applied to whole-slide image to make well-combined grids. After augmentation process is done, the next important step is the normalization of data for "ready-to-feed". To do this, we normalized each input image at the top of pretrained ResNet34 using mean value of each RGB channels as (0.485, 0.456, 0.406) and standard deviations as (0.229, 0.224, 0.225) [6]. Batch size was selected as 8 and training was performed using loss functions such as focal loss [7], tversky loss [8] and focal tversky loss [9].

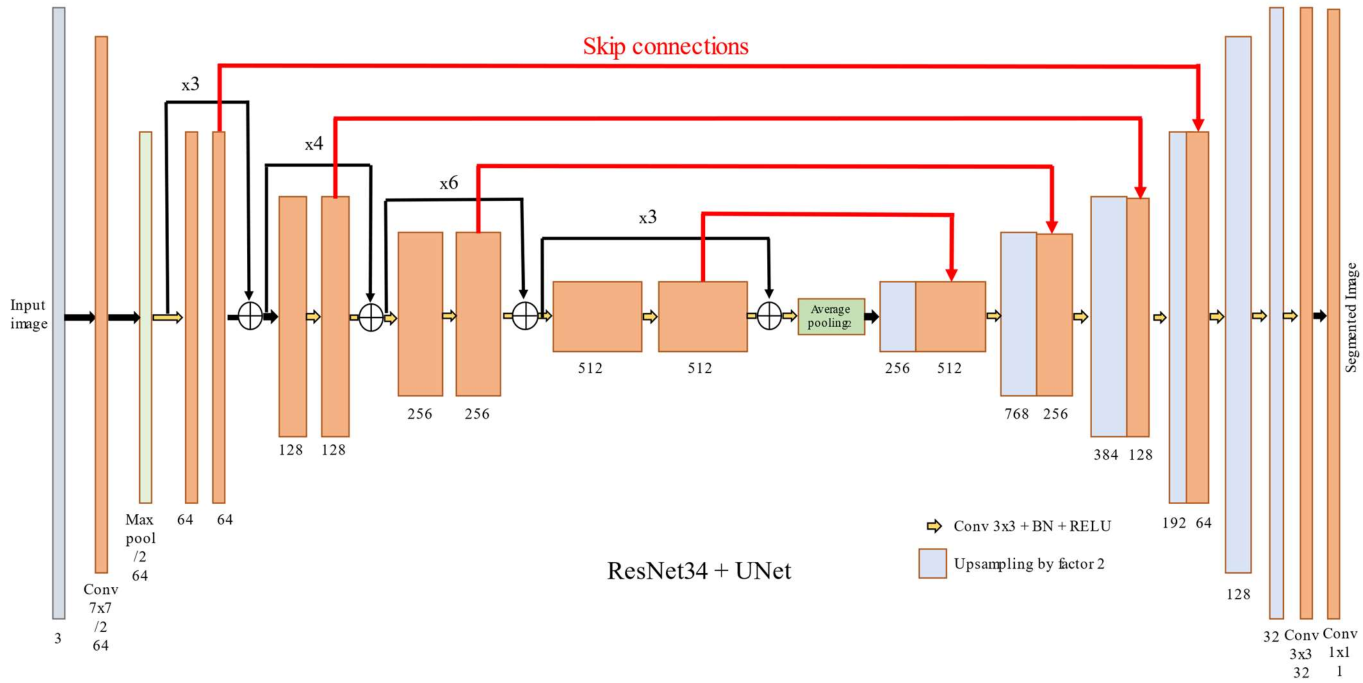


Figure 1. Training pipeline.

3.1. Training CNN

There are some crucial steps that affect the performance of deep neural networks. These steps are data acquisition and preparation, suitable neural network architecture, learning “from scratch” or using “transfer learning”, optimal loss function, and hyperparameter tuning. In this study, ResNet34 as an encoder, that has residual learning based building blocks, was preferred to use due to creating identity maps that have rich spatial information that is suitable for polyp segmentation. As shown in figure 1, four different identity shortcuts in encoder part were used as building blocks. We used Imagenet pre-trained weights to create feature maps and then, multiple feature maps were concatenated in UNet decoder by skip connections. 3x3 convolutional filters, batch normalization and relu activation functions were used during the training pipeline. Thereby, the vanishing gradient problem was prevented during training because the derivative of ReLu function doesn't goes to zero. The importance of using BN and ReLu ordered pair is to prevent overfitting issue. At the end of the network, sigmoid function was used to calculate the probabilistic value of each pixel. Depending on this, backpropagation algorithm was performed using loss function. In addition, each probabilistic map with the batch size were thresholded by 0.5 and the maps were binarized in order to calculate dice score and intersection over union using target masks as shown in figure 2. In our study, we aimed to compare the performances of different loss functions to decide which one is the best for our polyp segmentation model.

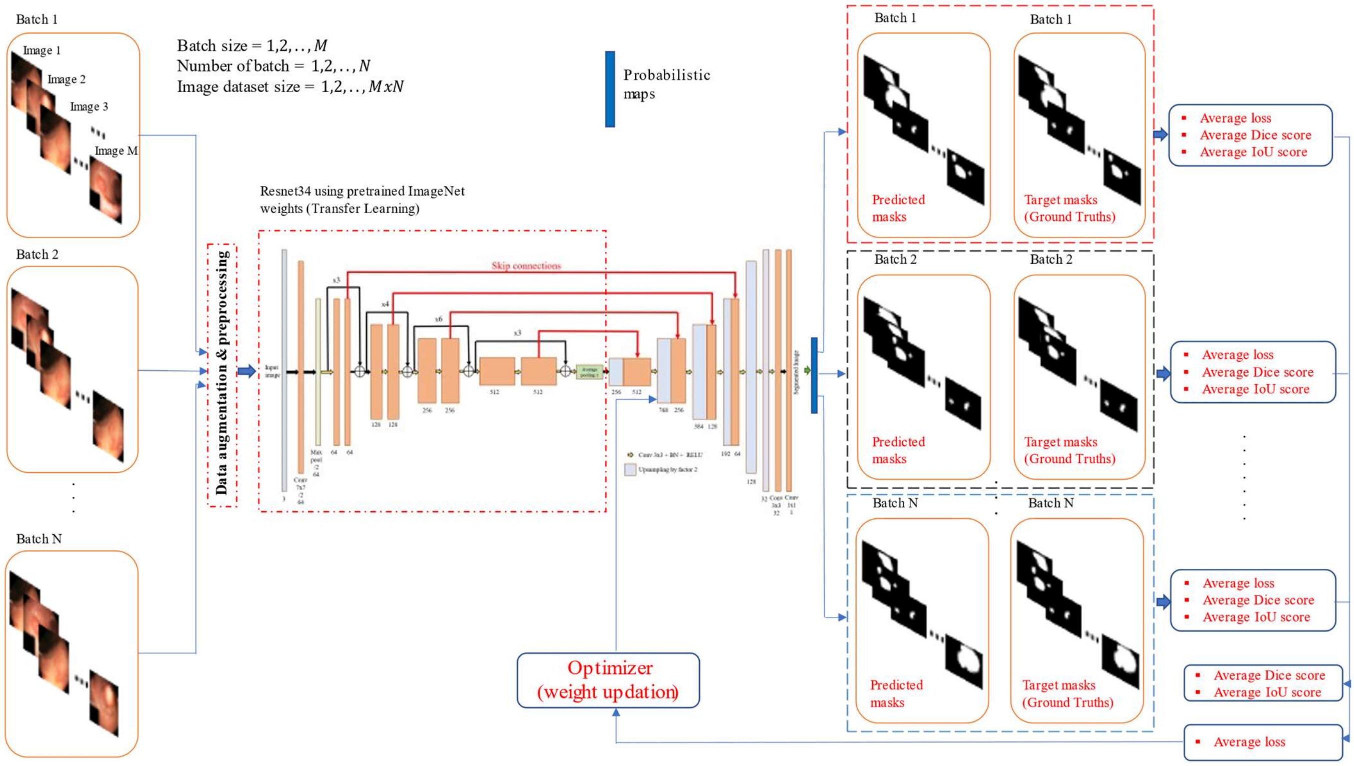


Figure 2. Data augmentation and training-validation process.

4. Loss Functions

Machines can learn better and faster with the use of proper objective or loss functions. For example, a loss function should be aware of imbalance distribution among different classes. In our study, we considered the case of unbalanced datasets which means almost each polyp image has large area of background and small part of foreground which is polyp region. Likewise, we analyzed all datasets we used and observed that there is an imbalance between foreground and background classes. This situation may cause two things: 1) a biased training model, 2) not providing a well-generalized model. Focal loss (FL) acts as a popular loss function for dealing with class-imbalance problem. It focuses more on background samples to down-weight the contribution of easy examples or true negatives during training. As can be seen in equation 1, there are two hyperparameters to fine-tune the function. These are α and γ, which are balanced factor and tunable focusing parameter, respectively. Also, it can be said that focal loss is α balanced and extended cross entropy. We set to α as 0.25 and γ as 2.0 because of the best produced performance of FL in our study.

$$\mathrm{FL}(\mathrm{p_t}) = -\alpha_t(1-\mathrm{p_t})^{\gamma}\, log(\mathrm{p_t}) \tag{1}$$

where p_t is the model's predicted output. Tversky loss (TL) was our second choice to perform backpropagation. TL uses tversky index that is a special case of dice similarity coefficient. The aim of using TL is to control the magnitude of penalties for FPs and FNs.

$$Tversky\ index\ = \frac{TP}{TP + \boldsymbol{\alpha} FP + \boldsymbol{\beta} FN}$$

$$Tversky\ loss\ = 1 - [(1+TP)/(1+TP+\boldsymbol{\alpha} FP + \boldsymbol{\beta} FN)] \tag{2}$$

where α and β are the control parameters that can be tunable. For example, we set α as 0.1 in the range of [0,1] and β as 0.9 in the range of [0,1]. In our case, we penalized more on FNs to reduce hard examples which are misclassified. Also we added 1 term to the both nemurator and denominator to avoid zero and nan case in tversky index [10]. In the case of using Focal tversky loss (FTL), there is extra controllable parameter, γ, aims to control between background and foreground region. In addition to the tversky loss, FTL balances the trade of between precision and recall, so it is possible to weight higher FNs than FPs to prevent high precision and low recall.

$$Focal\ Tversky\ loss\ = [(1 - Tversky\ index)]^{(1/\gamma)} \tag{3}$$

where, α=0.1 [0,1], β=*0.9* [0,1] and γ=1.33 [1,3].

5. Results

We compared three different losses to evaluate the performances of them as shown in Table 1. With the help of hyperparameter tuning, we achieved 84.33% accuracy as the best dice score using focal loss. To do so, we applied different values of control parameters such as α, β,and γ. For each loss function, we tuned the hyperparameters and produced the best results in each case. Hence we tuned α and γ values as 0.25 and 2.0 for focal loss; α and β values as 0.1 and 0.9 for both focal tversky and tversky loss. In addition, the number of total training epochs using focal loss, focal tversky loss and tversky loss were 40, 47, and 54, respectively. According to the Table 1, we can say that focal loss achieved the best scores on balancing the trade off between precision and recall for the class-imbalanced datasets we used.

Validation scores	Dice	IoU
Focal loss	**0.8433**	**0.7711**
Tversky loss	0.7747	0.6747
Focal tversky loss	0.7919	0.6952

Table 1. Performance comparisons of losses.

We implemented 5-fold stratified cross validation that allowed us to update learning rate during training. Also, early stopping criteria was taken into consideration to prevent overfitting issue. All training process were performed on Nvidia GTX 1070 hardware. Initial learning rate was set to 5e-4. Weight decay regularization were also performed using losses. As it is shown in figure 3, we calculated dice scores between ground truth and model's predicted binarized map with epoch by epoch using training dataset and validation dataset separately.

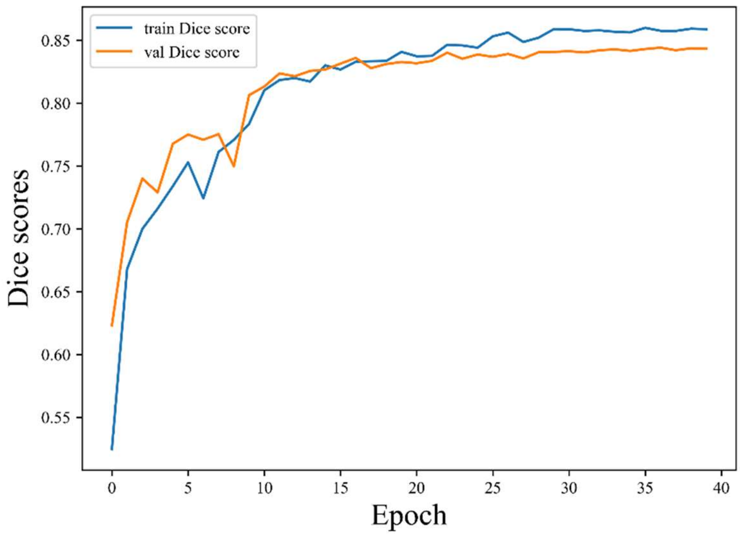


Figure 3. Dice scores for the case of focal loss.

6. Discussion and Conclusion

There are some difficulties during colonoscopic imaging for acquiring highly spatially resoluted images that affect the performance of the segmentation model. The morphology of polyps has patterns that can dynamically change due to the characterization of mucosal tissue from person to person. In addition, colonoscopic lightning condition, inadequate bowel preparation, mucus on the lesion, polyps that form behind the folds, blind spots can cause the increase of missed polyp rate. In this study, we focused on instance segmentation of polyps to determine precise region of polyps using three different imbalance-aware loss functions such as focal loss, tversky loss and focal tversky loss. We performed each loss function separately and observed the results for comparison. With using 34-layered ResNet as backbone and UNet, we trained CNN pipeline to analyze the perfomance of learning model and we saw that focal loss produced the best metrics among the others. ResUNet++ for polyp segmentation has the best performance metrics such as dice in ResUNet based studies. When comparing our study with ResUNet++ that produced as a dice score of 79.55% with 15 convolutional layers and 120 training epochs, we achieved validation dice score of 84.33% with 40 training epochs. Hence, our study has comparable results that were obtained for achieving a better score with much fewer epochs.

References

1. Jha D., Smedsrud H.P., Riegler A. M., Johansen D., ResUNet++: An Advanced Architecture for Medical Image Segmentation, IEEE, 2019.
2. Cassinotti A., Fociani P., Duca P. et al., Modified Kudo classification can improve accuracy virtual chromoendoscopy with FICE in endoscopic surveillance of ulcerative colitis, Endoscopy International Open, vol.8, 2020.
3. Doorn van C.S., Hazewinkel Y., East E. J. et al, Polyp Morphology: An Interobserver Evaluation for the Paris Classification Among International Experts, The American Journal of Gastroenterology, 2015.
4. Bernal J., Sánchez, F. J., Fernández-Esparrach, G., Gil, D., Rodríguez, C., Vilariño, F., WM-DOVA maps for accurate polyp highlighting in colonoscopy: Validation vs. saliency maps from physicians., Computerized Medical Imaging and Graphics, 2015.
5. Rodriquez N.A., Carbajales D. R., Fernandez L. H. et al, Deep Neural Networks approaches for detecting and classifying colorectal polyps, Elsevier Neurocomputing, 2021.
6. Nakamura A., Harada T., Revisiting Fine-Tuning for Few-shot Learning, 2019.
7. Lin Y.T., Goyal P., Girshick R., He K. et al., Focal loss for Dense Object Detection, Proceedings of the IEEE, ICCV, 2017.
8. Salehi M.S.S., Erdogmus D., Gholipour A., Tversky Loss Function for Image Segmentation, Using 3D Fully Convolutional Deep Networks, Springer, 2017.
9. Abraham N., Khan M. N., A NOVEL FOCAL TVERSKY LOSS FUNCTION WITH IMPROVED ATTENTION U-NET FOR LESION SEGMENTATION., IEEE, 2019.
10. Jadon S., A Survey of loss functions for semantic segmentation., IEEE, 2020.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Identification of Colorectal Polyp Region using Optimized Deep Convolutional Encoder-Decoder Network

Ozan GÖKKAN [1,*], Mehmet KUNTALP [2]

[1] *Ege University, Graduate School of Natural and Applied Science, Dept. of Biomedical Technologies, Turkey*
[2] *Dokuz Eylül University, Graduate School of Natural and Applied Sciences, Dept. of Biomedical Technologies, Turkey*

* Corresponding Author: Ege University, Graduate School of Natural and Applied Science, Turkey
E-Mail: ozangokkan@gmail.com

Publication Information

Keywords :

- Colorectal cancer,
- Polyp segmentation,
- Deep encoder-decoder neural network,
- Transfer learning,
- Class imbalance

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

Polyps in colon region of human body may cause colorectal cancers. Therefore, colonoscopists often use colonoscopy device to view the entire colon in their routine practice to remove polyps by excisional biopsy. However, different evaluation results may occur even among experts due to the facts that colonoscopic examination needs special training and experience and imaging conditions may dynamically change. Convolutional deep neural networks are being developed using multiple images for polyp segmentation in recent years. The aim of this study is to develop a polyp segmentation model to identify precise region of a polyp using ResNet18 as an encoder and UNet as a decoder neural network using transfer learning. At this point, we preferred to use the focal loss function to overcome the class imbalance problem. During training and 5-fold cross validation steps, we used publicly available datasets such as CVC-Clinic DB, CVC-Colon DB, ETIS Larib polyp DB and Kvasir-Seg with theirs augmented versions created by flipping, scaling, rotating and CLAHE (contrast-limited adaptive histogram equalization) operations. After providing hyperparameter tuning, we achieved validation scores as a dice score of 0.8135 and 0.7396 intersection over union (IoU).

1. Introduction

Colonoscopy is the gold standard for both monitoring and removing any type of colorectal polyps by excisional biopsy. Colonoscopists often use this procedure for its ability to view the entire colon in their routine practice for early diagnosis of precancerous lesions to prevent the development of colorectal cancer. However, colonoscopy devices are operator-dependent that they would require special training and experience to prevent misdiagnosis of clinically suspected lesions. Furthermore, even among endoscopists, adenoma detection rate and different evaluation results may occur [1]. For example, Zhao et. al. showed that the miss rate of serrated polyps reaches up to 27% [2]. Bressler et.al claimed that the rates of missed colorectal cancers is up to among %2 and %6 [3]. Lee et al. pointed out that adenoma detection rates changes according to colonoscopist's experience and physician characteristics [4]. At this point, for developing a computer aided diagnostic system (or decision making system), Jha et al. improved ResUnet++ deep convolutional neural network architecture for polyp segmentation and they achieved dice scores of 81.33% for Kvasir-SEG dataset and of 79.55% dice score for CVC-clinic DB [5]. Thereby, It can be tought that this study provides a helpful application model to prevent misdiagnosis of clinically suspected lesions (polyps) and a helpful guide to decide precise region or shape of polyps when making an excision without damaging healthy mucosal tissue. Hence, computer vision and its applications can be a good decision support system for polyp classification and segmentation tool for clinicians. For example, encoder-decoder networks can be used to segment a polyp content images. There are several encoders as backbones, such as Resnet, VGG or Mobilenet can be used to extract meaningful features of polyps. Then, a decoder is combined with one of encoders by skip connections to obtain resultant segmented images.

2. Methods

Convolutional neural networks can be well-generalized using different sets of data. Especially, it can be said that having a large number of different possible polyp content images will provide us to create a much better generalizable learning model. In this study, we used four different databases collected from different hospitals as shown in Table 1. All databases come with their annotated images. The purpose of using annotations is both making supervised learning during training-validation steps and testing the trained model using performance metrics such as precision, recall, dice and so on. When looking at the content of databases, CVC-Clinic DB consists of 612 polyp white light (WL) images extracted from 31 video sequences with 31 different polyps and it has been categorized into two groups: Adenomatous (488 images) and Hyperplastic (124 images) under histological examinations after biopsy []. CVC Colon DB has 380 sequential WL images with polyps extracted from 15 videos with annotated masks performed by clinicians. Kvasir-SEG database has 1000 polyp images with different spatial resolutions. ETIS-Larib DB 196 WL images with polyps extracted from 34 sequences with 44 different polyps [6].

Table 1. Properties of the datasets used in our experimental study.

Database	Modality	# of polyps	Pixel resolution	Annotation
CVC-Clinic DB	Colonoscopy	612	384x288	Binary mask
CVC-Colon DB	Colonoscopy	380	500x574	Binary mask
Kvasir-SEG DB	Colonoscopy	1000	1225x966	Binary mask
ETIS-Larib DB	Colonoscopy	196	712x480 or 1920x1080	Binary mask

Data augmentation plays an important role for providing meaningful and sufficient synthetic images. Thereby, it can be possible to overcome overfitting issue using augmented data. In our study, we applied different augmentation techniques on each image such as randomly selecting rotation angle among 0, 10, 45, 90, 180, 270 degrees, horizontal-vertical flipping, scaling and contrast-limited adaptive histogram equalization with clip limit as 0.01 and grid size as 8 by 8. We preferred to use the aforementioned techniques because they did not distort the general structure or morphology of polyp regions when analyzing all datasets. For example, we didn't apply brightness property because we saw that some images have been exposed to oversaturated white light on polyp region. After data augmentation was done, data normalization was performed using mean values of (0.485, 0.456, 0.406) and standard deviations of (0.229, 0.224, 0.225) for each red, green, and blue channel by the formulation of $x_k = [\left(x_{ij} - mean(c)\right)] / [std(c)]$ where x_k is k^{th} image, x_{ij} is the pixel value of $(i, j)^{th}$ coordinate, and c represents the red, green and blue channel where the mean and standard deviations are assigned, respectively [7]. In this way, all normalized images were prepared to be feeded to convolutional neural networks. Thereby, we provided to obtain better learning models by preventing overfitting that may cause high variance problem.

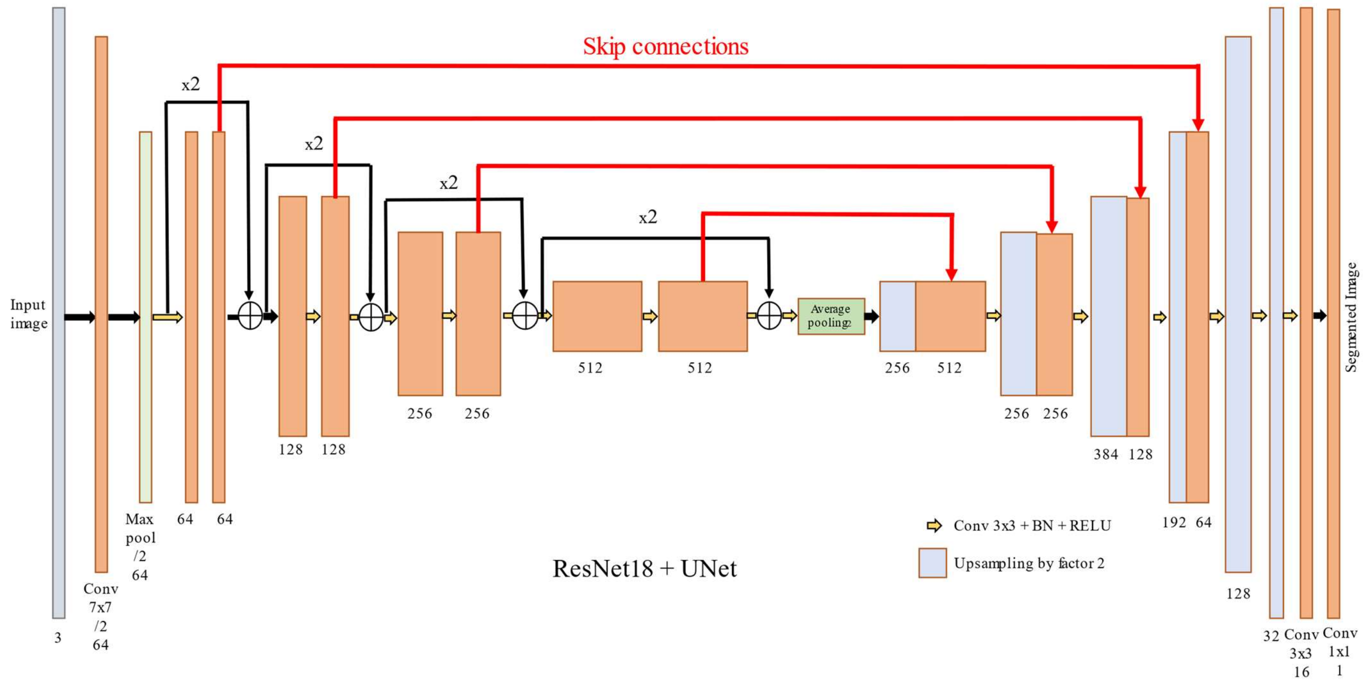


Figure 1. ResNet18 and UNet training pipeline.

In training phase, the combination of 18 layered ResNet and UNet was used by transfer learning. ResNet18 has 18 layered deep neural networks and one of its abilities is to use residual blocks in terms of getting an identity map. It has more comprehensive and richer spatial image content by using its input reference [8]. As shown in figure 1, we feeded images which are resized as $448x448$ and convolved with pretrained imagenet weights using 64 different 7x7 convolutional filters at the top of ResNet18. In residual blocks, we convolved each image two times to reach better spatial resolution. We also preferred to use ReLu activation function after batch normalization (BN) for both overcoming overfitting issue and vanishing gradient problem. Numbers at the bottom of each gray- and orange-colored sticks refer to channel numbers in figure 1.

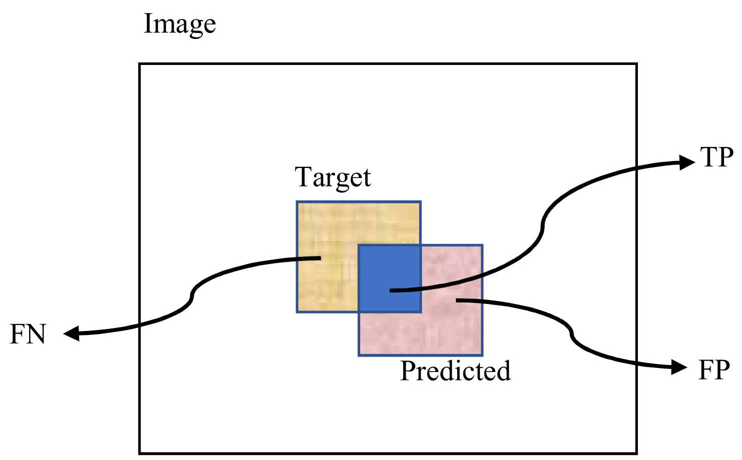


Figure 2. Calculation of true positive (TP), false positive (FP), false negative (FN).

In the decoder part, UNet was implemented after average pooling performed as shown in figure 1. Skip connections are one of the main bridge of the network architecture to provide both concatenated image channels and translation invariance property. For each passing step in the decoder part, feature maps were upsampled by factor 2. At the end of the network, sigmoid function was used to produce probabilistic maps and then loss function was calculated between probabilistic maps and target masks for performing backpropagation.

In validation phase, we thresholded the probabilistic maps by 0.5 and created binary predicted images (map) at each iteration. Depending on these binarized images, dice scores and intersection over unions were calculated by TP, FP, FN values that represent how pixel values matched between predicted map and target mask as illustrated in figure 2. According to the validation scores, we also took into consideration early stopping criteria, weight decay regularization, and the use of hyperparameter optimization. For example, we updated the current learning rate with a multiply factor of 0.1 as learning rate decay if there is no improvement at the end of each three epochs. Likewise, we terminated the training process if there is no improvement on dice and intersection over union scores at the end of each ten epochs. Also, weight decay regularization was used with Adam optimizer for adaptive gradient descent optimization.

3. Results

Our learning model was fine-tuned during the training and we achieved the performance metrics such as dice and intersection over union. As shown in figure 3, we wanted to summarize our deep learning concept in terms of software-hardware properties and hyperparameters. Depending on the optimization of our encoder-decoder neural networks, we determined the optimal values of hyperparameters and optimized adaptive gradient descent algorithm using weight decay regularization.

Architecture	K-fold CV	Training on hardware	Language	# of epoch	Initial Learning rate	Learning decay	Weight decay	Total Parameters (M)	GFLOPS	Optimizer
ResNet18+ UNet	5	NVIDIA GTX 1070	Python	39	5e-4	0.1	1e-5	14.3	16.6	AdamW

Figure 3. Summarized parameters of our deep learning concept.

Using training and validation datasets separately, we calculated the dice scores and plotted for each epoch as illustrated in figure 4. Dice aims to balance the tradeoff between precision and recall and intersection over union is used to create a similarity index varies between 0 and 1. By using focal loss [8], we achieved validation IoU score as 0.7396 and validation dice score as 0.8135 with 39 total number of epochs.

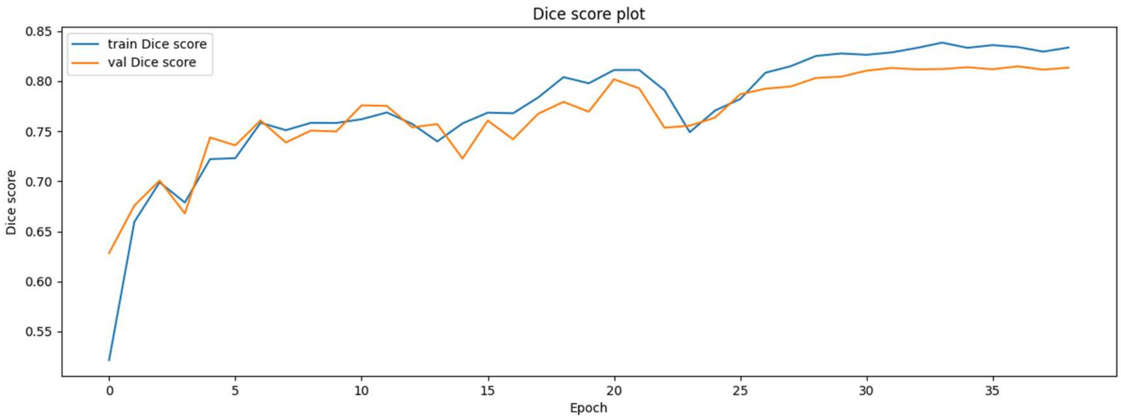


Figure 4. Dice scores using training and validation datasets.

4. Conclusion and Evaluation

In this study, we aimed to create a learning model for instance segmentation of polyp using colonoscopic white light images. Firstly, we carefully took into consideration about data augmentation process to avoid duplicate of original images and validated the training model to prevent overfitting issue. To be fairer on unbalanced datasets, we used focal loss. ResUNet++ has the best performance metrics in ResUNet based studies. ResUNet++ produced as a dice score of 79.55% with 15 convolutional layers and 120 training epochs. Likewise, another studies, such as ResNet-mode and UNet based polyp segmentation models, produced dice scores of 77.88% and 64.19%, respectively. We achieved validation dice score of 81.35% and intersection over union of 73.96% with 39 training epochs. In conclusion, our study has a potential to compete when comparing with ResUNet based studies.

References

1. Araujo, J.L., Jaiswal, P., Ragunathan, K. et al., Impact of Fellow Participation During Colonoscopy on Adenoma Detection Rates. Springer, Digestive Diseases and Sciences, 2021.
2. Zhao S., Wang S., Pan P. et al, Magnitude, Risk Factors, and Factors Associated With Adenoma Miss Rate of Tandem Colonoscopy: A Systematic Review and Meta-analysis, Elsevier, Gastroenterology, vol.156, 2019.
3. Bressler B., Paszat LF, Chen Z., et al., Rates of new or missed colorectal cancers after colonoscopy and their risk factors: a population-based analysis., Elsevier, Gastroenterology, 2007.
4. Mehrotra A., Morris M., Gourevitch A. R., Carrell S.D., et.al., Physician characteristics associated with higher adenoma detection rate., Elsevier, Gastrointestinal Endoscopy, vol.87, 2018.
5. Jha D., Smedsrud H.P., Riegler A. M., Johansen D., ResUNet++: An Advanced Architecture for Medical Image Segmentation, IEEE, 2019.
6. Rodriquez N.A., Carbajales D. R., Fernandez L. H. et al, Deep Neural Networks approaches for detecting and classifying colorectal polyps, Elsevier Neurocomputing, 2021.
7. Nakamura A., Harada T., Revisiting Fine-Tuning for Few-shot Learning, 2019.
8. He K., Zhank X., Ren S.,Sun J., Deep Residual Learning for Image Recognition., IEEE CVPR conference, 2016.
9. Lin Y.T., Goyal P., Girshick R., He K. et al., Focal loss for Dense Object Detection, Proceedings of the IEEE, ICCV, 2017.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

The Use of Artificial Intelligence in Organization and Increasing the Quality of Life of Disadvantaged People

Özden GÜNEŞ [1,*], Kader KUNDUZ [2]

[1] *Sakarya University, Faculty Science and Art, Dept. of Social Work, Turkey*
[2] *Sakarya University, Faculty Science and Art, Dept. of Social Work, Turkey*

* Corresponding Author: Sakarya University, Faculty Science and Art, Dept. of Social Work, Turkey
Tel.: +90 264 2916331. E-Mail: ozdengunes@sakarya.edu.tr

Publication Information

Keywords :

- Artificial intelligence,
- Disadvantaged,
- Social work,
- Quality of life,
- Public health

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

In this study, an artificial intelligence application was developed for the detection of lung diseases, which are quite prevalent in Turkey and the World to provide an example for biomedical applications of deep learning methods.

Lung diseases constitute a significant portion of chronic diseases. Respiratory diseases are the third most common cause of death in Turkey. Due to causes such as air pollution, smoking, lack of physical activity, disorganized life, and more recently, the damage caused by the COVID-19 virus, chronic lung diseases have become frequent. It is predicted that following the periods of little activity in limited areas made mandatory by the pandemic conditions, there will be an acceleration in the increases of lung symptoms with negative characteristics.

1. Introduction

The use and effect of artificial intelligence on the world is increasing day by day. The Covid19 pandemic directed humanity to a process that is far from social and without social contact. Sociality which is a social being, was deprived of sociality and prosociality, which we consider as one of its basic needs (see "Maslow Needs Pyramid"). The people we call “disadvantaged” in areas where social work works with them more have been affected the most by this negativity. The need for social work intervention increased even more when social conditions were added to the disadvantaged population. Due to Covid19 was social work intervention was unpossible.

Material: Practical tools should be developed in order to reach a level that can produce digital social work solutions for the healing of social diseases and increasing social health to every segment where people are available and accessible by technology - a large and increasing group.

The negative situation experienced in the labor market with the rise of robotization and delivery services without the need for human power in the industry is now a known fact. However, this situation brings along quite interesting questions. Are we ready for robots, which will increase our free time as a workforce, to combine with artificial intelligence and make us comfortable?

The changes experienced will contribute to human life both positively and negatively. Robots will replace people in workplaces where people are not needed, which will result in less employment. But the same could mean people doing business much faster. For example; Let's assume that a car factory produces five vehicles a day on average, the revival of this market is a very bad situation for the development of the economy, but if it is thought that one vehicle is produced every fifteen minutes a day with robots that help people, the perfect result of human power with robots equipped with artificial intelligence. we can say.

Although our expectations are in this direction, we hope even more. More productivity and performance will be achieved in the workplaces, the security situation will further increase and career development opportunities will increase.

The main companies that use artificial intelligence technology in Turkey are CBOT, the inverters, Sestek, Solvoyo, Greyhound is Vispera.

Commercial Use of Artificial Intelligence

The titles of the sections where artificial intelligence is used in many areas are as follows

- Language translation systems
- Speaking to the text system
- Air traffic control systems
- Automating personal systems
- Control systems
- Intelligent highways- traffic monitoring
- Robots for dangerous conditions
- Expert systems for law, medicine
- Neural network based forecasting- finance, stocks, pharmaceuticals
- Administrative summary production systems
- Automatic programming
- Summarizing the news from the articles
- Intelligent design- architectural, mechanical and electrical systems
- Game playing systems "dark blue"
- Medical diagnostic systems

Each line of business uses advanced artificial intelligence. In order to reduce the labor cost of the companies that benefit from this opportunity, there is no decrease in the employment rates, that is, not hiring people. This situation is likely to change in the future. With the developing age, it seems inevitable that people will be dismissed in order to reduce the operating costs in companies where robots and artificial intelligence play a more active role.

Looking at the research results of Infosys (2017: 8), "What are the benefits you provide in the use of artificial intelligence?" The results in Table 1 were obtained with the question.

Table 1: Proportional Benefits of Artificial Intelligence Applications in Retailing

Reduce costs	%49	Employees' knowledge and experience	%27
Increase in revenues	%44	Faster service and product delivery	%26
Increase in productivity	%43	Explanatory and predictive analysis	%24
More informed business decisions	%40	Testing and designing new ideas with consumers	%24
Faster business problem solving	%39	Increasing innovation	%22
Automating processes and jobs	%38	Reaching more experienced new employees	%11
Creating new revenue streams	%35	I am not aware of any benefits	%1.0

Source: Infosys (2017: 8)

Artificial intelligence has already taken its place in some business branches in order to make people's lives easier. All of these are in the most active and used areas of our lives. Some are made only to carry food, while others are made to save our lives. Some of them in "social care" are listed below.

2. Doctor From Robot Created With Artificial Intelligence

It can also be said that technological developments in the field of medicine, including artificial intelligence, are constantly evolving. After the technological developments in the field of medicine, by covering the classical treatment methods and giving more clear results and different treatment methods, machines will learn to perform surgery, prevent deaths from human error and help find a remedy for diseases that they think are incurable today. It will be one of the most beneficiaries and also provides numerous benefits such as integrating AI into the health ecosystem, automating tasks and analyzing large patient data sets to deliver better quality healthcare faster and at lower cost. Thanks to CureSkin, a mobile application based in All, it offers products for pre-diagnosis and treatment of skin diseases in humans. Thanks to a photo you upload to the application, it diagnoses problems such as face reading and acne under the skin, thanks to its own artificial intelligence algorithm. This development has now led to the disappearance of time-consuming situations such as going to the doctor and waiting in line by taking the diagnostic role of dermatologists away. Artificial intelligence is also a virtual doctor who will listen to your complaints and ask for your examinations, evaluate them, read and diagnose radiological graphs and give your medication when you have a health problem, or a friend who will chat with you in your stressful moment.

It is discussed how useful this technology is to disadvantaged patients. However, with a study developed so far, we can say that a robot with the ability to diagnose autism with 75% correct diagnosis has been developed (see reference no 36).

2.1 Assistant Imitating Human Voice

Assistant Imitating Human Voice "thinks" about it, it tells you what to eat for breakfast before you wake up, plans what to do at your workplace the day, you have a meeting and you need to cancel it because you have a different job that is much more important, but you can't even cancel it. It thinks like you and talks like you. It even reminds you of what is required for the house when coming home in the evening. Here is the name of this assistant; Google Duplex. Although he can do most of the task entirely himself, in situations where he cannot complete it, he can signal the operator, who is a human, to complete the task. Duplex has been created with the aim of making a natural sound similar to human beings and voice in spoken language. Can you witness how easy every moment of your life has become? In the future, all companies will now use these personal assistants as their right hand because the margin of error is set at almost 0%.

As it is known, human resources are used in recruiting personnel for companies. In the face of the questions they ask and the answers they receive, pay attention to their gestures and facial movements, and at the same time to decide whether they are the right person by reading their body language.

they give. Many companies are asking Facebook DeepFace to help them in this regard. This application is a biometric artificial intelligence application technology. There are many programs with face recognition systems, but this system generally works by comparing the features of the selected faces with the faces in a database, thanks to the image it has received. And with the examples presented, they analyze the person opposite and decide whether to recruit or not.

2.2 Assistants in Vital Tasks

Artificial intelligence assistants will help people who need someone's help for whatever reason or because of old age to live independently and live longer in their homes. There will be artificial intelligence tools around. For example, it is possible that you could not have breakfast because you woke up very early in the morning on your way to work, and these vehicles will support you in this regard wherever you can reach with nutritious foods. Or you had to buy anything from the upper shelf at home and you could not reach out and you will be able to do your work with these tools. All of these have passed the design stage and are implemented in places determined as pilots.

2.3 Your Guide to an Artificial Intelligence

Thanks to the specially developed artificial intelligence tourism virtual assistants located in the tourism and cultural conservation areas, tourists are now able to visit, entertainments, events, etc. It meets the expectations of the visitors by keeping the happiness of the visitors at the highest level from the beginning to the end of the holiday activities. Thus, people can access all information about the visiting points of historical monuments, restaurants, services and activities specific to the touristic region they have visited, watch the relevant promotional videos and reach every point they want to go within the touristic areas with navigation guidance. Then you can find out the flight time and price to the destination place at any date and time you want with the artificial intelligence airport experience when you want to go to a different place. You can also monitor the status of existing flights by using flight numbers. This means that no more people need to work at the airport. It seems that these are the most frequently used artificial intelligence programs today.

3. Artificial Intelligence and E-commerce

Nowadays, people do not have to go all the way and spend time to reach stores, markets or what they need. Thanks to e-commerce, many websites provide you this convenience. For example; You like a dress, but you cannot leave the workplace because you have no time, there are websites that can deliver it to your exact address thanks to smart applications. In fact, what you buy does not even have to exist in the same Country. You can reach products from all over the world. Does this situation have any disadvantages? Yes there is. Google records every information you search on the internet into its own artificial intelligence with an agreement that it keeps confidential and then reveals it to any site you research. Private life is intervened directly, perhaps without your knowledge.

3.1 Your New Teacher is Artificial Intelligence

The technologies of artificial intelligence and education can design and present a program that can analyze the shortcomings of the students in a suitable way for the individual. Thanks to the personalized education data program, it makes the students more individual, where they will be more active and productive and become much more successful. Artificial intelligence, whose educational software is tailored to the student's needs, better identifies the missing aspects of the students and creates personalized support for the development of the student.

Gathering, analyzing and presenting smart data with its underlying structure supported by smart computer systems is a process that is applied by many schools very actively today. Today, some schools are using artificial intelligence technology in order to follow the progress schedule of their students and to increase the performance of the student with the resulting analysis.

When developed for disadvantaged individuals, this “teacher” can assist an individual with Alzheimer's disease. Providing daily tasks and tasks in line with the condition of the disease and the patient's possibilities, the “teacher” can helps the patient to remain active on the one hand, and on the other hand, by doing what the patient cannot do, to live an individual independent life as much as possible despite his illness.
Thanks to the robot that supports disadvantaged individuals with autism and Asperger syndrome, it helps those who have communication difficulties to overcome this disadvantage by providing one-to-one training (see reference no. 36).

3.2 Pepper, the new playmate and care support in the Elderly care center

The developed humanoid robot Pepper supports the nursing staff in the elderly care center. For example, by taking care of the staff's tasks such as taking the dirty laundry to the laundry, the time that the staff will spare for the elderly increases. On the other hand, in order to prevent the elderly people from suffering from mental apathy, he is engaged in entertaining activities by addressing them by name, telling jokes, asking riddles, offering tea and coffee according to their desires (see reference no. 27-33).

4. Results

The study has been about the development of social intelligence and its use in the field of organization from past to present, and it is in search of how this organization can be used in the most effective way for the benefit of disadvantaged people and public health. We can say that artificial intelligence robots developed as personal assistants, teachers for personal needs and disabilities, and personal doctors can provide great convenience to human life. Since many studies have been tested limitedly within the scope of the pilot project, we do not yet have a clear idea about their positive and negative effects in real life.

5. Conclusion and Evaluation

Artificial intelligence takes place in our lives much better equipped, which gets a new power with developing technology. During the Covid19 pandemic, which unexpectedly affected the life of the world, directed humanity to a socially non-contact process -as far as possible. As a social being, humanity was deprived of sociality, which we consider as one of its basic needs (see "Maslow Needs Pyramid").

The people we call “disadvantaged” in areas where Social Work works with them more, have been affected the most by this negativity. The need for social work intervention increased even more when social conditions were added to the disadvantaged population. However, again, due to Covid19, access to this segment became difficult, and social work intervention was inadequate. Social service works cannot reach the person and where they reach falls short.

As a result of the researches, humanoid robot studies such as Pepper Robotic, Care-O-bot 3 and CASERO, which communicate by interpreting the emotions of Softbank Robotics company, were examined. There are many such examples that are particularly useful in elderly care centers in terms of helping social workers and nursing staff. However, according to the program loaded, it is possible to come across robots serving in the library, for example (See Reference no. 27, 28, 29, 30, 31,32).

Therefore, in order to cope with the social problems of the people we are talking about, to diagnose their social diseases and to find solutions to them. Social work and other professionals in many social fields should receive training in social information technologies and improve themselves. In this way, it should come to a level that can produce digital social work solutions for the improvement of social diseases and increasing social health to every segment, where people are present and accessible by technology - a large and increasing group. In the process of increasing need and difficult pandemic, such an initiative has become inevitable and perhaps necessary for the future.

In summary, although digital social work cannot replace one-on-one intervention, but it can provide a serious convenience in reaching disadvantaged individuals and groups, which are difficult to reach, in approaching people, solving their problems, and achieving a healthier social happiness. But, studies on this subject should be developed professionally and in a controlled manner. In the study, we can say that artificial intelligence robots developed as personal assistants, teachers for personal needs and disabilities, and personal doctors can provide great convenience to human life. Since many studies have been tested limitedly within the scope of the pilot project, we do not yet have a clear idea about their positive and negative effects in real life. We hope that artificial intelligence studies will provide an advantage, especially for people who have disadvantages in society.

References

1. Alon, Ilan, Min Qi ve Robert J. Sadowski (2001), “Forecasting Aggregate Retail Sales: A Comparison of Artificial Neural Networks and Traditional Methods”, Journal of Retailingand Consumer Services, 8, 147–156.
2. Altunışık, Remzi, Recai Coşkun, Serkan Bayraktaroğlu ve Engin Yıldırım (2012), Sosyal Bilimlerde Araştırma Yöntemleri (7.Baskı), Sakarya: Sakarya Yayıncılık.
3. Bradford W.; Sheafor-Charles; J. Horejsi: Sosyal Hizmet Uygulaması. Temel Teknikler ve İlkeler. Nika Yayınevi (2012)
4. Dai Y., Kim Y., Wee S., Lee D. ve Lee S., Symmetric caging formation for convex polygonal object transportation by multiple mobile robots based on fuzzy sliding mode control, ISA Trans., c. 60, ss. 321–332, 2016
5. Demir, Ayhan: Grupla Psikolojik Danışma. Pegem Akademi. Ankara 2016.
6. Doğan Abdullah, Yapay Zeka, Kariyer Yayıncılık, 2002
7. file:///C:/Users/lg/Desktop/yonetimde%20yapay%20z%20makalesi.pdf
8. Güneş, Özden: Prosozialitat im Islam. Ihre Lehren und Dimensionen im Koran und Hadith. Peter Lang Verlag. Frankfurt am Main, 2016)
9. Harris, Elaine K. (2013), Customer Service: A Practical Approach (6. Baskı), New Jersey: Pearson.
10. http://betadergi.com/ttad/yonetim/icerik/makaleler/245-published.pdf
11. http://www.ajit-e.org/?menu=pages&p=details_of_article&id=313
12. https://dergipark.org.tr/tr/download/article-file/661990
13. https://dergipark.org.tr/tr/download/article-file/738757
14. https://evrimagaci.org/varolussal-risk-ve-yapay-zeka-gelecek-neden-en-kotu-kabusumuz-olabilir-452
15. https://indigodergisi.com/2018/04/robot-sophia-yapi-kredi-reklam/ (alıntı tarihi: 22.01.2021)
16. https://jag.journalagent.com/adlitip/pdfs/adlitip_21_2_31_45.pdf
17. https://medium.com/analytics-vidhya/the-future-of-jobs-in-artificial-intelligence-era-93e34c33c25f

18. https://medium.com/t%C3%BCrkiye/d%C3%BCnyan%C4%B1n-en-zeki-13-yapay-zeka-%C5%9Firketi-94745821ba35
19. https://www.bbc.com/turkce/haberler-43144059
20. https://www.defenceturk.net/oncu-otonomi-ve-yapay-zeka-calismasi-shakey(alıntı tarihi: 30.01.2021)
21. https://www.dw.com/tr/abd-ordusunda-yapay-zeka-devri/a-52018242
22. https://www.haberturk.com/yazarlar/prof-dr-temel-yilmaz/1579824-degisen-biyolojik-zeka-mi-yapay-zeka-mi
23. https://www.hurriyet.com.tr/teknoloji/yapay-zeka-nedir-yapay-zeka-ne-demek-40888243
24. https://www.michaelpage.com.tr/haberler-ve-ara%C5%9Ft%C4%B1rma/ara%C5%9Ft%C4%B1rmalar/fw-gelecegin-is-dunyasi/artirilmis-gerceklik-is-araclari
25. https://www.researchgate.net/publication/341407595_Yapay_Zeka_Isletme_Yonetimi_Iliskisi_Uzerine_Bir_Degerlendirme
26. https://www.yapayzekatr.com/2020/01/06/yapay-zeka-ve-kullanim-alanlari/
27. https://www.youtube.com/watch?v=4jvsHum4zqU (caritas Deutschland, alıntı tarihi: 20.12.2021)
28. https://www.youtube.com/watch?v=xgFUtgzlwzY (Künstliche Intelligenz in der Pflege mit Pflegerobbe Paro; Yapay zekalı "su aygırı Paro ile yaşlı bakımı ve ilgisi" (alıntı tarihi: 20.12.2021)
29. https://www.youtube.com/watch?v=Px4_GTNLmWI (Pepper verteilt Medikamente - Szenario 1. Yapay zekalı "Pepper" ile yaşlı bakımında ilaç dağıtımı/sunumu.) (alıntı tarihi: 20.12.2021)
30. https://www.youtube.com/watch?v=-PL84eDAPbE Lebenlang-Interview mit "Pfleger Pepper" (Yaşlı bakım evindeki bireylerin ilgisizlikten mental düşüşlerini engellemek amaçlı yaşlıları yüzlerinden tanıma, sohbet ve mental ve duygu durumlarına göre cevap ve bilgi aktarımı ile boş zaman değerlendirme örneği.) (alıntı tarihi: 20.03.2021)
31. https://www.youtube.com/watch?v=nJj8wJg6jNM Serviceroboter im Altenheim: Care-O-bot 3 und CASERO (Yaşlı bakım evi yardımcısı, ms. Casero: kirli çamaşırları halletmek, çalışanlara destek verme,…) (alıntı tarihi: 20.03.2021)
32. https://www.youtube.com/watch?v=SCWwcxZ3p_o Fast schon menschlich: Roboter mit Gefühlen (Softbank Robotics firmasının duyguları yorumlayarak iletişim kuran Pepper Robotic) (alıntı tarihi: 20.03.2021)
33. https://www.youtube.com/watch?v=-negyZmzmOU Pepper der Roboter im Check: Was kann der CeBIT-Star? Humanoider Roboter. Kahve siparişi, sohbet, masal anlatımı, fıkra vs.)
34. https://www.youtube.com/watch?v=-gGQBuOBg7U (Technische Hochschulu Wilmar Araştırma Kütüphanesinde / Köln Üniversitesi Merkez Kütüphanesinde, … aktif çalışan asistan humanoid robot örneği…) (alıntı tarihi: 20.03.2021)
35. https://www.youtube.com/watch?v=GaqcM10Hnl4 Pepper - The Library Assistant (alıntı tarihi: 20.03.2021)
36. https://www.youtube.com/watch?v=jkuSREPgcME (Autismus-Therapie mit sozialen Robotern: So kann ein KI-Roboter helfen (Otizmli Asperger sendromlu bireylerin mimiklerini dikkate alarak iletişim eğitimi veren yapay zekâ (alıntı tarihi: 20.03.2021).
37. Infosys (2017: 8)
38. KPMG (2018), "Global RetailTrends", https://assets.kpmg/content/ dam/kpmg/xx/p
39. Liu F., Liang S. ve Xian X., Optimal Robot Path Planning for Multiple Goals Visiting Based on Tailo red Genetic Algorithm, c. 6891, sayı March, 2017
40. Lu LE, Zheng Y, Carneiro G, Yang L. Deep learning and convolutional neural networks for medical image computing: Advances in Computer Vision and Pattern Recognition, Springer (2017).
41. Nadimpalli, Meenakshi (2017), "Artificial Intelligence – Consumers and Industry Impact", International Journal of Economics& Management Sciences, 6 (4), 1–3.
42. Q. Tang ve P. Eberhard, "Relative observation for multi-robot collaborative localisation based on multi-source signals", c. 26, sayı 4, ss. 571–591, 2014.
43. Russel Stuart, Norvig Peter, Artificial Intelligence, A Modern Approach, PrenticeHall, 2nd Edition, (2003)

44. Sejati P., Suzuki H., Kitajima T., Kuwahara A. ve Yasuno T., Object Conveyance Algorithm for Multiple Mobile Robotsbased on Object Shapeand Size, c. 7, sayı 5, 2016.
45. Sterne, Jim (2017), Artificial Intelligence for Marketing: Practical Applications, New Jersey: Wiley.
46. Wang T., Dang Q. ve Pan P., A Multi-Robot SystemBased on A Hybrid Communication Approach, c. 1, sayı 1, ss. 91– 100, 2013.
47. World Health Organization, http://www.who.int/indoorair/en/ (November 2020).
48. Yolcuoğlu, İsmet Garip: Bireylerle Ailelerle Gruplarla ve Toplumlarla Sosyal Hizmet. Nar Yayınevi (2017)

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 **||** **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

Pressure Ulcer Management with Decision Support System in the Postoperative Intensive Care Unit

Gulnur GUL [1], Eylem ARI ESKİCİOGLU [2], Elif AKBAS [3, *]

[1] *Dokuz Eylul University, Institute of Health Sciences, Turkey*
[2] *SBÜ. DR. Suat Seren Chest Diseases and Surgery Training and Research Hospital, Turkey*
[3] *İzmir Bakırçay University, Çiğli Training and Research Hospital, Turkey*

* Corresponding Author: Izmir Bakircay University, Çiğli Training and Research Hospital, Turkey
Tel.: +90 232 3983700. E-Mail: elifbicer25082015@gmail.com

Publication Information

Keywords :
- Artificial intelligence,
- Decision support system,
- Nursing

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

In this study, an artificial intelligence application was shown to evaluate the diagnostic, management and follow-up processes of pressure ulcer with Decision Support System of patients in postoperative intensive care unit.

The retrospective, cross-sectional study was conducted using the "pressure ulcer diagnosis, evaluation, follow-up form" in which patients hospitalized between January 1 and December 31, 2020 in the postoperative intensive care unit.

It is seen that 957 patients were admitted in the relevant period, pressure ulcer evaluations of all patients were made during the system diagnosis, and it was performed at a rate of 100%. Pressure ulcers developed in only 18 patients (1.8%) in the postoperative intensive care unit. It was determined that the visual risk assessment scheme for risk diagnosis was used in the decision support system, and that the nurses performed diameter and depth evaluations for the detection of pressure wounds. When the patient data were examined, it was observed that the risk assessment score of the whole patient was high (18 points and below), and the nursing diagnosis of "risk of skin integrity deterioration" was taken and the necessary care was given to these patients.

In the preoperative period, it was determined that the decision support system in the management of pressure ulcers and care elements were fulfilled completely, but there was a minimal deviation in the care results. Due to the dynamic structure of decision support systems, systems can be increased according to need.

1. Introduction

In this study, an artificial intelligence application was shown to evaluate the diagnostic, management and follow-up processes of pressure ulcer with Decision Support System of patients in postoperative intensive care unit.

Seek to emulate the human mind through a computer, an application of the theory of artificial intelligence, decision support systems, digital applications in the process of nursing care in the health field, as well as artificial intelligence emerges as an instance, especially in inpatient clinics. These systems are defined as active intelligent systems that can help employees make decisions by making specific recommendations and decisions based on patient-specific information and analysis of relevant medical facts. These intelligent systems, which are an opportunity offered to us by technological developments, play a role in ensuring the safe care of the patient by providing information, guidance and reminder data to nurses, especially in intensive care units.

In addition, it is very important for nurses to prevent the formation of pressure ulcers in inpatient patients and to take the necessary measures to ensure patient safety.For this purpose, a retrospective, cross-sectional research the type of research that is performed in accordance with training and Research Hospital University of Health Sciences in the intensive care unit for postoperative 1 January - 31 December 2020 if the process is evaluated between the dates of care of hospitalized patients,"identification of pressure ulcers, evaluation of the following form using" was conducted.

2. Clinical Decision Support Systems

Artificial intelligence is defined as "digital technology and applications that can think and make decisions like humans "(2,5).Hospital Information Management System (HBYS) is used in our country to increase efficiency and reduce complexity due to the progress of technological developments in the world in the Health Sector (9). Clinical Decision Support Systems (PPE) are one of the methods that nurses use to support them in fulfilling their duties and responsibilities so that they can make more effective, fast and accurate decisions (5). PKDS are computer programs that help medical personnel make decisions.(7).

The Clinical Decision Support System takes the data and information entered into the system and processes it using models, algorithms and calculations for a number of organizations. Information collected about a patient in the Clinical Decision Support System is presented to the right user with reminders, warnings or suggestions at the appropriate time (8). A large part of the workforce in health care consists of nurses. Supporting nursing practices with information systems accelerates the use of information recorded in the hospital information management system (9,10). Nurses have to make clinical decisions in a short time using intensive knowledge in multifaceted and complex environments in the health care system. The nurse's accurate and effective clinical decision making can be achieved through Decision Support Systems.(10,11).

Clinical Decision Support Systems help make decisions by providing users with messages stating options for care and ensuring that the patient can receive comprehensive care for their problems. The time of each data entered manually or automatically, by whom it was entered, appears to be the time of entering the patient records (8,9). According to the data entered, the system matches the characteristics of the patients and the knowledge base and provides patient-specific recommendations (9,10). For example, when a user enters a high body temperature value as a result of his measurement in the system, the system can direct the user to the frequency of monitoring body temperature according to the institution protocol(5,7).

PPE provides an increase in the number of alternatives tested with its effective features such as early warning, quick response, instant analysis, cost reduction, correct decision, effective teamwork, time saving and good use of data sources in unexpected situations in the clinical departments in which they are used (5).

3. Pressure Ulcer

A pressure ulcer is a local injury that occurs in the skin or deep tissues, which usually develops as a result of friction and tearing in the protrusion parts of bones. In addition, pressure ulcers are important for both error and institution in terms of health care service criteria. On the other hand, pressure ulcer is one of the most important assessments in the patient safety assessment. The risk assessment of pressure ulcers, which must be performed when the patient is admitted to the clinic, provides planning, monitoring and continuity of care that will be applied to the patient(1,6).A reliable and effective first step in determining the risks of patients ' pressure wounds, planning interventions to prevent pressure wounds, is the use of risk identification forms. With the diagnosis of Risk, the development of wounds is prevented by planning appropriate interventions for the patient. Prevention of pressure wounds is one of the primary responsibilities of Nurses (6).

In order to prevent pressure ulcers, all patients in inpatient clinics must first perform a risk assessment with a structured risk assessment form within the first few hours. In addition, it is necessary to identify factors that increase risk along with risk assessment and take measures to address them (4).

In studies conducted in the literature, the incidence of pressure injuries in acute care clinics is reported to be 5.4% -9% 13.6% -20.1% in intensive care clinics (1,4). The content of the risk assessment scale used becomes even more important because intensive care units are more common units where pressure ulcers are seen (12). The Braden scale is commonly used in intensive care clinics (1). This scale includes the assessment of sensory perception, activity, mobility, humidity, friction-tear, nutrition risk factors(12). Advantages of using the Braden scale include that it takes less time to implement this scale and provides rapid evaluation, as it is important to use time efficiently in intensive care units. A 2019 study compared four pressure wound assessment scales used in the intensive care unit and concluded that the braden scale is the best scale for predicting the risk of developing pressure ulcers in patients in intensive care units (15). A study conducted by Fossum and others in Norway showed that using a computer-based decision support system in nursing homes had a positive effect on planning care for a pressure ulcer(3).

4. Findings

It is observed that 957 patients were hospitalized in the relevant period, that all patients ' Pressure Ulcer evaluations were performed during system diagnosis and were performed at a rate of 100%. It was found that only 18 patients (1.8%) developed pressure ulcers in the postoperative intensive care unit. It was found that the Visual Risk Assessment scheme for risk diagnosis was used in the decision support system,(Figure 1) nurses performed diameter and depth assessments for Pressure Wound detection (Figure 2).

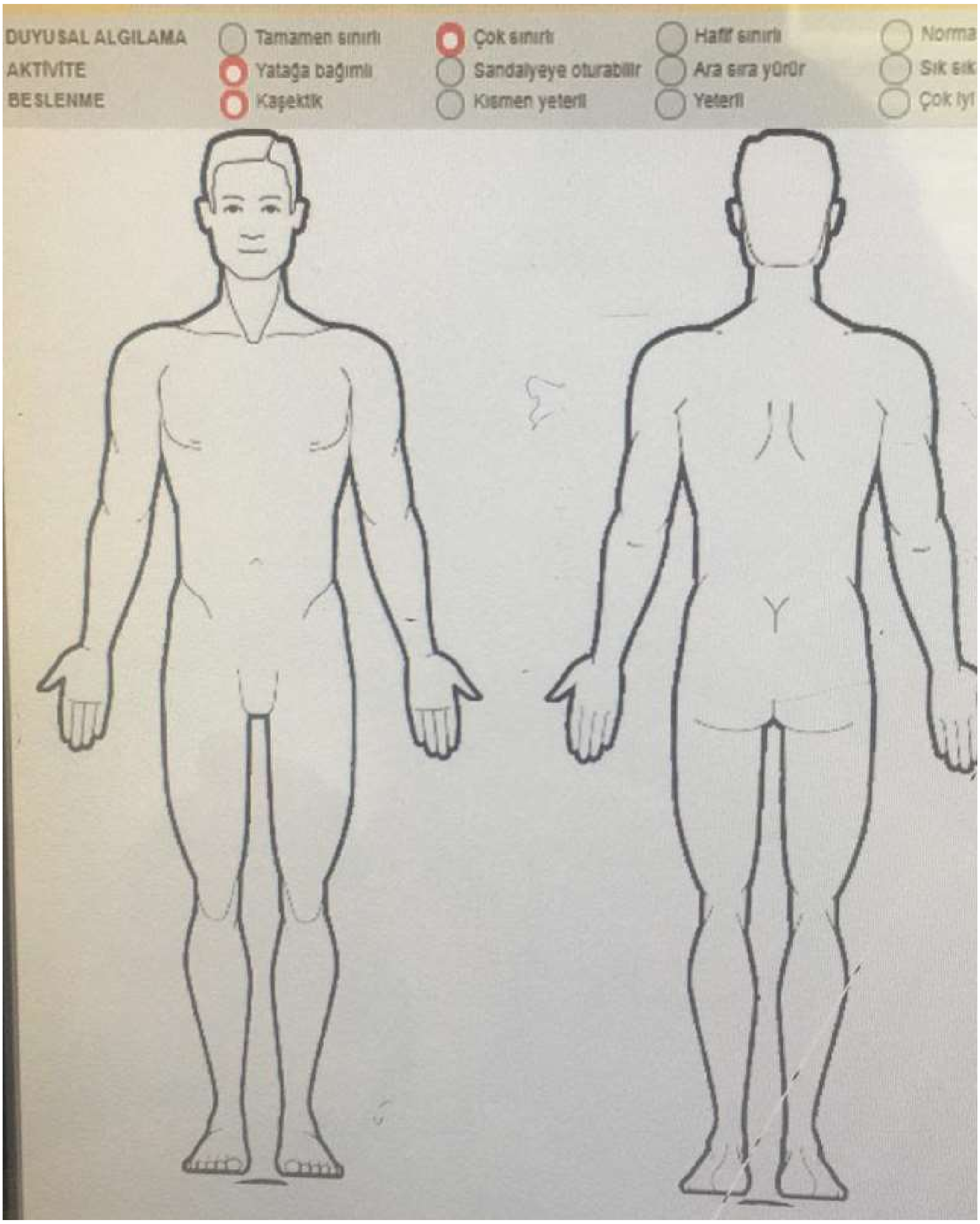


Figure 1. Risk Diagnostic Scheme

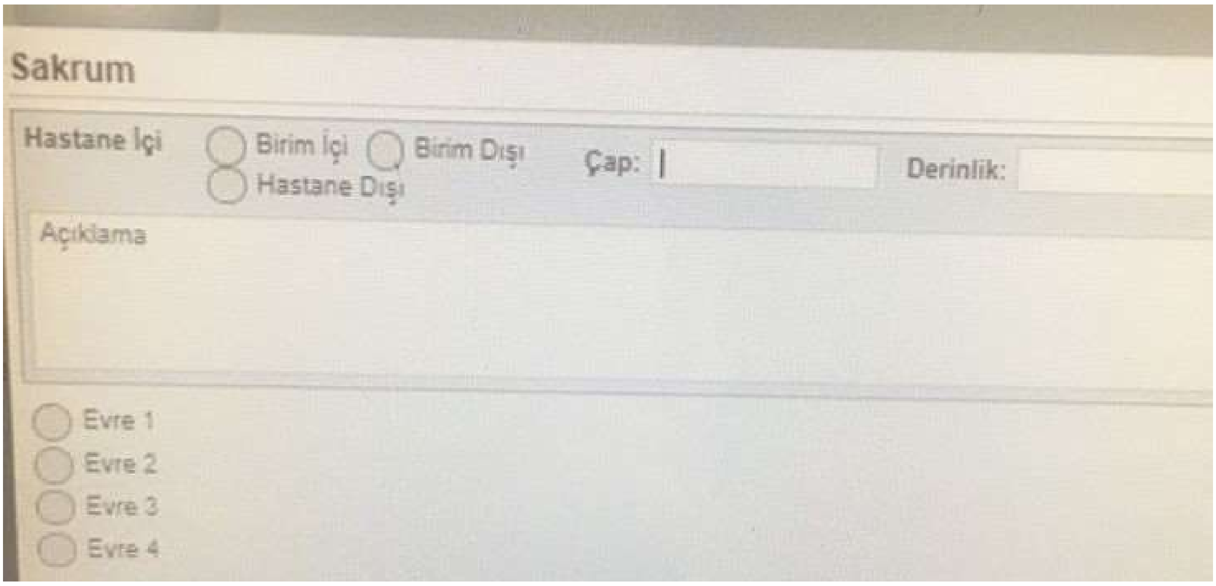


Figure 2. Diameter And Depth Assessments For Pressure Wound Detection

When the patient data were examined, it was found that the risk assessment score of the entire patient was high (18 points and below) and that the necessary care was performed by taking the diagnosis of nursing " risk of deterioration of skin integrity" for these patients.

5. Conclusion and Evaluation

In the post-operative process, it was found that the maintenance elements were fully fulfilled with the decision support system in the management of pressure ulcers, but there was a slight deviation in the maintenance results. Primiano and colleagues (2011) reported that in a study of 258 surgical patients, the prevalence of intraoperative pressure wounds ranged from 12 to 66%. In operations lasting more than 3 hours, it was determined that 23% of patients developed pressure wounds on the heels.Another study found that the length of the operation time increased the development of pressure wounds (14). In our study, the rate of development of pressure wounds in patients undergoing major thoracic surgery surgery (average duration of surgery 2-6 hours) is about 2%, which can be evaluated as the effectiveness of integrated care with the decision support system.

It is seen that there is a need for studies to develop clinical decision support systems that support nursing decisions in patient care in artificial intelligence applications in health. Due to the creation of Clinical Decision Support Systems, which are the stage of digital hospital application, with a dynamic structure, their implementation in all health care areas can be increased within the framework of the needs of the hospital.

References

[1] Beeckman D, Schoonhoven L, Fletcher J, Furtado K, Heyman H, Paquay L, et al. Pressure ulcers and incontinence-associated dermatitis:Effectiveness of the Pressure Ulcer Classification education tool on classification by nurses. Qual Saf Health Care. 2010;19(5).

[2] Doğan A. (2002). *Yapay Zeka*, Kariyer Yayıncılık.Ankara.

[3] Fossum M, Ehnfors M, Fruhling A, Ehrenberg A. An Evaluation of the usability of a computerized decision support system for nursing homes. Applied Clinical Informatics, 2011b; 2(4): 420-436.

[4] Karaman Özlü Z,vd;(2015). Cerrahi Hastalarda Bası Yarası Riski, *Kafkas Tıp Bilimleri Dergisi* 5(3):94–99

[5] Koç E, Şengül A. Y, Özkaya U. A, Klinik Karar Destek Sistemlerinin Sağlık Hizmetleri Verimliliğine Etkileri, *6.Sağlık ve Hastane İdaresi Kongresi*, 2012.

[6] Mallah Z, Nassar N, Badr LK. The effectiveness of a pressure ulcer intervention program on the prevalence of hospital acquired pressure ulcers: controlled before and after study. Applied Nursing Research. 2015;28(2):106-113.

[7] Müller-Staub M. Paans W. A. (2016). Standard for nursing process -clinical decision support systems (NP-CDSS). Stud Health Technol Inform, 225, 810-1.

[8] O'Neill, E. S., Dluhy, N. M., Ryan, J. R. (2004). Coupling the N-CODES system with actual nurse decision-making. CIN Computers Informatics Nursing, 24(1), 28-34.

[9] Özata M ve Aslan Ş. (2004). Afyon Kocatepe Üniversitesi Klinik Karar Destek Sistemleri ve Örnek Uygulamalar Clinical Decision Support Systems and Model Applications. *Kocatepe Tıp Dergisi The Medical Journal of Kocatepe* 5: 11 – 17.

[10] Padden, J. S., McBride, S., Tietze, M., Nelson, T., Eckbard, M. (2019). Clinical Decision Support System. Nursıng Informatıon fort he Advanced Practice Nurse 2.st Edıt. Mcbride S., Tietze M. New York: Springer Publishing Company

[11] Pıscotty, R., Kalısch, B. (2014). Nurses' use of clinical decision support: a literature review. Computers Informatics Nursing, 32(12), 562-568.

[12] Pressure Injury Prevention Points http://www.npuap.org/resources/educational-and-clinical-resources/2018-world-wide-pressure-injury-prevention-day/

[13] Primiano M, Friend M, McClure C, Nardi S, Fix L, Schafer M. et al. Pressure Ulcer Prevalence and Risk Factors During Prolonged Surgical Procedures. AORN J 2011;94(6):555-566.

[14] Schoonhoven L., Defloor T, Tweel I, Buskens E, Grypdonck MHF. Risk Indicators for Pressure Ulcers During Surgery. Applied Nursing Research 2002;16(2):163-173.

[15] Theeranut A., Ninbanphot, S., Limpawattana, P. 2020. Comparison of four pressure ulcer risk assessment tools in critically ill patients, British Association of Critical Care Nurses, Nurs Crit Care. 2021;26:48–54.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || ISBN : 978-605-69730-2-4

More information available at aita.bakircay.edu.tr

Design Process of an IoT based Patient Monitoring System

Mehmet Akif OCAK [1], Abdullah Alper EFE [2,*]

[1] *Gazi University, Faculty of Education, Dept. of CEIT, Turkey*
[2] *Kütahya Health Sciences University, KHSU Application and Research Center, Turkey*

* Corresponding Author: Kütahya Health Sciences University, KHSU ARC, Turkey
Tel.: + 0 (274) 260 00 43. E-Mail: abdullahalper.efe@ksbu.edu.tr

Publication Information

Keywords:
- Monitoring,
- Temperature,
- Heartbeat,
- ESP8266,
- Arduino,
- IoT

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

The purpose of this study is to design an IoT based patient monitoring system in which the temperature and heartbeat values are received from sensors and transferred to an IoT data analytics and cloud program. The hardware structure of the study is based on an Arduino UNO and ESP8266 wi-fi module. The study used the LM35 temperature sensor and heart rate sensor (pulse) to simulate the patients' body temperature values and heart rate values. The system checks the heartbeat rate regularly, and if the heartbeat value of the patients is critically low, LED alerts the healthcare workers to take necessary actions. Prior research clearly shows that an important area where IoT systems are developed is the health sector. IoT systems remotely monitor chronic diseases and transfer information to the relevant people in emergencies. This study proposes the design of an IoT based healthcare system by using Thingspeak to facilitate remote monitoring of patients' body temperature and heartbeat rate.

1. Introduction

The purpose of this study is to design an IoT based patient monitoring system in which the temperature and heartbeat values are received from sensors and transferred to an IoT data analytics and cloud program. In this way, this IoT system allows health workers to analyze patients' temperature and heart beat rate remotely and accelerates the intervention when necessary.

The idea of using IoT based systems in healthcare is growing rapidly. The reason for this has twofolds. One of them is that the Internet based technological tools have become popular in the healthcare system. Secondly, the economical aspect of IoT systems showed that using IoT systems in healthcare are cheap and IoT technologies allow healthcare workers to see and analyze data, and take necessary actions from anywhere. In this regard, Neyja, Mumtaz, Huq, Busari, Rodriguez and Zhou (2017) argued that IoT based healthcare systems provide critical challenges from different locations regarding real-time monitoring of patients' data.

From a different aspect, Valsalan, Baomar, and Baabood (2020), during Covid 19 pandemic period, focused on developing a remote health monitoring system using IoT. The study developed an IoT based system only authorized personnel can access and healthcare workers can diagnose the diseases from a distance. The basic idea behind developing this IoT system was to reduce healthcare costs by reducing expenses.

Prior research clearly shows that IoT systems in healthcare are providing rapid and feasible solutions in order to monitor patients' data remotely. For example, Tamilselvi, Sribalaji, Vigneshwaran, Vinu, and GeethaRamani (2020) developed an IoT based healthcare system in which patient's body temperature, coronary heart rate, eye movement and oxygen saturation percentage are monitored by using smart phones and laptops. The study argued that the IoT system allowed doctors and physicians to analyze patients' data for further evaluation and selection making. The hardware structure of the IoT system used an Arduino board and a cloud computing concept. Similarly, Sam, Srinidhi, Niveditha, Amudha, and Usha (2020) develop an IoT based healthcare system that, compared to others, seems to obtain more data regarding patients' health. In this sense, the paper argued that the developed IoT system checks pulse, circulatory strain, breath rate, body temperature, body development and saline dimensions. The study used an Arduino, Atmega 328 microcontroller and Wi-fi model to collect, analyze and to send the data to cloud servers.

Other studies, similarly, focused on the design and implementation of an IoT based healthcare system to provide rapid access to patients' data from anywhere. On the contrary, there are also several disadvantages regarding the utilization of IoT systems in healthcare. In this sense, Reena and Parameswari (2019) argued that accuracy in IoT based systems requires a high quantity of information. Thus, it is important to detect high accuracy in IoT based systems. Secondly, many IoT based systems only focus on two parameters in health care. This kind of IoT systems ignore different parameters of patients' data mostly. As discussed by Patil and Pardeshi (2018), the design and implementation process of IoT systems in healthcare must focus on various parameters of the ill patients. In this sense, the system allows health workers to analyze the data from different aspects.

In the light of all this, the purpose of this study is to design a patient monitoring system in which the temperature value obtained from the LM35 sensor and the heart rate (HR) obtained from the heartbeat (pulse) sensor and the values obtained are sent to the ThingSpeak server. Temperature and heart rate values are also printed on the LCD screen. In the ThingSpeak program, 2 widgets were created for temperature and heartbeat values at the same time.

2. Method

The hardware structure of the study is based on an Arduino UNO and ESP8266 wi-fi module. To simplify connection settings and increase working efficiency of ESP8266 wi-fi module, this study preferred to use ESP8266 wi-fi module adapter. The study used the LM35 temperature sensor and heart rate sensor (pulse) to simulate the patients' body temperature values and heart rate values. The reason for choosing LM35 and pulse sensors has two folds. One of them is that both sensors are plug-and-play sensors and do not need any additional libraries to run and secondly, both sensors are well designed for Arduino UNO development cards. The system checks the heartbeat rate regularly, and if the heartbeat value of the patients is critically low, LED alerts the healthcare workers to take necessary actions. The data obtained from the sensors are also displayed on the LCD screen, increasing the usability of the system. ThingSpeak IoT platform monitors data results coming from sensors by using two visual widgets, as well as graphical tools.

2.1. Design of IoT system

The following circuit elements will be needed for this application: An Arduino UNO board connected to the computer via USB, 1 piece of ESP8266 module adapter, 1 piece of ESP8266 module, 1 piece of 2X16

LCD screen, heart rate sensor (pulse), 1 piece of LM35 temperature sensor, 1 piece of 10K potentiometer, 1 piece of red LED, 1 piece of circuit board and connection cables.

In this application, the diagram showing how an IoT based patient tracking system works by using ESP8266 and Arduino is given in Figure 1. The LM35 temperature sensor and Heart rate sensor (HR) measure body temperature and heart rate, respectively. The IoT server used in the application is ThingSpeak. The measured values are sent to the ThingSpeak server with the help of the ESP8266 wi-fi module. The sensor values can be read from 2 channels created in ThingSpeak dashboard and can be watched from anywhere.

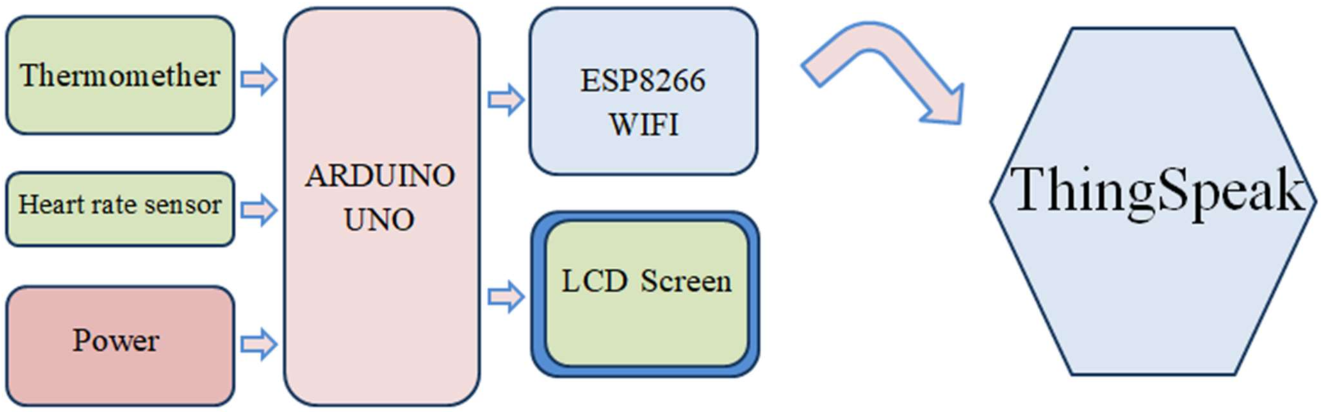


Figure 1. The block diagram of the system.

2.2. Sensors

Heart rate (pulse) sensor is a plug and play heart rate sensor for Arduino (Figure 2). It can be easily used for those who want to use live heart rate data in projects. It has a structure that contains an integrated optical amplifier circuit and a noise canceling circuit inside. The measurement is made by attaching the heart rate sensor to the fingertip. The heart rate sensor has three pins: Vcc, GND, and Analog Pin. There is also a LED in the middle of this sensor module that helps detect heartbeat. Below the LED is a noise canceling circuit that prevents noise from affecting the readings.

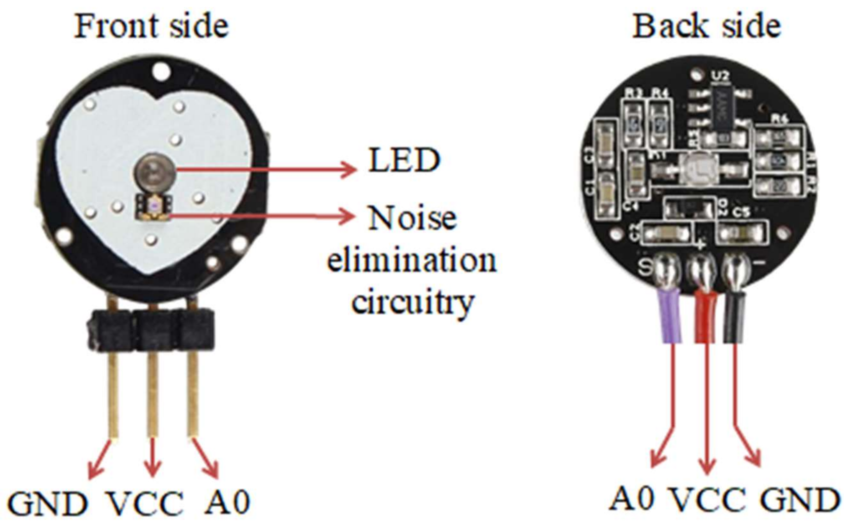


Figure 2. Pulse sensor view of the front and the back sides

LM35 is a precession integrated circuit temperature sensor, whose output voltage varies, based on the temperature around it (Figure 3). It is a small and cheap IC which can be used to measure temperature anywhere between -55°C to 150°C. It can easily be interfaced with any Microcontroller that has ADC function or any development platform like Arduino.

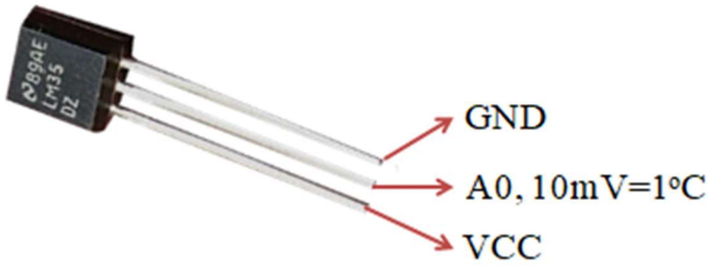


Figure 3. LM35 connection legs

Figure 4 shows the schema of the application. These steps must be followed to connect an ESP8266 module, LCD display, heart rate sensor (pulse) sensor, LM35, 10K potentiometer and 1 red LED to an Arduino UNO board.

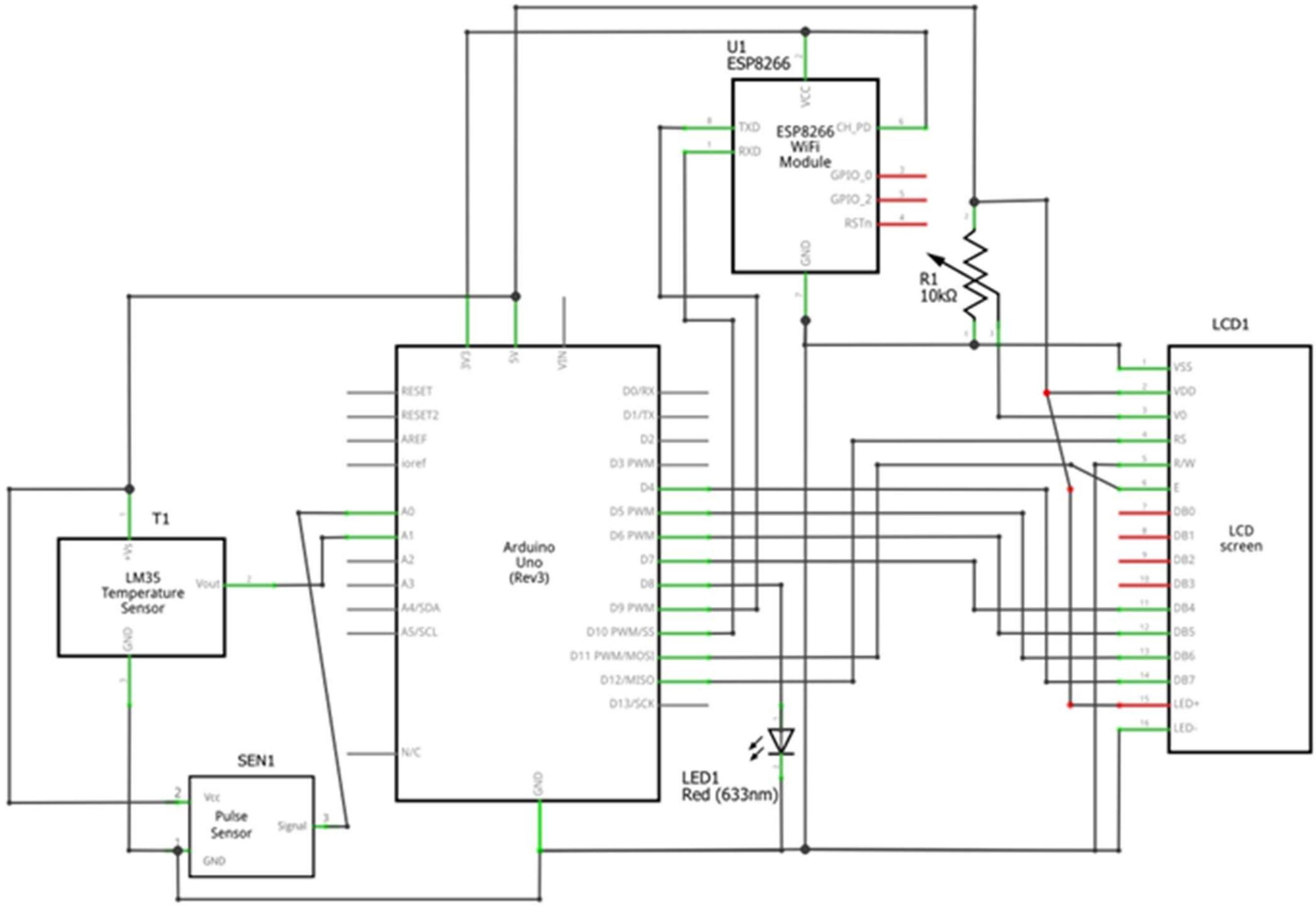


Figure 4. Schema of the IoT based healthcare system

2.3. ThingSpeak configuration

The ThingSpeak configuration of the application must be done properly to run the widgets in the program. The API key number obtained from ThingSpeak should be written in the relevant place in the code. In this application, 2 widgets (visual tools) are also used. With the help of widgets, temperature and heart rate are instantly monitored visually. Following the upcoming steps yields to create widgets from thingspeak:

1. Firstly, users must click on the add widgets link on the ThingSpeak channel screen.
2. In the menu that opens, the gauge image, the gauge type, which is one of the widget types, is selected.
3. In the menu that opens, the field used for temperature, Field1, is selected and the "Body temperature" title is written in the Name box. The upper and lower values to be used for the temperature are adjusted from the Min and Max boxes, and since the measurement is made in centigrade in the Units box, write "C" and click the Save button.
4. All the operations in 3 are repeated to create a heartbeat widget. However, since the heart rate is read by Field2, care should be taken to select Field2 from the Field field. Likewise, the Name, min, max and Units boxes are filled as shown in the screenshot below and the Save button is clicked.
5. The 2 widgets created are given as follows (Figure 5).

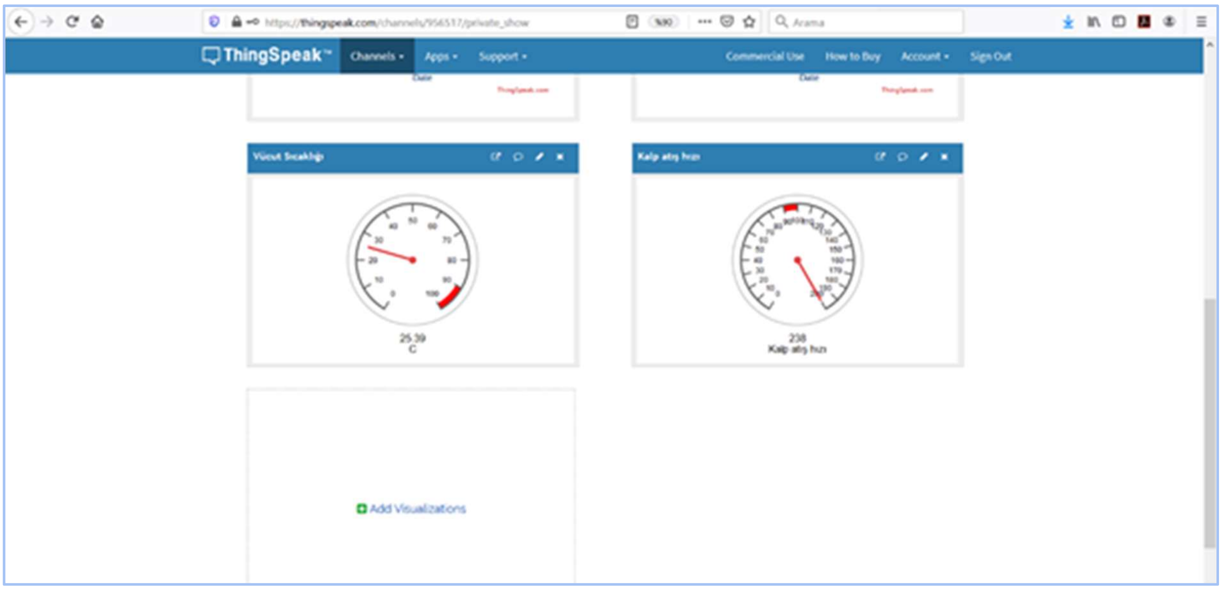


Figure 5. Widgets created in ThingSpeak for body temperature and heartbeat

3. Findings

Prior research clearly shows that an important area where IoT systems are developed is the health sector. IoT systems remotely monitor chronic diseases and transfer information to the relevant people in emergencies. Besides, IoT systems reduce health expenses with the remote health monitoring method. For example, Kaur and Jasuja (2017) proposed a system for remote monitoring of vital body parameters such as heart rate and body temperature of patients, together with Raspberry Pi, Arduino, and IoT in their study. The collected data was stored in the Bluemix cloud system and also monitored graphically on the IBM Watson IoT platform. Similarly, Koshti, Ganorkar, and Chiari (2016) developed an IoT monitoring system that monitors a patient's heart rate. Other studies (Woo, Lee, and Park, 2018; Strielkina, Uzun, and Kharchenko, 2017; Bradley, El-Tawab, and Heydari, 2018) also indicate that IoT based healthcare systems are getting attention and continue to evolve in this area.

4. Discussion and Conclusion

This study proposes the design of an IoT based healthcare system by using ThingSpeak to facilitate remote monitoring of patients' body temperature and heartbeat rate. Design features like simplicity, low cost, and accurate measurement gives an idea that such applications can be used easily in real-world connected situations. In this sense, IoT based technological solutions continue to provide reliable and effective healthcare solutions. Figure 6 shows how to do the circuit application.

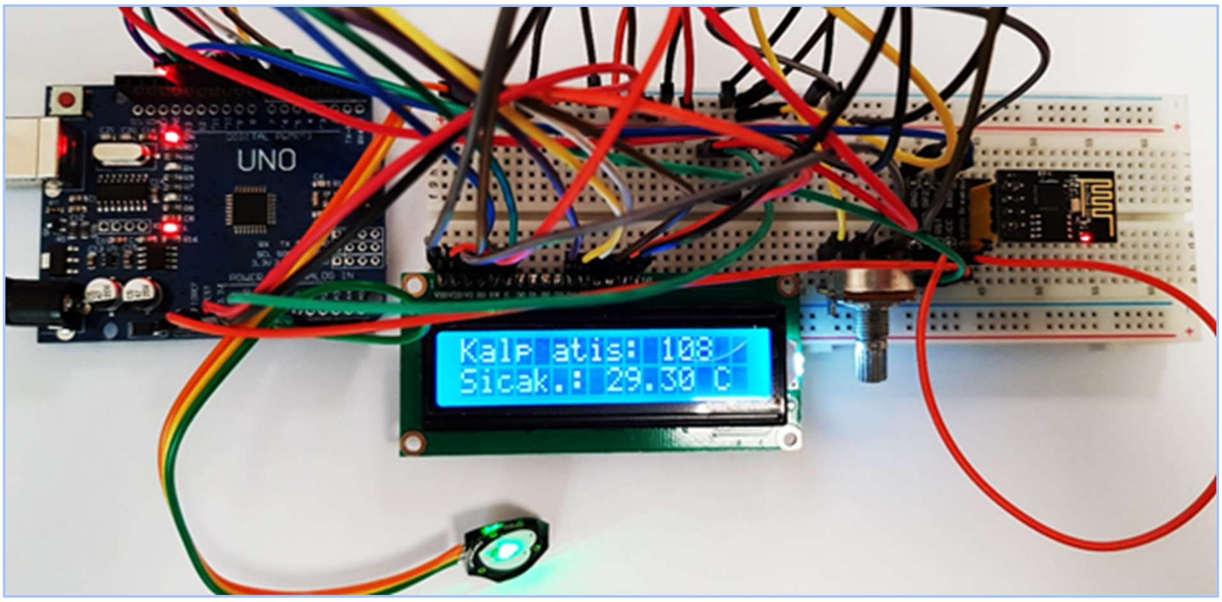


Figure 6. Arduino, ESP8266 module, LCD, pulse sensor and LM35 connection circuit

ThingSpeak server holds body temperature and pulse parameters as well as two widgets showing data visually (Figure 7).

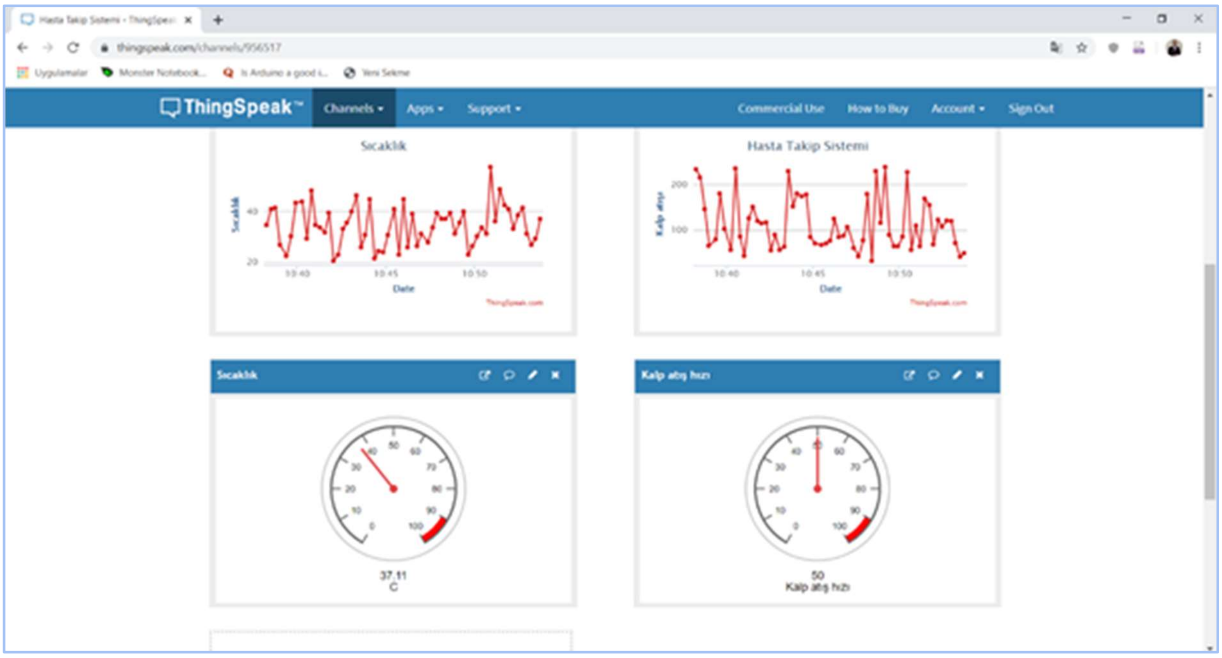


Figure 7. ThingSpeak server showing parameters and widgets

Temperature and pulse values read in the *loop* function are continuously sent to the ESP8266 module and from there to the server. The temperature and heart rate read in this function are printed on the LCD screen. It is expected as LM35 reads every 2 seconds. Thingspeak needs 15 seconds while updating the values. According to the interval where the value read from the sensor falls, ASCII characters printed on the serial port screen are determined with the *"case"* function. TCP connection is connected to the server with the CIPSTART command using AT + CIPSTART = 4, "TCP", "184.106.***.***", 80. The connection link is printed on the serial screen. If an error is detected in the server connection, a warning message will be printed on the serial port screen.

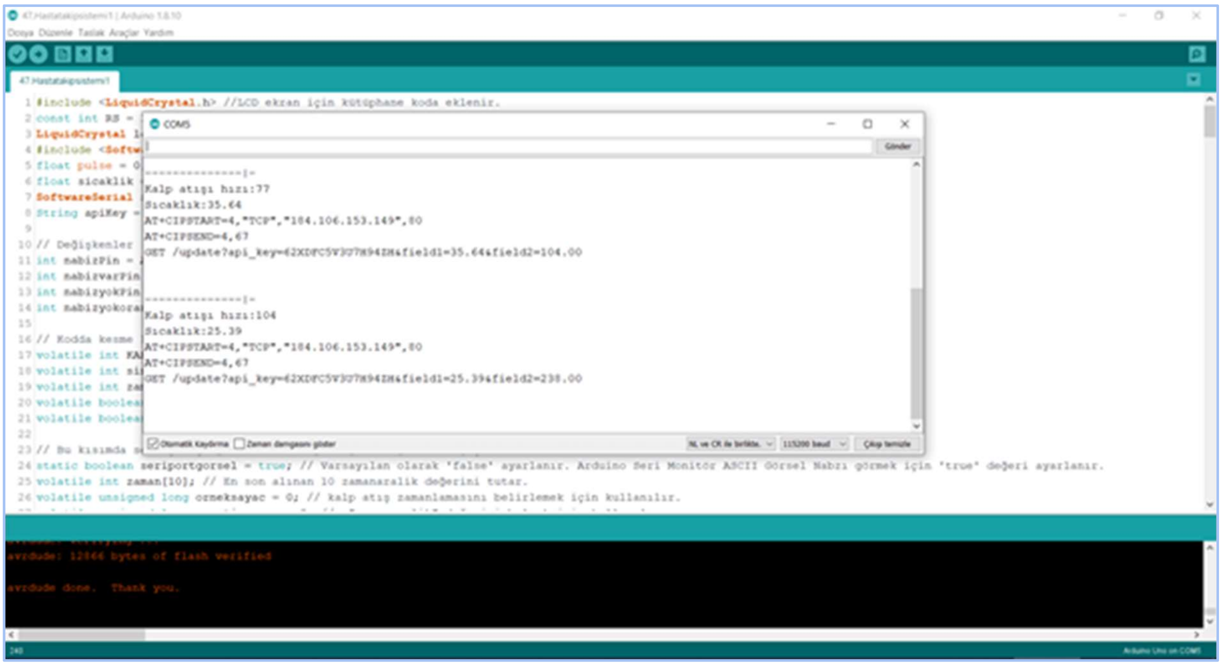


Figure 8. Serial port screen showing the values transmitted to ThingSpeak server via AT commands

This study proposes to create an IoT based health system, transfer patients' body temperatures and heart rate values to the cloud system at certain intervals, enabling healthcare professionals to view and analyze data from wherever they want. In this respect, the Internet of Things system developed in this study is important in terms of being economically inexpensive and functional. The development of such systems is supported by the review of the relevant literature and is expected to set an example for researchers.

References

1. Bradley, C., El-Tawab, S., & Heydari, M. H. (2018, April). Security analysis of an IoT system used for indoor localization in healthcare facilities. In 2018 Systems and Information Engineering Design Symposium (SIEDS) (pp. 147-152). IEEE.
2. Kaur, A., & Jasuja, A. (2017, May). Health monitoring based on IoT using Raspberry PI. In 2017 International Conference on Computing, Communication and Automation (ICCCA) (pp. 1335-1340). IEEE.
3. Koshti, M., Ganorkar, S., & Chiari, L. (2016). IoT based health monitoring system by using raspberry Pi and ECG signal. International Journal of Innovative Research in Science, Engineering and Technology, 5(5), 8977-8985.
4. Strielkina, A., Uzun, D., & Kharchenko, V. (2017). Modelling of healthcare IoT using the queueing theory. In 2017 9th IEEE international conference on intelligent data acquisition and advanced computing systems: technology and applications (IDAACS) (Vol. 2, pp. 849-852). IEEE.
5. Woo, M. W., Lee, J., & Park, K. (2018). A reliable IoT system for personal healthcare devices. Future Generation Computer Systems, 78, 626-640.
6. Yattinahalli, S., & Savithramma, R. M. (2018, April). A personal healthcare IoT system model using raspberry Pi 3. In 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT) (pp. 569-573). IEEE.
7. Neyja, M., Mumtaz, S. Huq, K. M. S.., Busari, S. A., Rodriguez, J., & Zhou, Z. (2017). An IoT-Based E-Health Monitoring System Using ECG Signal, GLOBECOM 2017 - 2017 IEEE Global Communications Conference, Singapore, 2017, pp. 1-6, doi: 10.1109/GLOCOM.2017.8255023.
8. Valsalan, P. Baomar, T. A. B., & Baabood, A. H. O. (2020). Iot Based Health Monitoring System. Journal of Critical Reviews, 7(4), 2020

9. Tamilselvi, V., Sribalaji, S., Vigneshwaran, P., Vinu, P., & GeethaRamani (2020). IoT Based Health Monitoring System. 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 2020, pp. 386-389, doi: 10.1109/ICACCS48705.2020.9074192.

10. Sam, D., Srinidhi, S., Niveditha, V. R., Amudha, S., & Usha, D. (2020). Progressed iot based remote health monitoring system. International Journal of Control and Automation, 13(2s), 268-273.

11. Acharya, A. D., & Patil, S. N. (2020, March). IoT based health care monitoring kit. In 2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC) (pp. 363-368). IEEE.

12. Reena, J. K., & Parameswari, R. (2019, February). A smart health care monitor system in IoT based human activities of daily living: a review. In 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon) (pp. 446-448). IEEE.

13. Patil, S., & Pardeshi, S. (2018). Health monitoring system using IoT. Int. Res. J. Eng. Technol.(IRJET), 5(04).

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 **||** **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

IoT Platforms and Data Analytics Tools in Healthcare Services

Abdullah Alper EFE [1,*], Mehmet Akif OCAK [2]

[1] *Kütahya Health Sciences University, KHSU Application and Research Center, Turkey*
[2] *Gazi University, Faculty of Education, Department of CEIT, Turkey*

* Corresponding Author: Kütahya Health Sciences University, KHSU ARC, Turkey
Tel.: + 0 (274) 260 00 43. E-Mail: abdullahalper.efe@ksbu.edu.tr

Publication Information

Keywords :

- Internet of Things,
- Healthcare IT,
- Medical Services,
- Data Analytics,
- IoT Platforms

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

The purpose of this study is to investigate IoT platforms and data analytics tools used in healthcare service. In this regard, researchers conducted an extensive literature review to focus on which IoT platforms and data analytics tools are suitable and preferable in healthcare service.

This study reviewed related literature and prior research and identified 21 IoT platforms and 9 data analytic tools that are popular and in active use for healthcare IoT studies. This study found that the most used IoT platforms are as follows: Google Cloud, IBM Watson, Microsoft Azure, AWS IoT Core, Thingsboard, Ayla Networks, Ubidots, ThingSpeak, Adafruit.io, thethings, myDevices Cayenne, Blynk, Thinger.io etc. Data analytic tools mostly used in healthcare are Tableau, Splunk, MS PowerBI, Apache Spark, Talend, Qlik, Knime, RapidMiner and Google Firebase. This study argues that IoT based platforms and data analytics tools will continue to affect healthcare services and applications by providing safe, rapid and cost effective solutions.

1. Introduction

The purpose of this study is to investigate IoT platforms and data analytic tools used in healthcare services. In this regard, researchers conducted an extensive literature review to focus on which IoT platforms and data analytics tools are suitable and preferable in healthcare services. The need for instantaneous data collected from the field in applications of the IoT to take up a large amount of space made it necessary to use IoT platforms and data analytics tools. One of the important fields of this kind is Healthcare Service. In order to monitor patients' critical data from a distance and take necessary precautions, it is critical to review IoT platforms and data analytic tools used in the healthcare area.

Prior research shows that some studies directly focus on reviewing healthcare related IoT platforms. In this sense, Sonune, Kalbande, Yeole, and Oak (2017) reviewed different IoT platforms in their study from different aspects. The study argued that management and interoperability are two important factors in healthcare, thus, IoT platforms provide such services to operate data in an effective way. From this perspective, the study listed the following platforms: EveryAware, Everyware, IFTTT, IoTframework, OpenIoT, Xively, ZettaJS, and IoTIGNITE and compared platforms in terms of "Support for heterogeneous devices", "Architecture", "Open source, "Rest API", and "Service discovery".

Other studies also focused on definitions and characteristics of IoT platforms from academic as well as commercial aspects. For instance, Asemani, Abdollahei, and Jabbari (2019) reviewed IoT platforms in three categories: scientific research perspective, commercial/market perspective, and open source perspective. The study focused on marketing perspective of IoT platforms and compared the following platforms from each other: Cisco Connected Streaming Analytics, Jasper Control Center, IoX, IBM Watson, Intel IoT Platform, Bosch IoT Suite, Google Cloud IoT, Brillo, ARM mbed, AT&T M2X, Oracle IoT, HPE IoT, AWS IoT, Soliar, Azure IoT Azure IoT suite, Edge, Predix, Samsung Artik. The study argues that there are seven main properties need to be taken into account while using commercial IoT platforms: "1) connectivity/device management, 2) data storage and management, 3) data analysis and visualization, 4) development tools and platforms, 5) edge/fog computing, 6) integration and interoperation, 7) Service management, and 8) auditing and payment." (p.174).

Some studies, regarding using IoT platforms in healthcare, proposed IoT based healthcare framework. In this regard, Ahmed, Ahmad, Jeon, and Piccialli (2021) presented a framework for analysis, prediction, and detection of the pandemic disease such as Covid 19. The study focused on four types of analysis: descriptive, diagnostic, predictive and prescriptive. In this sense, the idea of using this framework is to collect data from different hospitals, to analyze data by using four different data analytics techniques. If needed, healthcare workers may transmit the data by using server clouds.

It is important to identify the capabilities of IoT based platforms, especially if planned to use in healthcare. Asemani, Abdollahei, and Jabbari (2019) described seven properties of IoT based platforms that must be taken into account for health care systems: connectivity and device management, data storage, management, analysis, visualization, development and deployment tools, auditing and payment
service management, integration, fog/edge computing. Literature review clearly shows that Arduino support and Raspberry Pi support are another important capability of IoT based platforms.

The purpose of this study is to analyse the most commonly used IoT platforms and data analytic tools in healthcare areas. From this perspective, the study both reviewed both licensed (paid) and open source (free) IoT based platforms. The study used five selection criteria which included 1) Google Trend/prevalence (How known is the platform used?, how widespread it is?) 2)whether IoT platform supports Arduino development cards, 3) whether IoT platform supports Raspberry Pi cards, 4) Is there a charge for IoT platform, or is it free?, and 5) project implementation scale of IoT platforms in healthcare. Moreover, the study contributes to the literature review by bringing a different perspective to IoT platforms and data analytic tools and allows us to compare and contrast from different categories.

2. Method

This study reviewed related literature and prior research and identified 21 IoT platforms and 9 data analytics tools that are popular and in active use for healthcare IoT studies. While choosing the tools, researchers also checked with Google Trend prevalence criterion to make sure that choosing criteria was consistent with prior research. IoT platforms and data analytic tools have also been examined with such criteria like pricing, project implementation scale, Arduino support, and Raspberry Pi support.

According to the IoT Analytics report, the number of NIT platforms has been increasing rapidly in recent years. While the number of globally known NIT platforms was 250 in 2015, this number reached 620 at the end of 2019. However, as of the end of 2019, it is seen that the top 10 service providers in the market hold 58% of the market. Some well-known companies are also turning to meet specialized end-user services such as current platform technologies, such as monitoring the healthy operation of machines, and monitoring factory overall equipment efficiency.

3. Findings

This study found that the most used IoT platforms are as follows: Google Cloud, IBM Watson, Microsoft Azure, AWS IoT Core, Thingsboard, Ayla Networks, Ubidots, ThinpSpeak, Adafruit.io, thethings, myDevices Cayenne, Blynk, Thinger.io, Kaa IoT Cloud, SiteWhere, SAP Leonardo, Bosch IoT Suite, Particle.io, Cisco Kinetic, Oracle IoT Cloud, and PTC ThingWorx. Data analytics tools mostly used in healthcare are Tableau, Splunk, MS PowerBI, Apache Spark, Talend, Qlik, Knime, RapidMiner, and Google Firebase. Findings clearly show that the idea of using IoT technologies in healthcare is promising and still continuing to grow with rapid changes. In this sense, Table 1 shows 10 licensed/pricing IoT platforms and their properties.

Table 1. Most commonly used IoT platform in healthcare (licensed, paid)

No.	IoT platforms (Licensed, Paid)	Google Trend / Prevalence	Arduino Support	Raspberry Pi Support	Pricing	Project Implementation Scale
1	Google Cloud	69	Available	Available	Free trial	Corporate
2	IBM Watson	10	Available	Available	Licensed	Corporate
3	Microsoft Azure	28	Available	Available	Paid	Corporate
4	AWS IoT Core	1	Available	Available	Paid	Medium-Enterprise
5	ThingsBoard	3	Available	Available	Paid	Medium-Enterprise
6	Ayla Networks	2	N/A	N/A	Paid	Middle
7	Ubidots	0,7	Available	Available	Paid	Middle
8	ThingSpeak	3	Available	Available	Free limited	Middle
9	Adafruit.io	0,5	Available	Available	Paid	Small
10	Thethings.io	0,5	Available	Available	Paid	Small

The study also indicates that there are several IoT platforms that are open source and free and might be used in healthcare systems. Table 2 shows six unlicensed/free IoT platforms and their properties.

Table 2. Most commonly used IoT platform in healthcare (open source, free)

No.	IoT platforms (open source, free)	Google Trend / Prevalence	Arduino Support	Raspberry Pi Support	Pricing	Project Implementation Scale
1	myDevices Cayenne	6	Available	Available	Free	Small-Medium-Enterprise
2	Blynk	2	Available	Available	Free	Small
3	Thinger.io	1	Available	Available	Free	Small

4	Kaa IoT Cloud	0,5	Available	Available	Free	Small
5	SiteWhere	0,5	Available	Available	Free	Small Medium

This study further argues that there are also other IoT platforms that although they do not have a high level of Google Trend score, some studies prefer to use them in their projects. In this regard, Table 3 shows other less known IoT based platforms.

Table 3. Other less known IoT based platforms (Licensed, Paid)

No.	IoT platforms (Licensed, Paid)	Google Trend / Prevalence	Arduino Support	Raspberry Pi Support	Pricing	Project Implementation Scale
1	SAP Leonardo	0,65	N/A	Available	Paid	Middle
2	Bosch IoT Suite	1	Available	Available	Paid	Middle
3	Particle.io	2	Available	Available	Paid	Small
4	Cisco Kinetic	1	Available	Available	Paid	Corporate
5	Oracle IoT Cloud	1	Available	Available	Paid	Corporate
6	PTC ThingWorx	1	Available	Available	Paid	Medium-Enterprise

Regarding data analytic tools, this study conducted an extensive literature review and identified several data analytics tools used in healthcare systems. Data analytic tools also were classified based on Google Trend/Prevalence, Arduino Support, Raspberry Pi Support, Pricing, and Project Implementation Scale.

Table 4. Shows the most common used data analytics tools in healthcare systems.

No.	Data Analytic Tools	Google Trend / Prevalence	Arduino Support	Raspberry Pi Support	Pricing	Project Implementation Scale
1	Tableau	66	Available	Available	Paid	Corporate
2	Splunk	26	Available	Available	Paid	Corporate
3	MS PowerBI	6	Available	Available	Paid	Corporate
4	Apache Spark	24	Available	Available	Paid	Corporate
5	Talend	12	N/A	N/A	Paid	Corporate
6	Qlik	5	Available	Available	Paid	Corporate
7	Knime	1	Available	Available	Paid	Corporate
8	RapidMiner	1	Available	Available	Paid	Corporate
9	Google Firebase *(Real Time Database)*	3	Available	Available	Paid	Corporate

Results clearly showed that Google Cloud (Google Trend prevalence=69) and Microsoft Azure (Google Trend prevalence=29) are two well known and used IoT based platforms in healthcare. In this regard, Google Cloud Platform products include a wide range of applications such as artificial intelligence & machine learning, API management, computing, data analytics, databases, developer tools, internet of things, hybrid and multi-cloud operations, management tools, media, data transport, networking, security, storage. With these categorical services running on Google servers, a wide variety of activities are carried out at the personal corporate level. There are different products offered by the Google Cloud platform. Considering the Internet of Things specifically, the Google Cloud IoT Core product stands out. Google Cloud IoT Core is a service that allows you to easily and securely connect, manage and receive data even if there are tens of thousands of devices in very different locations. Cloud IoT Core offers a useful solution to collect, process, analyze and visualize data from end devices in real time. Cloud IoT Core uses Cloud Pub / Sub infrastructure for real-time message and data transmission. In this way, it is able to collect scattered device data in a single global system that is seamlessly compatible with Google Cloud data analysis services. The platform has operational efficiency features such as advanced analysis, visualizations, and machine learning.

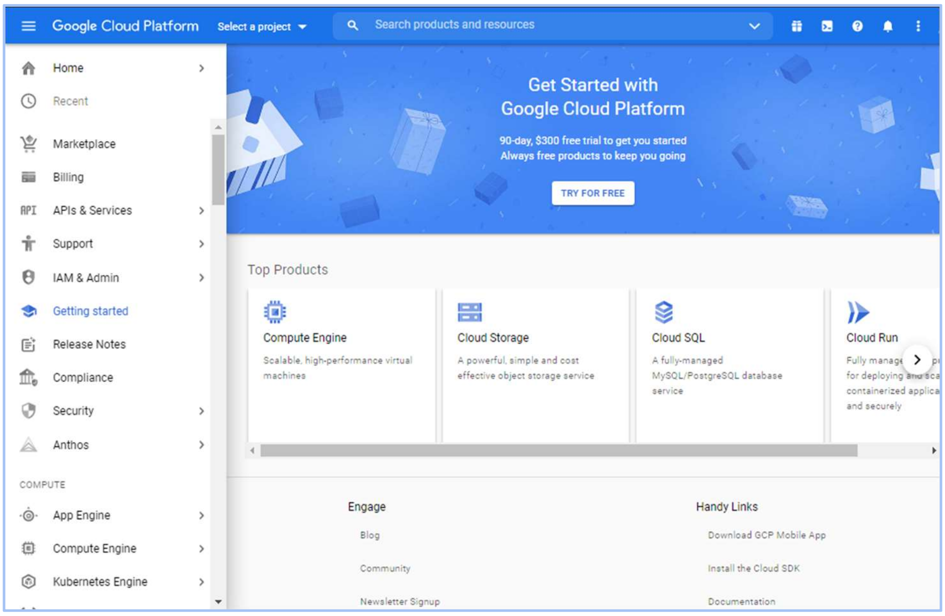


Figure 1. Interface of Google Cloud Platform

Azure is a cloud computing platform owned by Microsoft, whose resources and services can be accessed and managed online. All resources and services can be accessed from the Azure home page (Figure 2). It is a platform frequently preferred by corporate companies. Microsoft Azure services are over 200 under 18 main categories. These leading categories are computing, networking, storage, internet of things, system migration, mobile, data analytics, artificial intelligence and machine learning, integration, management tools, developer tools, security, databases, devops, media, identity and web.

Common uses of the Microsoft Azure platform can be listed as: (1) Application development, (2) Application testing, (3) Application hosting, (4) Creating virtual machines, (5) Integrating and synchronizing a feature, (6) Collecting and storing metrics. One of the important services offered by Microsoft Azure is the Internet of Things. Today, the Internet of Things is used in many areas, from healthcare, online shopping, wearable technologies, smartphones, gadgets, smart building, music, personal computers, industrial automation to flight services. The Internet of Things components of the Microsoft Azure platform are listed as: IoT Hub, IoT Central, Azure Sphere, IoT Solution Accelerators, Digital Twins, Time Series Insights, Azure Sphere, Azure Maps.

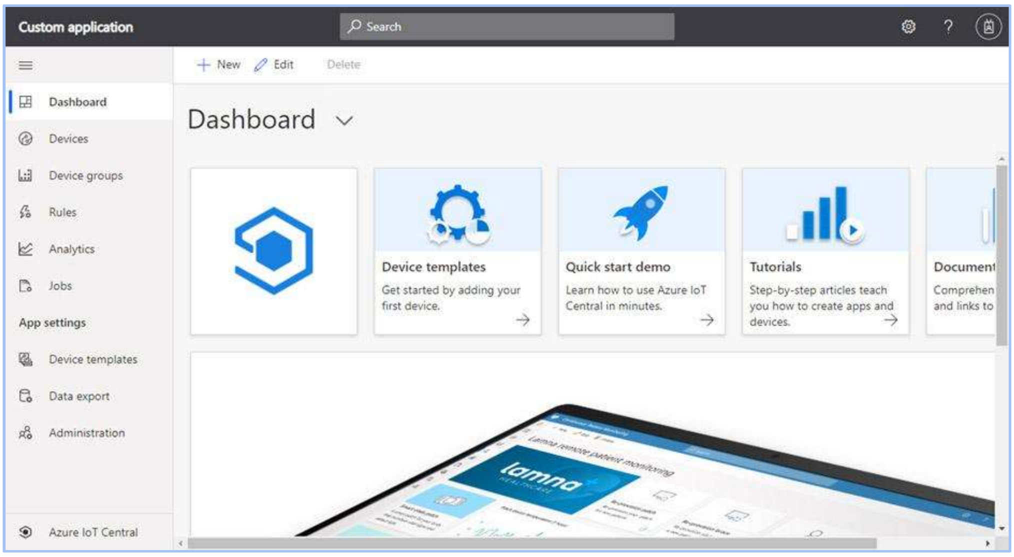


Figure 2. Interface of Microsoft Azure

4. Discussion and Conclusion

With the Internet of Things, it is possible to monitor many events in the field, to make meaningful by collecting data and to take action when necessary. With the increasing developments in Internet technologies, applications of Internet of Things are becoming widespread day by day. The platforms and tools used without the need for advanced operations, data analytics programs and services such as device management, data collection, storage, integration made it easier for users to develop NIT applications. Usually, NIT applications offer the opportunity to process data that increases productivity by keeping the digital and real world together. For this reason, it is possible to visualize and report the obtained information. In almost all NIT applications, the first step is to collect data from the physical world. Previously, this collected data was only analyzed using a lot of code writing and complex algorithms. However, nowadays, these data obtained from sensors or physical devices with the help of NIT applications are collected, analyzed and transferred to every point with internet access by means of licensed or open source cloud platforms with the help of data programs that perform visualization and are relatively lean.

This study focused on IoT Platforms and data analytics tools that can be used in healthcare, and analyzed licensed, and open source platforms and tools in terms of versatile criteria and features. Internet of Things (IoT)-enabled gadgets have made inaccessible checking within the healthcare segment conceivable, unleashing the potential to keep patients secure and sound, and engaging physicians to convey superlative care. Furthermore, more frequent monitoring of patients' health makes a difference in reducing the length of clinic stay and preventing re-admissions. IoT platforms, moreover, have a major affect on lessening healthcare costs and progressing treatment results.

One of the main outputs of this research was to introduce the Internet of Things platforms and data analytics tools used in healthcare services and to make them widespread among researchers and practitioners. The idea of displaying most commonly used IoT platforms and data analytics tools in healthcare areas is the core of this study. In this sense, as supported by prior research (Pace, Gravina, Aloi, Fortino, Fides-Valero, Ibanez-Sanchez, Traver, Palau, and Yacchirema, 2017; Shah, and Chircu, 2018), this study argues that IoT based platforms and data analytics tools will continue to affect healthcare services and applications by providing safe, rapid and cost effective solutions.

References

1. Ahmed, I., Ahmad, M., Jeon, G., & Piccialli, F. (2021). A framework for pandemic prediction using big data analytics. *Big Data Research*, *25*, 100190.
2. Asemani, M., Abdollahei, F., & Jabbari, F. (2019). Understanding IoT platforms: towards a comprehensive definition and main characteristic description. In *2019 5th International Conference on Web Research (ICWR)* (pp. 172-177). IEEE.
3. Pace, P., Gravina, R., Aloi, G., Fortino, G., Fides-Valero, K., Ibanez-Sanchez, G., Traver, V., Palau, C. E., Yacchirema, D. C. (2017).IoT platforms interoperability for active and assisted living healthcare services support, 2017 Global Internet of Things Summit (GIoTS), Geneva, Switzerland, 2017, pp. 1-6, doi: 10.1109/GIOTS.2017.8016250.
4. Shah, R., & Chircu, A. (2018). Iot and AI in Healthcare: A Systematic Literature Review. Issues in Information Systems,19(3), 33-41.
5. Sakr, S., & Elgammal, A. (2016). Towards a comprehensive data analytics framework for smart healthcare services. Big Data Research, 4, 44-58.
6. Sonune, S., Kalbande, D., Yeole, A., & Oak, S. (2017). Issues in IoT healthcare platforms: A critical study and review. In *2017 International Conference on Intelligent Computing and Control (I2C2) (pp. 1-5)*. IEEE.

ARTIFICIAL INTELLIGENCE THEORY and APPLICATIONS

ISSN: 2757-9778 || **ISBN :** 978-605-69730-2-4

More information available at **aita.bakircay.edu.tr**

A Comparison of Machine Learning Algorithms using Feature Selection for Predicting Breast Cancer

Tuba PARLAR [1]

[1] *Hatay Mustafa Kemal University, Dept. of Computer Technologies, Turkey*

* Corresponding Author: Hatay Mustafa Kemal University, Turkey
E-Mail: tparlar@mku.edu.tr

Publication Information

Keywords :

- Breast cancer,
- Feature selection,
- Machine learning,
- Wisconsin breast cancer dataset

Category : Special Issue

Received :
Accepted : 26.05.2021

A B S T R A C T

One out of every six deaths in the world is caused by cancer. Breast cancer is the most common type of cancer. The main purpose of this study is to investigate the classification performances of three machine-learning algorithms, namely Logistic regression, multilayer perceptron and random forest using Wolf Search Algorithm (WSA), which is a bio-inspired feature selection method for predicting breast cancer. Feature selection methods are used to remove uninformative and noisy features to improve the classification accuracy. Experiments are conducted on Wisconsin Diagnostic Breast Cancer Database using ten-fold cross validation. The experimental results from the Wisconsin Diagnostic Breast Cancer dataset show that multilayer perception is the best algorithm with 96.31% accuracy. For the reduced set of features using WSA, the accuracy is increased to 97.01%. We can conclude that the classification accuracy is the highest with an artificial neural network-based classifier by choosing reduced size of features with WSA.

1. Introduction

One out of every six deaths in the world is caused by cancer. Breast cancer is the most common type of cancer (Ferlay et al., 2019). According to the World Health Organization 2020 cancer report, breast cancer ranks fourth in the world and second in Turkey. Many researchers have been studied machine learning methods in different domains and approaches since they can be automatically trained and improved with the training datasets (Cinarer & Emiroglu, 2020; Ganggayah et al., 2019; Sharma et al., 2017; Solanki et al., 2021; Wang et al., 2018; Zheng et al., 2014). Feature selection is an important phase in choosing informative features to improve classification performances and speed up training computation time. This phase provides a simpler classification process using a smaller subset of the features (Chandrashekar & Sahin, 2014).

There are many studies for predicting Breast Cancer (Sharma et al., 2017; Solanki et al., 2021) . These studies apply various machine learning methods such as Decision Tree, Naive Bayes, Support Vector Machines, Random Forest and Neural Networks. Solanki et al. (2021) analyze different feature selection methods using three machine learning algorithms on Wisconsin Diagnostic Breast Cancer dataset. They use Particle Swarm Optimization, Genetic Search, Greedy Stepwise to select informative features. Then they run Support Vector Machines, C4.5 and Multilayer Perceptron algorithms obtain classification performances. They conclude that C4.5 classifier is the optimum classifier to diagnose breast cancer with Genetic Search algorithm with an accuracy of 98.83%.

In (Sharma et al., 2017) the authors apply three machine learning algorithms namely logistic regression, nearest neighbor, support vector machines to classify features of Wisconsin dataset. Their method achieves with accuracies between 93% and 97%. In another study, Mondal et al. (2020) compare four machine learning algorithms namely support vector machines, Naïve Bayes, k nearest neighbor, random forest to predict breast cancer. They obtain best classification performance using support vector machines with an accuracy of 91.5%. Zheng et al. (Zheng et al., 2014) develop a hybrid of K-means and SVM algorithm. Their proposed method achieves on accuracy of 97.38% on WDBC data set.

In this study, we aim to analyze the impacts of feature selection and classification methods for predicting Breast Cancer. For this purpose, we investigate the performance of three machine learning algorithms with a bio-inspired feature selection algorithm. The next section introduces the methodology that is used for the study. Section 3 presents the experimental results. Finally, Section 4 concludes the paper.

2. Methodology Used

In this paper, we implemented Wolf Search Algorithm, which is a bio-inspired feature selection method and investigated its effects on classification performances for selected machine learning algorithms.

2.1. Feature Selection Method

Feature selection is one of the most important phase of data mining when working on a large-scale and multi-dimensional data set. Removing the worthless attributes in the data set, that is, separating the most valuable attributes, will reduce both classification accuracy and processing time (Chandrashekar & Sahin, 2014; Kira & Rendell, 1992; Xue et al., 2015; Zhao et al., 2015). Feature selection methods are generally divided into three groups.

Filtering methods are performed based on statistical information. Fisher score, t-score, Chi-square, entropy-dependent information gain, information gain-dependent gain ratio, correlation-based methods can be considered as the main methods used as filtering-based feature selection methods. Embedded feature selection methods are structures with higher computational costs that include feature selection and classification algorithms at the same time. For example, machine learning algorithms such as Lasso and random forest have their own feature selection algorithms suitable for their structure (Xue et al., 2015; Zhao et al., 2015). Spiral feature selection methods try to select the most valuable attributes by using various search algorithms on the attributes. Ant colony optimization, particle swarm optimization algorithms, and wolf search algorithms can be given as examples (Zhao et al., 2015).

The Wolf Search Algorithm (WSA) is inspired by the hierarchy of wolf packs and their hunting behaviors in nature (Tang et al., 2012). The wolves in the pack distribute tasks and take consistent steps when they hunt. Among the pack, some wolves are assigned as search wolves, and when they find their prey, they report the location of the prey by reaching out to other wolves. Other wolves approach the prey and encircle the prey. The rule for assigning a wolf pack is that food is given first to the strongest wolf and then to the weakest wolf. During the search, the wolves simultaneously search for prey and watch out for threats. Each wolf in the pack chooses its own location, constantly moving to better positions while pursuing potential threats. Each wolf has a visual range that creates a detection radius. The wolves in the WSA are limited to this visual range in terms of foraging, awareness of their peers in the pack in search of a better position, and awareness of enemies that may be nearby (to jump from visual range). The pseudo code of WSA is presented in Figure 1.

```
Algorithm: Wolf Search
Initialize the population x_i (i = 1 ,2,..,W) and parameters
repeat
   for each wolf do
         initiative_prey()
         generate_new_location()
         if (dist(x_i,x_j) < r && x_j is better as f(x_i) < f(x_j))
                x_i moves towards x_j
         else if
                x_i = initiative_prey()
         end
         generate_new_location()
         if rand() > p_a     // p_a is a user defined threshold value
                x_i = x_i + rand() + v
         end
   end
until stop criteria is met
```

Figure 1. Pseudo-Code of Wolf Search Algorithm

2.2. Machine Learning Classifiers

We investigate that if WSA feature selection method can improve the classification performances and compare different machine learning algorithms. We apply three machine learning classifiers: logistic regression, multilayer perceptron and random forest.

Logistic Regression (LR) is a discriminative model that assigns a class to an observation by computing a probability from an exponential function of a weighted set of features of the observations. In logistic regression, every training instance contributes to the solution vector. If feature f_1 and feature f_2 are correlated, regression assigns half the weight to w_1 and half to w_2. Logistic regression classifier estimates $p(c|x)$ by extracting features from the datasets as follows:

$$p(c|x) = \frac{\exp(\sum_{i=1}^{N} w_i f_i)}{\sum_c \exp(\sum_{i=1}^{N} w_i f_i)}$$

where N is the number of features, and features are a property of the observation x and output class c (Daniel & Martin James, 2006).

Multilayer Perceptron (MLP) contains multiple layers of neurons. A neuron feeds all the neurons in the next layer. Sigmoid function is used to activate each neuron and trained with the back-propagation algorithm based on recursively using gradient descent to adjust the weights. An artificial neural network consists of an input layer, one or more hidden layers and an output layer. The only disadvantage is this method needs more computation time than the other methods.

Random Forest (RF) classifier randomly selects subsets from the data set to create decision trees and classifies them based on the predictions from each of the decision trees to make an average prediction. Decision trees are grown using random feature selection and there is no pruning. The reason why the random forest algorithm is faster and more accurate than other algorithms is this method. The low correlation is important to produce ensemble predictions because de-correlated models protect from individual errors (Breiman, 2001).

2.3. Dataset

We use a publicly available dataset named Wisconsin Diagnostic Breast Cancer (WDBC) Dataset from the University of Wisconsin Hospitals at Irvine Machine Learning Repository by Dr. Wolberg et al. (1995). Features are computed from a digitized image of a fine needle aspirate of a breast mass. They describe characteristics of the cell nuclei present in the image. Class distribution of the dataset is 357 benign and 212 malignant. WDBC dataset consists of 569 samples with 32 features. Features are such as radius, texture, perimeter, area, smoothness, compactness, concavity, concave points, symmetry, fractal size for each cell nucleus as shown in Table 1:

Table 1. Explanations of WDBC Dataset Features

Features	Explanations
1	ID Number
2	Diagnosis (Malign, Benign)
(3-32) Ten real-valued features for each cell	
A	Radius
B	Texture
C	Perimeter
D	Area
E	Smoothness
F	Compactness
G	Concavity
H	Concave points
I	Symmetry
J	Fractal dimension

2.4. Performance Evaluation

In order to evaluate the performance of the classification models, the confusion matrix, which compares the predictions and real values of the target feature, is used. The classification estimates will have one of four assessments as shown in Table 2:

Table 2. Contingency table

		Actual Class	
		positive	**negative**
Labeled	**positive**	True positive (*TP*)	False positive (*FP*)
	negative	False negative (*FN*)	True negative (*TN*)

True Positive (*TP*) is the number of correct classifications of the positive instance. We predicted positive (they have cancer), and they do have cancer. True Negative (*TN*) is the number of correct classifications of the negative instance. We predicted no, and they don't have cancer. False Positive (*FP*) is the number of incorrect classifications of the positive instance. We predicted yes, but they don't have cancer. False Negative (FN) is the number of incorrect classifications of the negative instance. We predicted no, but they do have cancer. Based on the Table 2, the accuracy, sensitivity, and specificity are defined as follows (Han et al., 2011).

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

3. Experiments and Results

In this study, our aim is to obtain the most accurate classification results. Therefore, we apply three machine learning algorithms to obtain baseline classification performances, using all the features in the training dataset. We use the machine learning algorithms from the Weka data mining tool version 3.8.1 (Frank et al., 2009). We run the classifiers by using ten-fold cross validation. First, we obtain the baseline results to investigate the effects of Wolf Search Algorithm as a feature selector using all the features of the dataset. The baseline results are presented in Table 3.

Table 3. Baseline classification results for the WDBC Dataset

	LR	**RF**	**MLP**
Accuracy	0.9385	0.9596	0.9631
Sensitivity	0.9600	0.9563	0.9667
Specificity	0.9041	0.9655	0.9569

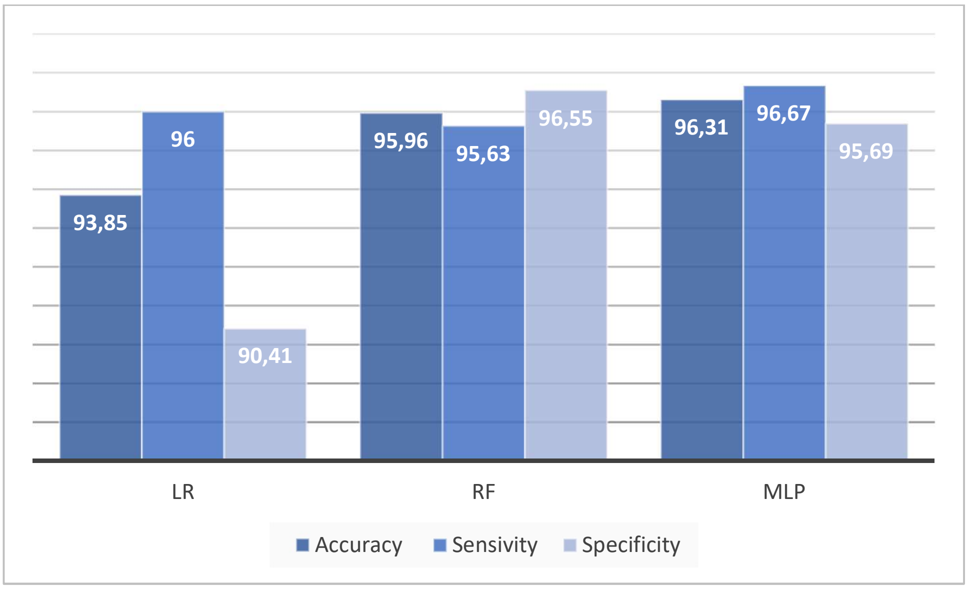


Figure 2. Performance evaluations before applying WSA feature selection method

As can be observed in Table 3 and Figure 2, Multilayer perceptron (MLP) classifier is the best performer with an accuracy of 96.31% for the dataset. Random forest (RF) classifier is the second-best performer with an accuracy of 95.96%. Logistic regression (LR) classifier is the worst classifier among others with an accuracy of 93.95%.

Table 4. Classification Results of WSA Feature Selection Method

	WSA+LR	**WSA+RF**	**WSA+MLP**
Accuracy	0.9684	0.9596	0.9701
Sensitivity	0.9748	0.9613	0.9722
Specificity	0.9575	0.9565	0.9665

In the feature selection phase, we select the most important features using a bio-inspired method Wolf Search Algorithm (WSA) and the algorithm selects 11 features. Then, we apply three machine learning algorithms namely logistic regression (LR), random forest (RF) and multilayer perceptron (MLP) on the features selected by WSA to classify the dataset. As can be seen in Table 3 and 4, applying feature selection method improves the classification accuracies.

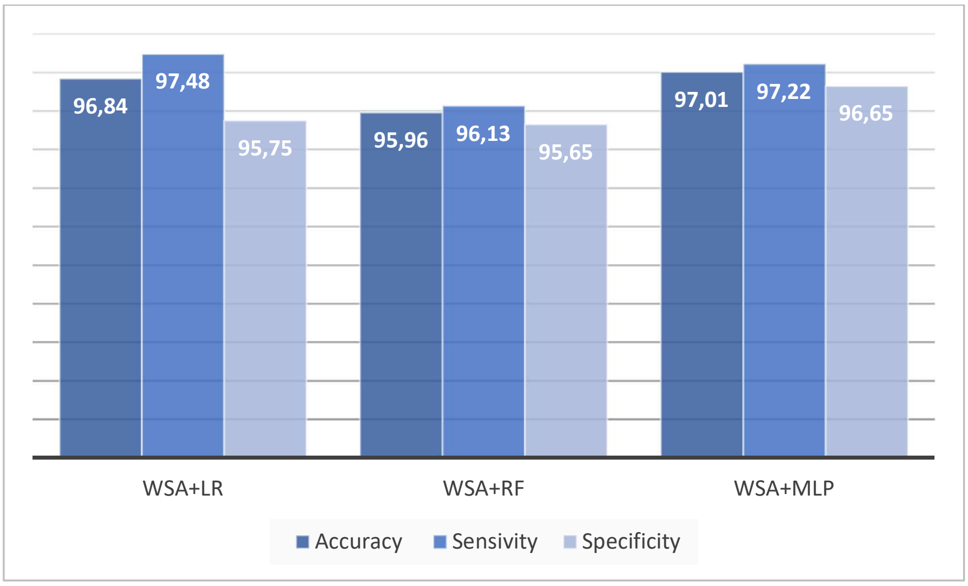


Figure 3. Performance evaluations after applying WSA feature selection method

As can be observed in Table 4 and Figure 3, Multilayer Perceptron (MLP) classifier is the best performer again. The accuracy is increased from 96.31% to 97.01% after applying WSA feature selection algorithm. Logistic regression (LR) classifier is the second-best performer with an accuracy of 96.84%. Random Forest (RF) classifier is the worst classifier among others with an accuracy of 95.96%.

4. Conclusions

Breast cancer is the most common type of cancer. We aim to analyze the impacts of feature selection and classification methods for predicting breast cancer. We examined the impacts of three machine learning algorithm with a bio-inspired optimization method: Wolf Search Algorithm (WSA). We obtained the most accurate performance classification results with MLP algorithm using WSA feature selection method among all the other methods. When running the three classifiers, MLP classifier presented the most accurate classification results of all classifiers for the WDBC dataset. As can be observed in Tables 3 and 4, WSA selects the most valuable features and works well compared with baseline accuracy values. Our results show that using WSA - a bio inspired feature selection method WSA for Wisconsin Diagnostic Breast Cancer dataset improved the classification performances. Multilayer perceptron achieved the best performance among all the classification methods. The only disadvantage of MLP method is this method needs more computation time than the other methods.

References

Breiman, L. (2001). Random forests [Article]. *Machine Learning*, *45*(1), 5-32. https://doi.org/10.1023/a:1010933404324

Chandrashekar, G., & Sahin, F. (2014). A survey on feature selection methods. *Computers & Electrical Engineering*, *40*(1), 16-28.

Cinarer, G., & Emiroglu, B. G. (2020). Classification of brain tumours using radiomic features on MRI. *New Trends and Issues Proceedings on Advances in Pure and Applied Sciences*(12), 80-90.

Daniel, J., & Martin James, H. (2006). speech and language processing: An introduction to natural language processing, computational linguistics and speech recognition. *prentice-Hall*.

Ferlay, J., Colombet, M., Soerjomataram, I., Mathers, C., Parkin, D., Piñeros, M., Znaor, A., & Bray, F. (2019). Estimating the global cancer incidence and mortality in 2018: GLOBOCAN sources and methods. *International journal of cancer*, *144*(8), 1941-1953.

Frank, E., Hall, M., Holmes, G., Kirkby, R., Pfahringer, B., Witten, I. H., & Trigg, L. (2009). Weka-a machine learning workbench for data mining. In *Data mining and knowledge discovery handbook* (pp. 1269-1277). Springer.

Ganggayah, M. D., Taib, N. A., Har, Y. C., Lio, P., & Dhillon, S. K. (2019). Predicting factors for survival of breast cancer patients using machine learning techniques. *BMC medical informatics and decision making*, *19*(1), 1-17.

Han, J., Kamber, M., & Pei, J. (2011). Data mining concepts and techniques third edition. *The Morgan Kaufmann Series in Data Management Systems*, *5*(4), 83-124.

Kira, K., & Rendell, L. A. (1992). A practical approach to feature selection. In *Machine learning proceedings 1992* (pp. 249-256). Elsevier.

Mondal, M., Semwal, R., Raj, U., Aier, I., & Varadwaj, P. K. (2020). An entropy-based classification of breast cancerous genes using microarray data. *Neural Computing and Applications*, *32*(7), 2397-2404.

Sharma, A., Kulshrestha, S., & Daniel, S. (2017). Machine learning approaches for breast cancer diagnosis and prognosis. 2017 International conference on soft computing and its engineering applications (icSoftComp),

Solanki, Y. S., Chakrabarti, P., Jasinski, M., Leonowicz, Z., Bolshev, V., Vinogradov, A., Jasinska, E., Gono, R., & Nami, M. (2021). A Hybrid Supervised Machine Learning Classifier System for Breast Cancer Prognosis Using Feature Selection and Data Imbalance Handling Approaches [Article]. *Electronics*, *10*(6), 16, Article 699. https://doi.org/10.3390/electronics10060699

Tang, R., Fong, S., Yang, X.-S., & Deb, S. (2012). Wolf search algorithm with ephemeral memory. Seventh international conference on digital information management (ICDIM 2012),

W. Wolberg, N. S., O.L. Mangasarian. (1995). *{UCI} Machine Learning Repository*. University of California, Irvine, School of Information and Computer Sciences.

Wang, H. F., Zheng, B. C., Yoon, S. W., & Ko, H. S. (2018). A support vector machine-based ensemble algorithm for breast cancer diagnosis [Article]. *European Journal of Operational Research*, *267*(2), 687-699. https://doi.org/10.1016/j.ejor.2017.12.001

Xue, B., Zhang, M., Browne, W. N., & Yao, X. (2015). A survey on evolutionary computation approaches to feature selection. *IEEE Transactions on Evolutionary Computation*, *20*(4), 606-626.

Zhao, X., Li, D., Yang, B., Chen, H., Yang, X., Yu, C., & Liu, S. (2015). A two-stage feature selection method with its application. *Computers & Electrical Engineering*, *47*, 114-125.

Zheng, B., Yoon, S. W., & Lam, S. S. (2014). Breast cancer diagnosis based on feature extraction using a hybrid of K-means and support vector machine algorithms. *Expert Systems with Applications*, *41*(4), 1476-1482.

AITA

ARTIFICIAL INTELLIGENCE

THEORY and APPLICATIONS

2021
Vol :1 Num : 2

Special Issue
Full Papers

Bi-annual

ISSN : 2757-9778
ISBN : 978-605-69730-2-4

Open Access

Izmir Bakircay University

Artificial Intelligence Studies in Healthcare Research and Application Center

Izmir / TURKEY

https://aita.bakircay.edu.tr