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PREDICTION AND CLASSIFICATION OF PRESSURE INJURIES BY DEEP LEARNING

WYKRYWANIE I KLASYFIKACJA ODLEŻYN Z WYKORZYSTANIEM DEEP LEARNING

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Authors' contribution
Wkład autorów:
A. Study design/planning
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B. Data collection/entry
zebranie danych
C. Data analysis/statistics
dane – analiza i statystyki
D. Data interpretation
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wyszukiwanie i analiza literatury
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Summary
Pressure injuries are a serious medical problem that both negatively affects the patient's quality of life and results in significant healthcare costs. In cases where a patient doesn't receive appropriate treatment and care, death may result. Nurses play critical roles in the prevention, care, and treatment of pressure injuries as members of the healthcare team who closely monitor the health status of the patient. Today, the use of artificial intelligence is becoming more prevalent in healthcare, as in many other areas. Artificial intelligence is a method that aims to solve complex problems by using computers to mathematically simulate the way the brain works. In this article, we compile and share information about a deep learning model developed for the detection and classification of pressure injuries. Deep learning can operate on many types of data. Convolutional Neural Networks (CNN) prefer images because they can handle 2D arrays. In this case, the images, annotated according to the National Pressure Injury Advisory Panel pressure injury classification system, have been fed into a deep learning model using CNN. The developed CNN model has a 97% success in detecting and classifying pressure injuries, and as more images are collected and fed into the CNN, the prediction accuracy will increase. This deep learning model allows for the automatic detection and classification of pressure injuries, an indicator of health outcomes, at an early stage and for quick and accurate intervention. In this context, it is expected that the quality of nursing care will increase, the prevalence of pressure injury will decrease, and the economic burden of this health problem will decrease.

Keywords: deep learning, pressure ulcers, artificial intelligence, nursing care

Streszczenie
Odleżyny są problemem zdrowotnym, który negatywnie wpływa na jakość życia pacjenta i powoduje poważne koszty opieki. W przypadku braku odpowiedniego leczenia i opieki może to doprowadzić do śmierci pacjenta. Pielęgniarki odgrywają kluczową rolę w zapobieganiu, opiece i leczeniu odleżyn jako członkowie zespołu opieki zdrowotnej, którzy ściśle i stale monitorują stan zdrowia danej osoby. Obecnie w dziedzinie zdrowia, podobnie jak w wielu innych dziedzinach, coraz częściej wykorzystuje się sztuczną inteligencję. Sztuczna inteligencja jest metodą, która ma na celu rozwiązywanie złożonych problemów poprzez matematyczne symulowanie sposobu działania mózgu z wykorzystaniem komputerów. Niniejszy artykuł jest przeglądem zaprojektowanym w celu podzielenia się informacjami na temat modelu deep learning opracowanego do wykrywania i klasyfikacji odleżyn. Deep learning może działać na wielu typach danych. Konwolucyjne sieci neuronowe (ang. *convolutional neural networks*, CNN) preferują obrazy, ponieważ mogą obsługiwać macierze 2D. Obrazy, uporządkowane zgodnie z systemem klasyfikacji odleżyn według National Pressure Injury Advisory Panel (NPIAP), zostały przekształcone w "Deep Learning Model" z wykorzystaniem CNN. Opracowywany model CNN ma 97% skuteczności w wykrywaniu i klasyfikowaniu odleżyn, a im więcej obrazów zostanie zebranych i wykorzystanych w CNN, tym większe będzie prawdopodobieństwo trafnej prognozy. Ten model deep learning daje możliwość automatycznego wykrywania i klasyfikacji odleżyn, które są wskaźnikiem jakości zdrowia, na wczesnym etapie oraz dokładnej i szybkiej interwencji. W tym kontekście oczekuje się, że jakość opieki pielęgniarskiej wzrośnie, zmniejszy się częstość występowania odleżyn oraz obciążenie ekonomiczne związane z tym problemem zdrowotnym.

Słowa kluczowe: deep learning, odleżyny, sztuczna inteligencja, opieka pielęgniarska

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Introduction

Pressure injuries, which are indicators of the quality of a health care system, are a serious patient safety problem, and the severity of these injuries affects the length of a patient's hospital stay and the cost of care [1-3]. Pressure injuries are defined as localized injuries caused either by the force of tearing and pressure combined or by pressure that can build up on bony prominences. These types of injuries can lead to a decrease in quality of life for the patient and their family and can also cause social isolation, the need for long-term nursing care, mortality, morbidity, and nosocomial infections when appropriate treatment and care is not provided [4-7]. According to 2016 data from the National Pressure Ulcer Advisory Panel (NPUAP), the prevalence of pressure injury in the United States varies between 1.3-3 million, while the annual cost to the country is 2.2-3.6 billion dollars [4]. In Turkey, on the other hand, pressure injury incidence is 5.5%-17.5% [5,7-9], and pressure injury prevalence overall (between Stage 1 and Stage 4) is 12.7%. Except for Stage 1, the prevalence is 6.7%, and 48.5% of all pressure injuries are Stage 1 [3,10].

Pressure injuries occur in more than 1.5 million patients treated in healthcare facilities in the United States each year, which increases healthcare spending by $15,229 per patient and lengthens patients' stay in healthcare institutions by approximately 8.2 days [1,2,7,8]. Worldwide, the daily health expenditure for pressure injuries is 2.34-77.36 € per patient, and the average cost to prevent pressure sores in a patient known to be at risk is 7.88 € [8,11].

While care in the nursing process is exhibited in an analytical and systematic structure rather than intuitively [12,13], this structure is formed by nurses following innovations in care and benefiting from technology in care. Now we are living in the technology age, and the use of information technologies and artificial intelligence has become inevitable in nursing, as in many areas. John McCarthy was the first scientist to define the term artificial intelligence: "the science and engineering of making intelligent machines, especially intelligent computer programs" [14,15]. Artificial intelligence is a branch of science that aims to design machines that can learn from past experiences and have the ability to perform analytical feats similar to how humans think and reason [14-16]. In today's technology-driven world, artificial intelligence plays an important role in creating devices that can think, reason, and make decisions like humans. Therefore, the proposal to model the human brain has been put forward. Artificial intelligence has enabled the human brain, its way of thinking, and its decision-making power and learning capabilities to be imitated by machines [16].

Aim of the work

With artificial intelligence, it is possible to design systems that mimic certain human behaviors and simulate the thinking process for tasks that require specific expertise [1,5,6,17-19]. Medical expert systems – using artificial intelligence as the expert – are the most frequent application in artificial intelligence and have been developed to find solutions to common problems in the healthcare [17-25]. The purpose of medical expert systems is to provide advice and recommendations to the physician based on patient data rather than replacing the physician [12,24].

Based on this information and using the deep learning model we are developing, it will be possible to accomplish four tasks: 1) to perform the recommended risk assessment for the prevention of pressure injury, 2) to plan preventive care by determining the individuals at risk, 3) to correctly and systematically identify the stage of the wound when pressure injury develops, and 4) to determine the necessary care required based on wound stage. With this deep learning model, it is expected that the quality of nursing care for the prevention and treatment of pressure injury will increase and that the prevalence of pressure injury will decrease.

This article is a review designed study to share information about the deep learning model developed for the detection and classification of pressure injuries.

The innovative approaches used in the detection and classification of pressure injuries in the world and Turkey

Today, computer and information technologies are widely used in the healthcare fields as in almost every field. Innovative products and services enable early diagnosis and treatment of diseases and reduce health expenditures, and these products have emerged with the spread of innovation, which is a product of technology advances [14,26-31]. Studies have shown that transferring nurses' innovative thinking and developing abilities to clinical areas provides several benefits, including allowing for increased quality of care, earlier diagnosis of risky conditions and diseases, and additional measures to eliminate risk factors [13]. Examples of innovations used in nursing practices related to patient safety are prevention of falls, home care, medication administration, infection control, and pressure injury and wound care [11,14,32].

Pressure injuries are an internationally defined preventable problem. However, pressure injuries can occur widely in clinics despite all possible interventions [24-27,33]. Studies have shown that the prevalence of pressure injuries is 7.8% -13.5% in general, 3-18.5% in acute care wards, and 14% -33.7% in intensive care wards [3,10,28]. Pressure injuries have a substantial impact on the affected patient, and they can be painful, become severely infected, or have a foul odor. After adjusting for age, sex, and comorbidities, it has been shown that people with pressure injuries have a lower health-related quality of life than those without pressure injuries [1,4-6,17,18,29-31,34,35]. It is important to perform the risk analysis of such a common and serious health problem, which can bring morbidity and mortality, and to correctly determine the staging and appropriate nursing interventions when it occurs. Nurses are the entities responsible for determining the stage of the injury and for providing appropriate care for the stage [8,9,12,36,37]. Studies focusing on the prevention, detection, and treatment of pressure injuries have shown that innovative approaches such as mobile applications, biosensors, augmented reality, and artificial intelligence are currently being applied [35,36,38-42].

A literature review was performed for published works on pressure injury. Using Google Academy, Thesis Center, PUBMED, and CINAHL databases to find studies conducted after 2015, we searched for combinations of "pressure injury" and "artificial intelligence", "biosensor", "augmented reality", "virtual reality", "serious game", and "mobile application". In this context, 3052 articles were found, and 45 articles met the criteria detailed above. The study acceptance criteria are the following: 2015 and later, full text available in English.

The use of mobile health applications, defined as responding to healthcare services with mobile devices, is rapidly increasing. Mobile applications are also used for a wide range of detection and classification of pressure injuries [19,32-34]. Shepherd et al. [35] stated that the detection, staging, and treatment of pressure injuries using information technology would be more effective. Garcia-Zapirain et al. [34] developed a mobile application for the non-contact assessment of pressure injuries and found that this application allows for staging of injuries, obtaining relevant information for diagnosis, and monitoring the progress of injuries. Fraiwan et al. [32] developed a mobile application that detects body temperature and analyzes the risk of pressure injury. Tibes et al. [36] stated that the error rate in staging and risk calculation of the Braden scale decreased with the use of mobile application developed for the prevention and classification of pressure injury. Poon et al. [37] developed a mobile application that allows for the color and size of the pressure injury to be accurately determined. Kim et al. [38] made it easier to identify risky individuals by analyzing the risk of pressure injury with the mobile application called SAPPIRE. Barreno et al. [29] developed a mobile application that provides information about pressure injury classification, evaluation, treatment, and the care products to be used, thereby increasing patient knowledge.

Biosensors are sensor systems consisting of biological sensors and physicochemical transducers combined with biological systems. Compared to traditional methods, biosensors have many innovative features, such as being fast, low-cost, portable, simple-to-use, and facilitating sample preparation [42-51]. Biosensors have been used in healthcare fields for many years, and they provide opportunities to improve healthcare services and increase patient quality of life [39]. Studies have shown that biosensors are effective in detecting pressure injury [40,41]. Lee et al. [40] have achieved great success in early detection of pressure injuries with the position and pressure zones they predefined for biosensors and pressure sensors. In another study, Tavares et al. [41] demonstrated successful early detection of pressure injuries by placing biosensors in wheelchairs.

Augmented reality is a system created by the integration of the virtual environment with the real environment. Augmented reality systems store information about the real world using perceptual data gathered by computers, thus enabling the augmentation of reality for the user [42]. Mamone et al. [31] reported that augmented reality technology is an objective and operator-independent tool for evaluating morphological images of pressure injuries. Deprez et al. [42] stated that ultrasound technology converted to simulation is useful in the early detection of pressure injury.

Deep learning is an artificial intelligence method that uses multi-layered artificial neural networks for applications such as object recognition, speech recognition, and natural language processing, and it is one of the types of machine learning. Deep learning is able to automatically learn from the symbols belonging to pictures, videos, sounds, and text instead of learning with coded rules like traditional machine learning methods [20,23]. Therefore, we propose that deep learning can help with detection and classification of pressure injuries. Studies have shown, for example, that deep learning and artificial intelligence models can estimate pressure injury risk [11,13,43]. However, there are currently no studies focusing on the classification of pressure injury. Raju et al. [13] used data from a four-year follow-up in a military hospital to provide a more accurate and faster prediction of Braden risk scale scores with a deep learning model they developed.

Alderden et al. [11] developed a deep learning model that demonstrates the risk analysis of pressure injury in intensive care patients, and they used more accurate measurements and a more meaningful pressure injury risk analysis for these intensive care patients, who are considered to be high risk. Demircan et al. [43] developed a mathematical model that analyzes the risk factors for the formation process of pressure injury, and their model enabled early detection of pressure injuries. The use of these innovative applications, which are being employed around the world, is limited in our country. In an environment where technology develops rapidly and is consumed equally rapidly, training innovative nurses by integrating technology into nursing practices will increase the visibility of our profession.

Deep learning model in detection and classification of pressure injuries

Nowadays, with the increasing use of technology, it is clear that more data is needed to solve complex problems. In order to respond to this need, Convolutional Neural Networks (CNN) have emerged as a type of artificial neural network that can learn from the symbols of images, video, sound, and text, instead of learning with coded rules as in machine learning, and they are used for many applications, such as object recognition, speech recognition, and natural language processing [16]. CNN are one of the deep learning methods, which is a sub-branch of machine learning and has the ability to learn through examples. CNN can learn from raw image or text data and can increase prediction accuracy according to the size of the data [6,35,37,44,45,52-55]. In this work, detection and classification of pressure injuries will be accomplished with a deep learning model. Our study is the only study that has used machine learning to predict the stage of pressure sores. It is thought that the proposed method will contribute to the detection and treatment of pressure injury in healthcare.

Data set

In this study, the images of 175 patients diagnosed with pressure injuries form a data set. Each image consists of 128x128x3 dimensional image data.

Ethics

The Ethics Committee of Istinye University (Turkey) issued approval (No. 21-04. of 27th Jan 2021) to conduct the research. The study was conducted according to the principles in the Declaration of Helsinki.

Data pre-processing methods

1. The size of each image is changed to 200x200x3 for preprocessing.
2. The number of image data has been multiplied for the preprocessing. To increase the size of the image data set, several image processing techniques are applied, including 0.02 zooming in, zooming out, rotating, and random shearing processes.
3. Prior to pre-processing of the image data, pixel normalization is performed on the images. Pixel values in the raw images between (0-255) are normalized and converted to values between 0-1.
4. To preprocess the image data, color changes are applied to the images, and grayscale optimization is applied to these images [56].
5. Images are labeled with a classification corresponding to pressure injury severity, which is staged according to NPUAP pressure injury.

Image data classification model

For the classification of image data, we used the Alex Net Convolutional Neural Network model, which won first place in the ImageNet large-scale visual recognition competition in 2012 [40,57]. We use this model for a new application to classify the available image data of pressure injuries.

Structure and properties of the classification model

The CNN model to be used in the classification of pressure injuries is called the BYT-CNN model. BYT refers to pressure injury detection (PID). Figure 1 shows the suggested BYT-CNN model. In this model, there are 5 convolution layers, 5 average pooling layers, 3 release layers, 1 smoothing layer, and 3 density layers.

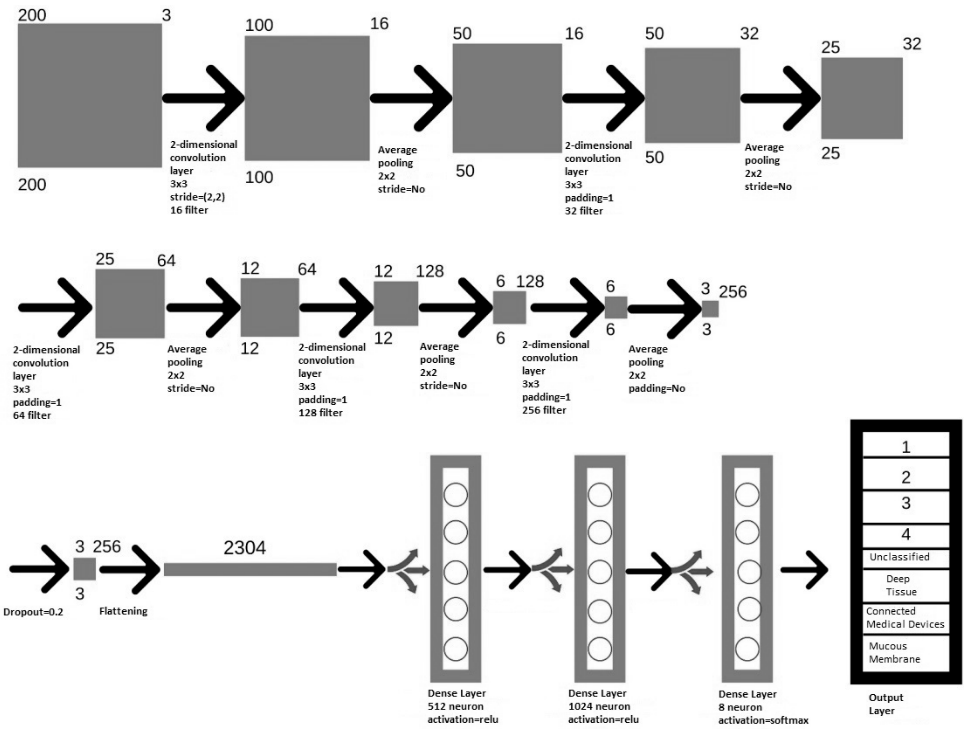

Figure 1. BYT-CNN model

1. **Input Layer:** It is the input layer where the images are defined as 128x128x3.
2. **Convolution Layer:** It is the layer where the convolution process is applied to images [24]. 16 3x3 filters are applied to the images for convolution. For RGB images, filters are circulated 3 times. The dot multiplication operation between 3x3 matrices is accomplished by shifting 2 steps. An activation map is created using the activation function (ReLU), with the negative value remaining 0 and the positive value being derived from the matrix elements after the dot multiplication process. Padding has been applied to keep the size of the image unchanged. This is done by adding a zero to the empty edges in the matrix.
3. **Pooling Layer:** It is the layer on which the pooling process is applied to images for feature extraction. The average pooling process is done by dividing the images into 2x2 dimensional matrices. The average pooling process is carried out by taking the arithmetic mean of four values in the matrix and transferring it to the newly created matrix.
4. **Drop Layer:** It is the layer on which a random 2% drop operation is applied to the matrices that are created after the pooling process. This dropping process is applied to prevent memorization. It randomly sets the value of 2% of the pixels in each matrix to zero.
5. **Smoothing Layer:** It is the layer in which the matrix that is obtained after the drop layer is transformed into a column vector.
6. **Density Layer:** It is the layer where the activation process is applied to the value obtained by multiplying each pixel of the column vector (created after the smoothing process) by the random weight values of the neurons and adding the bias value to the multiplication result. If the value obtained is higher than the thresholding value, the value is transferred from this neuron to the neurons in the other layer. If the value obtained is lower than the thresholding value, the value is not transferred to the neurons in the other layer.
7. **Output Layer:** This layer consists of four neurons, and each neuron represents one stage. The value obtained after the dropout layer is applied, and whichever neuron's value is close to the index value is considered the output result. The neuron output result also shows the stage of pressure injury. The softmax function is used for the classification process and calculates the probability of the class obtained as a result of the drop operation. Back propagation is the process to minimize the error of the incorrectly calculated class, and it is performed by updating the weights in density layers and comparing the recalculated output with the final output to minimize the error [27].

Conclusions

Since deep learning models used in healthcare do not have human-induced observation errors by their nature, they give more accurate results than other methods. The BYT-CNN model we are developing has achieved a classification estimation success of approximately 97% by training with 175 sample patient images. Since CNN models in general offer better performance with more images, the BYT-CNN model will be used to both predict the presence of the disease and to solve the classification problem of disease stage using image data of 500 patients. Early detection of pressure injury and early stage classification together will provide faster and more effective treatment to the patient. Moreover, deaths caused by this disease may be prevented, thereby increasing the quality of patient care.

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References:

1. Ferris A, Price A, Harding K. Pressure ulcers in patients receiving palliative care: a systematic review. Palliative Medicine. 2019; 33(7): 770-782. https://doi.org/10.1177/0269216319846023
2. McGinnis E, Brown S, Collier H, Faulks P, Gilberts R, Greenwood C, et al. Pressure RElieving Support SUrfaces: a Randomised Evaluation 2 (PRESSURE 2) photographic validation sub-study: study protocol for a randomised controlled trial. Trials. 2017; 18(1): 1-10. https://doi.org/10.1186/s13063-017-1851-5
3. Ören N. [Examination of nurses' pressure ulcer knowledge and levels of diagnosis] [master's thesis]. Zonguldak: Zonguldak Bulent Ecevit University; 2019 (in Turkish).
4. Edsberg LE, Black JM, Goldberg M, McNichol L, Moore L, Sieggreen M. Revised National Pressure Ulcer Advisory Panel pressure injury staging system: revised pressure injury staging system. Journal of Wound, Ostomy, and Continence Nursing. 2016; 43(6): 585. https://doi.org/10.1097/WON.0000000000000281
5. Moore ZE, Patton D. Risk assessment tools for the prevention of pressure ulcers. Cochrane Database of Systematic Reviews. 2019; 1(1):35-45. https://doi.org/10.1002/14651858.CD006471.pub4
6. Moore ZE, van Etten MT, Dumville JC. Bed rest for pressure ulcer healing in wheelchair users. Cochrane Database of Systematic Reviews. 2016; 10(10): 15-20. https://doi.org/10.1002/14651858.CD011999.pub2
7. Yap TL, Kennerly SM, Ly K. Pressure injury prevention: outcomes and challenges to use of resident monitoring technology in a nursing home. Journal of Wound, Ostomy, and Continence Nursing. 2019; 46(3): 207. https://doi.org/10.1097/WON.0000000000000523
8. Kottner J, Cuddigan J, Carville K, Balzer K, Berlowitz D, Law S, et al. Pressure ulcer/injury classification today: an international perspective. Journal of Tissue Viability. 2020; 1(1): 210-212. https://doi.org/10.1016/j.jtv.2020.04.003
9. Zingarelli EM, Ghiglione M, Pesce M, Orejuela I, Scarrone S, Panizza R. Facial pressure ulcers in a COVID-19 50-year-old female intubated patient. Indian Journal of Plastic Surgery: official publication of the Association of Plastic Surgeons of India. 2020; 53(1): 144. https://doi.org/10.1055/s-0040-1710403
10. Aydoğmuş Ünlü A. [Examination of surgical nurses' knowledge of pressure wound, risk factors and prevention] [master's thesis]. Karabuk: Karabuk University; 2020 (in Turkish).
11. Alderden J, Pepper GA, Wilson A, Whitney JD, Richardson S, Butcher R, et al. Predicting pressure injury in critical care patients: a machine-learning model. American Journal of Critical Care. 2018; 27(6): 461-468. https://doi.org/10.4037/ajcc2018525
12. Padula WV, Pronovost PJ, Makic MBF, Wald HL, Moran D, Mishra MK, et al. Value of hospital resources for effective pressure injury prevention: a cost-effectiveness analysis. BMJ Quality & Safety. 2019; 28(2): 132-141. https://doi.org/10.1136/bmjqs-2017-007505
13. Raju D, Su X, Patrician PA, Loan LA, McCarthy MS. Exploring factors associated with pressure ulcers: a data mining approach. International Journal of Nursing Studies. 2015; 52(1): 102-111. https://doi.org/10.1016/j.ijnurstu.2014.08.002
14. Bruce TA, Shever LL, Tschannen D, Gombert J. Reliability of pressure ulcer staging: a review of literature and 1 institution's strategy. Critical Care Nursing Quarterly. 2012; 35(1): 85-101. https://doi.org/10.1097/CNQ.0b013e31823b1f22

15. Martinengo L, Yeo NJY, Tang ZQ, Kasturi D, Markandran O, Kyaw BM, et al. Digital education for the management of chronic wounds in health care professionals: protocol for a systematic review by the Digital Health Education Collaboration. JMIR Research Protocols. 2019; 8(3): 124-128. https://doi.org/10.2196/12488
16. Alpaydın E. [Machine learning]. 1st edition. İstanbul: Boğaziçi Üniversitesi Yayınevi; 2013. p. 20-40 (in Turkish).
17. McCarthy J. What is artificial intelligence? [Internet]. Stanford, CA: Stanford University; 2004 [cited 2021 Sep 1]. Available from: http://www.formal.stanford.edu/jmc/whatisai/
18. Yılmaz A. [Artificial intelligence]. 6th edition. İstanbul: Kodlab Yayınevi; 2017. p. 5-55 (in Turkish).
19. Adamson AS, Smith A. Machine learning and health care disparities in dermatology. JAMA Dermatology. 2018; 154(11): 155-160. https://doi.org/10.1001/jamadermatol.2018.2348
20. Etienne H, Hamdi S, Le Roux M, Camuset J, Khalife-Hocquemiller T, Giol M, et al. Artificial intelligence in thoracic surgery: past, present, perspective and limits. European Respiratory Review. 2020; 29(157). https://doi.org/10.1183/16000617.0010-2020
21. Gomolin A, Netchiporouk E, Gniadecki R, Litvinov IV. Artificial intelligence applications in dermatology: where do we stand?. Frontiers in Medicine. 2020; 7(1): 112-115. https://doi.org/10.3389/fmed.2020.00100
22. Gefen A, Alves P, Ciprandi G, Coyer F, Milne CT, Ousey K, et al. Device-related pressure ulcers: SECURE prevention. Journal of Wound Care. 2020; 29(Suppl. 2a): S1-S52. https://doi.org/10.12968/jowc.2020.29.Sup2a.S1
23. Gonçalves-Bradley DC, Maria ARJ, Ricci-Cabello I, Villanueva G, Fønhus MS, Glenton C, et al. Mobile technologies to support healthcare provider to healthcare provider communication and management of care. Cochrane Database of Systematic Reviews. 2020; 8(1): 20-30. https://doi.org/10.1002/14651858.CD012927.pub2
24. Goodfellow I, Bengio Y, Courville A, Bengio Y. Deep learning. Cambridge: MIT Press; 2016.
25. Gutierrez G. Artificial intelligence in the intensive care unit. Critical Care. 2020; 24: 1-9. https://doi.org/10.1007/978-3-030-37323-8_51
26. Kaya U, Yılmaz A, Dikmen Y. [Deep learning methods used in the field of health]. Avrupa Bilim ve Teknoloji Dergisi. 2019; 16: 792-808 (in Turkish).
27. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015; 521(7553): 436-444. https://doi.org/10.1038/nature14539
28. Bader D, Worsley P, Gefen A. Bioengineering considerations in the prevention of medical device-related pressure ulcers. Clinical Biomechanics. 2019; 67: 70-77. https://doi.org/10.1016/j.clinbiomech.2019.04.018
29. Barreno DP, Areosa LA. [Guide UPP: all the knowledge on the pressure ulcers on your mobile phone (at the bedside)]. Enfermería Dermatológica. 2013; 7(18): 48-55 (in Spanish).
30. Bhattacharya S, Mishra R. Pressure ulcers: current understanding and newer modalities of treatment. Indian Journal of Plastic Surgery: official publication of the Association of Plastic Surgeons of India. 2015; 48(1): 4-5. https://doi.org/10.4103/0970-0358.155260
31. Choudhury A, Asan O. Role of artificial intelligence in patient safety outcomes: systematic literature review. JMIR Medical Informatics. 2020; 8(7): e18599. https://doi.org/10.2196/18599
32. Lal A, Pinevich Y, Gajic O, Herasevich V, Pickering B. Artificial intelligence and computer simulation models in critical illness. World Journal of Critical Care Medicine. 2020; 9(2):13. https://doi.org/10.5492/wjccm.v9.i2.13
33. Lee K-H, Kwon Y-E, Lee H, Lee Y, Seo J, Kwon O, et al. Active body pressure relief system with time-of-flight optical pressure sensors for pressure ulcer prevention. Sensors. 2019; 19(18): 3862. https://doi.org/10.3390/s19183862
34. Ünver S, Arslan Ü, Demirci S, Cebeci H. [Status of nursing students about identifying pressure injury risk factors]. Turkiye Klinikleri Hemsirelik Bilimleri. 2020; 12(1): 10-15 (in Turkish). https://doi.org/10.5336/nurses.2019-70214
35. Cunha DRd, Salomé GM, Massahud Junior MR, Mendes B, Ferreira LM. Development and validation of an algorithm for laser application in wound treatment. Revista Latino-Americana De Enfermagem. 2017; 25(1): 15-25. https://doi.org/10.1590/1518-8345.1998.2955
36. Mamone V, Di Fonzo M, Esposito N, Ferrari M, Ferrari V. Monitoring wound healing with contactless measurements and augmented reality. IEEE Journal of Translational Engineering in Health and Medicine. 2020; 8: 1-12. https://doi.org/10.1109/JTEHM.2020.2983156
37. Ziraldo C, Mi Q, An G, Vodovotz Y. Computational modeling of inflammation and wound healing. Advances in Wound Care. 2013; 2(9): 527-537. https://doi.org/10.1089/wound.2012.0416
38. Kim H, Chung H, Wang S, Jiang X, Choi J. SAPPIRE: a prototype mobile tool for pressure ulcer risk assessment. Studies in Health Technology and Informatics. 2014; 201: 433.

39. Koepp J, Baron MV, Martins PRH, Brandenburg C, Kira ATF, Trindade VD, et al. The quality of mobile apps used for the identification of pressure ulcers in adults: systematic survey and review of apps in app stores. JMIR mHealth and uHealth. (2020); 8(6): 142-166. https://doi.org/10.2196/14266
40. Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. Communications of the ACM. 2017; 60(6): 84-902012. https://doi.org/10.1145/3065386
41. Kruger EA, Pires M, Ngann Y, Sterling M, Rubayi S. Comprehensive management of pressure ulcers in spinal cord injury: current concepts and future trends. The Journal of Spinal Cord Medicine. 2013; 36(6): 572-585. https://doi.org/10.1179/2045772313Y.0000000093
42. Tavares C, Domingues MF, Paixão T, Alberto N, Silva H, Antunes P. Wheelchair pressure ulcer prevention using FBG based sensing devices. Sensors. 2020; 20(1): 212. https://doi.org/10.3390/s20010212
43. Fraiwan L, Ninan J, Al-Khodari M. Mobile application for ulcer detection. The Open Biomedical Engineering Journal. 2018; 12: 16. https://doi.org/10.2174/1874120701812010016
44. Friesen MR, Hamel C, McLeod RD. A mHealth application for chronic wound care: findings of a user trial. International Journal of Environmental Research and Public Health. 2013; 10(11): 6199-6214. https://doi.org/10.3390/ijerph10116199
45. Garcia-Zapirain B, Sierra-Sosa D, Ortiz D, Isaza-Monsalve M, Elmaghraby A. Efficient use of mobile devices for quantification of pressure injury images. Technology and Health Care. 2018; 26(S1): 269-280. https://doi.org/10.3233/THC-174612
46. Shepherd MM, Wipke-Tevis DD, Alexander GL. Analysis of qualitative interviews about the impact of information technology on pressure ulcer prevention programs: implications for the wound ostomy continence nurse. Journal of Wound, Ostomy, and Continence Nursing: official publication of The Wound, Ostomy and Continence Nurses Society/WOCN. 2015; 42(3): 235. https://doi.org/10.1097/WON.0000000000000136
47. Mayara Tibes C, Alvares Cherman E, Mourão Alves de Souza V, Martinez Évora YD, Zem-Mascarenhas SH. Image processing in mobile devices to classify pressure injuries. Journal of Nursing UFPE/Revista de Enfermagem UFPE. 2016; 10(11): 320-325.
48. Poon TWK, Friesen MR. Algorithms for size and color detection of smartphone images of chronic wounds for healthcare applications. IEEE Access. 2015; 3: 1799-1808. https://doi.org/10.1109/ACCESS.2015.2487859
49. Dhir A. BIOSENSORS – analytical device. Journal for Research. 2016; 2(02): 220-225.
50. Kökbaş U, Kayrin L, Abdullah T. [Biosensors and their applications in medicine]. Arşiv Kaynak Tarama Dergisi. 2013; 22(4): 499-513 (in Turkish).
51. Tüylek Z. [Biosensors and nanotechnological interaction]. Bitlis Eren Üniversitesi Fen Bilimleri Dergisi. 2017; 6(2): 71-80 (in Turkish). https://doi.org/10.17798/bitlisfen.299340
52. Deprez JF, Brusseau E, Fromageau J, Cloutier G, Basset O. On the potential of ultrasound elastography for pressure ulcer early detection. Medical Physics. 2011; 38(4): 1943-1950. https://doi.org/10.1118/1.3560421
53. Demircan FÖ, Toz M, Yücedağ İ. Analysis of pressure ulcer formation risk of in different regions of human body. Konuralp Journal of Mathematics. 2016; 6(2): 233-239.
54. Roessel J, Knoell M, Hofmann J, Buettner R. A systematic literature review of practical virtual and augmented reality solutions in surgery. In: Proceedings of 44th Annual Computers, Software, and Applications Conference (COMPSAC); 2020 Jul 13-17; Madrid, Spain. Piscataway Township, New Jersey: IEEE; 2020. https://doi.org/10.1109/COMPSAC48688.2020.0-204
55. Van den Oord A, Dieleman S, Schrauwen B. Deep content-based music recommendation. Advances in Neural Information Processing Systems. 2013; 26(3).
56. Gupta R, Sehgal P. A survey of attacks on iris biometric systems. International Journal of Biometrics. 2016; 8(2): 145-178.
57. Russakovsky O, Deng J, Su H, Krause J, Satheesh S, Ma S, et al. Imagenet large scale visual recognition challenge. International Journal of Computer Vision. 2015; 115(3): 211-252.