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ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN HEALTHCARE APPLICATIONS

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A B S T R A C T

Artificial intelligence (AI) is a field of computer science concerned with the simulation of human intelligence by smart machines and computational rationality. AI is about to transform medical practice. With the help of this technology, a doctor can examine and treat the patient without visiting any hospital or clinic. Thus, this technology is now accessible to provide online services to patients. Any patient complaints may be rapidly addressed with various health issues. AI has been studied in several fields of medical practice and health science, including population health, precision medicine, and natural language treatment. Our objective is to review the applications of AI in the field of health science research. In this research, how AI helps solving the difficult medical problems through extensive research and development is demonstrated.

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Introduction

In recent years, AI has utility and effectiveness in solving many real-world computation-intensive problems, such as intelligent transportation systems, agriculture, education, Chatbot, Sentiment Analysis, Prediction, and especially healthcare systems [1-3], etc. AI has been introduced into the field of medicine to keep a digital medical record and perform examinations by utilizing intelligent technologies. It has solutions, specifically in targeted therapy, single-composition medicament, and personalized cures. AI simulates human intelligence characteristics through the use of machine-like computer systems. It's also able to rapidly analyze, conclude, predict, learn, and even correct itself. Also, it can plan images, recognize speech, and learn a specific trait. AI systems train certain datasets to better outcomes and accurately solve complicated issues [4, 5]. AI is an innovative technology that aims to help the surgeon through medication [6], treatment, and surgery [7]. Its principal application for complicated cases is to improve decision-making. Besides, this technology detects, investigates, tracks, and controls infections in hospitals [8]. It can also develop and optimize the online appointment platform for patients. Moreover, to serve humanity, AI will be useful in all medical areas.

AI behaves as any human being science. It quickly captures text, images, medical data, and bioinformatics. AI-based machines can understand human languages to decide without making any errors which helps AI-assisted surgery robots in better quality and results [7, 9, 10]. In rural areas there is a lack of health care providers and this technology may be successfully utilized for filling this gap. It ameliorates the quality of medical studies to meet an urgent demand in rural areas [11, 12]. Indeed, AI increases the efficiency of health professionals. It also ameliorates the quality of health services with a lower cost. Accordingly, physicians are advised towards an accurate diagnosis [13, 14]. Furthermore, it was an important function in scanning technologies like 3D scanners, magnetic resonance imaging, computed tomography, and X-rays [15]. AI creates data through various virtual media and regularly communicates with the patient, therefore, a better decision will be made [1]. Patients profit from timely and accurate decisions [16-18]. AI appeared as a very good technology to be used for higher life expectancy.

This technology is very useful. It is flexible, adaptable and it recognizes patterns and computes fast [19]. Many superb computer scientists have carried out AI for 30 years. In the last decades, medical doctors have utilized AI to overcome medical issues. More recently, a significant AI branch has been developed which is called Machine Learning (ML) [1].

The main purpose of this review paper is the exploration of the AI and ML in the evolution of Health science. In this work, we provided the latest developed applications in various intelligent medical field based on AI and ML. We focused on the

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role and impacts of previous technologies on the most important aspects of health science, such as health recommender systems, electroencephalography analysis, disease identification and diagnosis, intelligent robot surgery, and image recognition technology. To achieve this aim, the structure of the review is as follows. In section 2, we define ML and the most used categories. In section 3, a detailed literature review of AI and ML techniques applied to health care are conducted. In section 4 a discussion is provided. Finally, the 5th section is a conclusion.

Machine learning

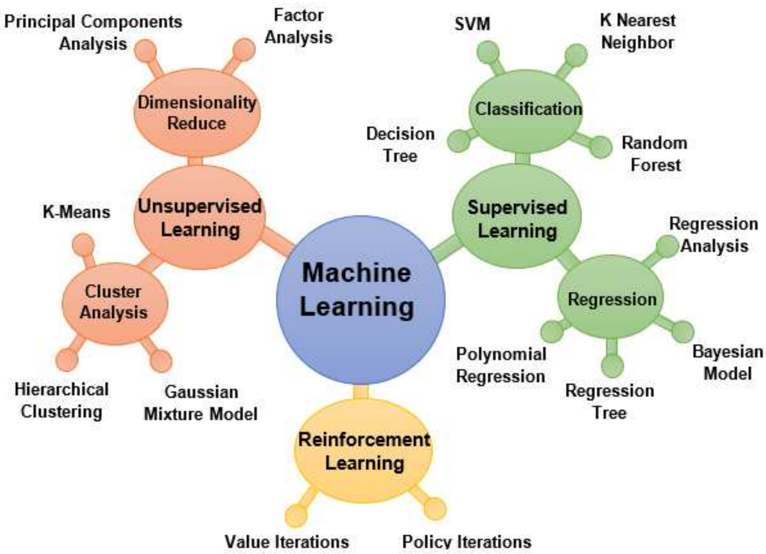

Figure 1: Classification of ML techniques

ML enables machines to be smarter without the humans' intervention. The machines can learn from previous experiences and observations, when focusing on the design, analysis, development, and implementation of methods for accessing and using data. Thus, observations like instructions, direct experience, or examples are necessary to make a good decision [20].
ML automatically evaluates medical results and accurately presents them [21, 22]. The algorithm decisions can be made, including supervised learning, unsupervised learning, semi-supervised and reinforced learning by using ML. ML is used to identify disease probability [23-25]. It actually saves patients' record for better treatment [26-28].
ML is subcategorized into three subtypes, as shown in figure 1. First, the system in supervised learning infers a function from labeled training data. Second, the system in unsupervised learning tries to infer the unlabeled data structure. Third, the system in reinforcement learning interacts with a dynamic environment.

- **Supervised machine learning**

Supervised learning is an automatic learning approach derived from the data of labeled training. These latter are made up of a set of training samples. Each example of the supervised training data set includes one input vector, a pair of input objectives, as well as one preferred output value. An algorithm, within supervised ML, will analyze the training data. Then an inferred function named a classifier will be made. Indeed, such an inferred function must predict the output value in an accurate way for any suitable input object. The learning algorithm will reasonably generalize the training data to situations unobserved previously. Supervised learning is divided into two types of learning tasks: classification and regression. The classification models seek to predict distinct classes, like the example of blood groups, whereas the regression models try and seek to predict numerical values. Some famous examples of supervised learning are decision trees, linear regression, random forest, logistic regression (LR), and Support Vector Machines (SVM).

- **Unsupervised machine learning**

In contrast, unsupervised ML concerns a situation that tries to discover a structure that is hidden in unmarked data. Because the examples provided to the learner are not labeled. In general, no error or reward signal exists for evaluating a potential solution. A reward signal can be an important factor in distinguishing supervised and unsupervised ML. In the field of statistics, unsupervised learning is linked to the estimation of density. We look forward to learn how to inherit the structure of our data without using explicitly supplied labels. In addition, unsupervised learning is utilized for dimensionality reduction, association analysis, and clustering. The latter is to separate data in meaningful subclasses. These latter are named clusters, according to the similarity between data objects, the data objects likeliness is an important criterion for clustering. Few examples of such algorithms include auto-encoders, principal component analysis, and k-means clustering.

- **Reinforcement machine learning**

It is a new type of ML that recently got much attention. In reinforcement learning, machines are not provided with examples of correct input-output pairs. On the other hand, a method is provided for the machine with the target of quantifying its performance as a reward signal. Reinforcement learning methods are like animals' and humans' learning. Machines try multiple and various things and are rewarded when doing something good.

This kind of learning is useful when solution spaces are large and infinite, and when machines can be thought of as agents that interact within their environment. Video games, like AlphaGo or others, fit this task because scores work well as rewards. The machine will go on learning by simulating which patterns maximizes its reward.

- **Supervised versus unsupervised learning**

The distinct outputs of both principal types of ML methods are illustrated and presented in figure 2. Labeled samples with output and input data in supervised learning are used for the development of a model approximating the relationship between these values. The developed model is used for making future specific output predictions which provided a set of input values. The output value in regression analysis is continuous. On the other hand, for conventional classification tasks, the test case will be classified by the output into a specific class. In unsupervised learning, the algorithm will just use the input data to propose the natural structure present globally in the data points, without the use of one specific output for prediction. Similar to the outputs of supervised learning, the outputs of unsupervised learning are grouped into more discrete or continuous clusters.

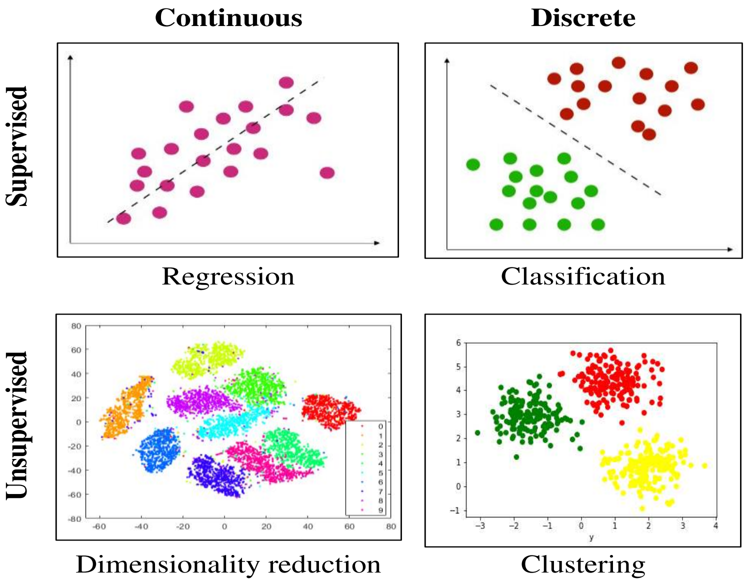

Figure 2: Differences between machine learning methods.

Machine Learning in the Medical Field

ML has shown its utility and effectiveness in solving many real-world computation-intensive problems, such as chatbot, sentiment analysis, finance prediction, medical field, and search engines [29]. In medicine field, ML facilitates different highly complicated and time-consuming tasks. We will briefly discuss the most recent research trends as well as the activities related to health care based on ML.

- **Health Recommender System**

A Health Recommender System (HRS) contains several phases according to the basic architectures of health information systems as depicted in figure 3. Cloud computing, an increase in data rates, high-performance internet of things (IOT) devices, and advanced sensors are four significant concern keys for a successful HRS in health informatics.

HRS led an extensive use of AI and ML techniques in advanced health care systems. These are known as health intelligence [29-32]. These techniques have played an essential role in disease diagnosing [33], medical imaging, social media analytics, and cure prediction, for disease [34, 35]. For chronic disease diagnosis and monitoring, HRSs have an essential function of a continuous monitoring and supporter. The authors in [36] proposed an intelligent smartphone-based HRS, to monitor patients depression and mental disorders.This device provides treatment if necessary. They divided 1047 volunteers' data into a testing set and a training one. Then, they constructed a depression prediction model through the use of a decision tree and support vector machine (SVM) algorithms.

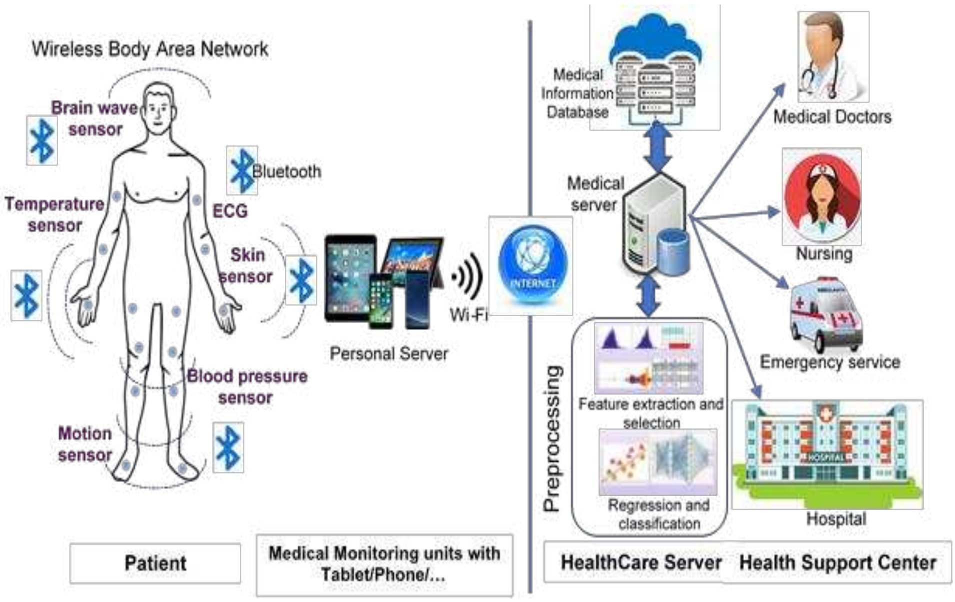

Figure 3: Health recommender system architecture.

In [37], an HRS,especially for patients with diabetes, was designed to ameliorate life quality by helping a patient to predict disease risks and reliable health recommendations. Also, a precise prediction model was built for diagnosing the risks linked to diabetics via the application of several classifications utilizing decision tree algorithms for prescribing more precise medical advice through the application of unified collaborative filtering about some external features, medical history, etc. They applied the decision tree to build one model that predicts, and diagnoses diseases and their risks. One overall random forest model was developed utilizing some decision trees. As a result, the HRS presented in [37] proved to be more efficient in terms of recall and accuracy utilizing the random forest algorithm in comparison with the other algorithms like the REP-tree and the decision stump.

The decision tree algorithm has been utilized for regression and classification of problems and can be utilized for HRSs on its own or combined with other supervised classifiers. The authors in [38-40] studied smartphones based on wrist-worn motion sensors to identify several complex daily actions such as eating, smoking, and drinking coffee. In [38], three different classifiers, which were Naive Bayes, decision tree, and K-Nearest Neighbor (KNN) were utilized to function with various window sizes to recognize a complex or simple activity. In [39], the authors achieved a good accuracy to classify stationary, running, and walking activities. The writers of [40] deployed both SVM and decision trees in their framework.

Deep learning, as an ML sub-field has been founded upon algorithms for learning multiple representation levels with the objective of modeling complex relationships among data [41], as well as the neural network theory while using multiple processing layers. Generally, these latter will learn the abstract representations of input data. Such algorithms will extract low and high-level features, in an automatic manner, needed for classification. Convolutional Neural Networks (CNNs) which are deep learning algorithms and their inputs are images, extract the features of the objects in such images and differentiate them from one another. Also, the need for pre-processing in CNNs is less than the other classification algorithms. CNN's represent very well-known techniques utilized in computer vision systems and image recognition. In [42], they proposed a novel approach to detect an automatic way of diagnosing the Myocardial Infarction (MI) using electrocardiogram (ECG) signals. In their work, the authors implemented a CNN algorithm to automatically detect normal and MI ECG beats. The writers also achieved an average accuracy of 93.53% through the use of ECG beats with noise and 95.22% without noise. This suggested algorithm could perfectly detect the unknown ECG signals even with noise. Thus, such a good system can be introduced in hospitals to support the clinicians' diagnosis of MI. The proposed system has been good and advantageous for the early diagnosis of cardiovascular diseases.

Existing studies based on SVMs [43,44], logistic regression [45], CNN's [46], Neural Networks (NNs) [47], and others [48], have proposed and developed HRSs for people suffering from dementia. This has caused memory loss to patients whose number has been rising worryingly worldwide. The authors in [49] provided an ML state-of-the-art review. The ML approaches were applied to health informatics for what related to dementia care. Indeed, the writers collected and reviewed the existing scientific methodologies. They identified the relevant issues and challenges in case they had faced big health data. ML demonstrated promising applications for the analysis of neuroimaging data concerning dementia care. In general, little effort has been made to take advantage of heterogeneous integrated information using sophisticated ML approaches.

- **Electroencephalography analysis of machine learning methods for EEG analysis**

Electroencephalography (EEG) has been a vital method to identify certain health conditions in patients starting from the date of its discovery. Researchers have proposed several ML methods developed with bioengineering applications for EEG analysis. Table 1 discusses and presents different ML methods developed for EEG analysis.

In paper [50], the authors reviewed literature within the period 1988-2018 to capture earlier as well as present EEG classification methods in multiple applications. Accordingly, they determined the overall effectiveness of every ML method. The writers also noticed that all the primary methods utilized for ML were applied in some EEG classification forms. These methods include decision tree, naïve Bayes (NB), SVMs, CNNs, logistic regression, KNNs, recurrent neural network (RNN), and random forest. Each method has its accuracy within respective applications. From another perspective, higher overall classification accuracy will be achieved when some methods are combined and implemented correctly. The authors in [50] presented a comprehensive summary of the ML applications utilized for EEG analysis. They gave an overview of every method and its applications.

Table 1: ML methods for EEG analysis

Machine Learning Method	Application	Authors	Accuracy Results
Logistic Regression	Epilepsy Classification	[51]	95.88%
Linear Regression	Robust ECG Artifact Removal	[52]	98.11%
Logistic Regression	Motion Discrimination	[53]	77.0%
RNN, CNN, neural networks, Logistic Regression,	Identification of Automatic Abnormal EEG	[54]	3.47% Better accuracy was obtained with RNN
SVM	Emotion Classification	[55]	96.83%
SVM	Multimodal Facial Recognition	[56]	82.75%
SVM, KNN	Multiple Sclerosis Detection	[57]	93.08%
SVM	Alcohol Use Disorder Detection	[58]	98.0%
Naive Bayes	EEG Classification	[59]	81.07-91.60%
Naive Bayes	Major Depressive Disorder	[60]	93.6%
Naive Bayes	Brain Activity Classification	[61]	87%
SVM, Naive Bayes	epileptic seizure detection	[62]	100%
Random Forest	Characterize and Quantify Tonic Thermal Pain	[63]	89.45%

- **Infection prediction through the use of AI**

ML is effective in predicting the infection risk within patients, while creating ahead of time alarms, hence helping medical teams respond quickly. Early diagnosis provides patients with appropriate care, enables patients to minimize the damage produced by disease or isolate and avoids the spread risk.

In [8], the authors surveyed the state of the art in what concerns AI-based infection prediction through the use of a systematic literature review. They reviewed 101 relevant documents published within the period 2003-2019. The objective was to study the papers where AI and ML were utilized to predict infections in patients by the means of physiological data as features. The writers described all the whole review process carefully, and eight databases were taken into account indexing most of the literature which were in different scholarly formats. Indeed, these authors concluded that the most usually focused infection was by a considerable margin of the sepsis, followed by the infections of both Clostridium difficile and surgical site. Most studies used AI and ML techniques. The logistic regression, SVMs, naive Bayes, and random forest were the most common ones. The authors showed that the automatic diagnosis of any infectious disease utilizing ML was well documented within the medical literature. Table 2 discusses and presents different ML methods developed for predicting infections utilizing AI.

Table 2: ML methods for Predicting Infections

Paper	**Infection**	**ML Methods**	**Features**	**Accuracy**
[64]	Sepsis	LR, SVM, ANN	Temperature, respiratory rate heart rate, blood pressure	93%
[65]	Sepsis	LR	oxygen saturation, temperature, respiratory rate heart rate,	73.98%
[66]	Sepsis	KNN	Microbiology data	94.55%
[67]	Sepsis	CNN, SVM, LR	oxygen saturation, temperature, respiratory rate, heart rate, Lab Test	87.5%
[68]	Surgical site infection	SVM	oxygen saturation, temperature, respiratory rate heart rate, Lab Test	not mentioned
[69]	General Infection	SVM, KNN, LR	Temperature, respiratory rate heart rate	90.2%
[70]	Surgical site infection	SVM, LR	Laboratory tests	86%
[71]	Sepsis	LR	Temperature, respiratory rate heart rate, blood pressure	78.9%

- **Disease identification/diagnosis**

The identification and diagnosis of diseases are the main motivations that the medical field can benefit from largely. ML can be used to help doctors save time through the detection of diseases in their early stages. Cancer detection is an area that has been greatly studied in ML research. Microsoft launched in 2010 "nnerEye" [72], which was an ML project that could detectbrain tumors and identify its stage in minutes, instead of a lot of hours by humans. Other research has to concentrate on the detection of breast cancer [73] to facilitate the earlier detection of the disease and the analysis of breast cancer diagnoses.
Parkinson's disease can be described as a neurological movement disorder. The accelerometer signals captured by portable sensors tied into every patient can be beneficial for monitoring this illness. The writers in [74], developed such a system. They compared standard ML pipelines to CNN-based deep learning. The experimental results showed that deep learning was better than the other state-of-the-art ML algorithms, in terms of classification rate, by at least 4.6 %. The authors also discussed deep learning disadvantages and advantages of movement assessment based on the sensor. They concluded that deep learning was a promising method.
Dyslexia is a learning disability that affects nearly 10% of the world population. Identifying dyslexic children at an early phase is extremely important. Researchers forwarded various respective techniques to identify dyslexic children. Research found in the literature has basically utilized SVMs [75,76], naive Bayes [77,78], logistic regression [79], CNN's [80], KNNs [81] and linear discriminant analysis as ML algorithms for classifying participants. SVMs have generally been the most commonly used algorithm. The problem has been in essence a binary classification problem (identifying dyslexic and non-dyslexic users). The authors in [82] reviewed existing dyslexia detection techniques which had utilized ML approaches.
Decision tree algorithms were applied in a successful way to diagnose MR imaging Alzheimer's disease and schizophrenia and to also classify lung nodules [83,84]. Specifically, these types of algorithms were utilized in cardiac imaging to predict cardiac risks and mortality [85,86].

- **Intelligent robot surgery**

Robots have been greatly utilized in surgery. Previously, discrete robots with reduced mobility assisted surgeons in clinical practice. With the constant progress of AI and medical technologies and the appearance of intelligent and sophisticated robots, old robots have been gradually replaced by flexible characteristics and good environmental adaptability. These intelligent robots are expected to become a very significant force of future surgery [7, 87]. They are manufactured to gradually adapt to the direction of future surgical development [88].
The authors of the papers [88,89] showed that using various ML approaches would enable the improvement of the accuracy of lengthy robot-assisted surgeryprediction, hence it increases the utilization of this resource.

- **Image recognition technology**

Image recognition technology is defined as a method for recognizing images to analyze and process them by computer. This is an important AI technology. Indeed, it has been based on deep learning [90]. The authors in [91] showed that deep learning had an essential part in applying the image recognition technology for detecting and identifying lesions. In 2017, a study [90] used CNNs to identify cancerous breast lesions. The accuracy of CNN recognition was better. In another deep learning-based study [92], intelligent cervical image recognition could help doctors to diagnose cervical cancer early with a precision rate of around 90%.
Many researchers have claimed that several difficulties were encountered when applying image recognition technology. For example, the learning model within multilayer neural convolution needed much data, and the efficiency of computers required further improvement. Moreover, high-performance supercomputers were not popular. Therefore, in the future more investigations will be needed to resolve issues related to hardware, technology integration as well as optimization algorithms [90, 91].

- **Other medical fields based on machine learning**

There are a lot of other sectors where ML is effectively used, such as recording and storing medical data [93,94], managing all medication systems [95,96], analyzing different tests [94], and correct diagnosis and treatment [97,98].

Discussion

The application of AI and ML in health care science is a very common area of research.Thousands of papers have been published in this field each year since 2012. Considerable effort is needed for researchers to keep up with the latest developments in this area, and dedicated literature reviews are necessary to save researchers time. The number of articles published in this area is essential for an in-depth review, so we proposed two criteria for selecting the articles to be examined in this study: *i)* journal articles are preferred to conference articles; *ii)* recent articles are preferred to older articles; about multiple similar articles, those with higher citation were mentioned, and new contribution and better data sets were selected for review.
Through this review paper, we found a difficulty to compare studies. This is because several ML methods are trained and validated on different datasets in a variety of studies, making results difficult to be compared with other studies. As a result, almost all studies reported better performance compared to other studies. A study presented in [99] proved that AdaBoost is the most excellent ML method. But, in other papers [100] it is demonstrated that the ANN method is more precise than

AdaBoost, SVM, and logistic regression. Other studies [55] and [58] demonstrated that the SVM was more precise than both ANN and naive Bayes. Nevertheless, the authors in [51, 52] asserted that logistic regression and linear regression classifiers had better predictive results compared to the SVM classifier. Additional conflicts appeared in other researchers' works, their writers confirmed that SVM combined with naive Bayes is more accurate than ANNs and decision trees [62]. A suitable workspace with a large-scale open-source dataset is necessary to improve comparability between studies by examining different methods on a standardized dataset.

Conclusion

In this research paper, a literature review of AI and mainly ML techniques for the health science and medical field is conducted. ML can help to supervise and decide a suitable treatment for patients. It evaluates images without any medical doctors, clinicians, or surgeons. ML-based technologies provide an assessment that facilitates predicting medical emergencies. It is useful to offer any medical consultation with a digital application. Practically, implementing such technology will improve the accuracy and performance of the diagnosis and treatment. We can apply it to reduce the medical cost and prevent diseases. It is also used to decrease unnecessary hospital appointments and answer patient questions. ML can identify problems during the unavailability of the doctor. It is helpful in the identification of the origin of the disease, and it can provide better medication for the patient. It accelerates the clinical examinations to produce a decisive result. ML creates the analytical algorithms of various features from the patientsdata, which are useful for providing knowledge about the patient and the disease degree.

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References

1. Haleem A, Javaid M, Khan IH. Current status and applications of artificial intelligence (AI) in medical field: an overview. Current Medicine Research and Practice. 2019 Nov 1;9(6):231-7.
2. Qureshi KN, Abdullah AH. Localization-based system challenges in vehicular ad hoc networks: survey. SmartCR. 2014 Dec;4(6):515-28.
3. Ullah Z, Al-Turjman F, Mostarda L, Gagliardi R. Applications of Artificial Intelligence and Machine learning in smart cities. Computer Communications. 2020March; 154 (15): 313-323. DOI: 10.1016/j.comcom.2020.02.069
4. Haleem A, Vaishya R, Javaid M Khan MI. Artificial Intelligence (AI) applications in orthopaedics: An innovative technology to embrace. Journal of Clinical Orthopaedics and Trauma. 2019; 11, S80-S81. DOI: 10.1016/j.jcot.2019.06.012
5. Lupton M. Some ethical and legal consequences of the application of artificial intelligence in the field of medicine. Trends in Medicine. 2018; 18(4): 1-7. DOI: 10.15761/TiM.1000147
6. He J, Baxter SL, Xu J, Xu J, Zhou X, Zhang K. The practical implementation of artificial intelligence technologies in medicine. Nature medicine. 2019 Jan;25(1):30-6.
7. Bashir M, Harky A. Artificial intelligence in aortic surgery: the rise of the machine. InSeminars in Thoracic and Cardiovascular Surgery 2019 Dec 1 (Vol. 31, No. 4, pp. 635-637). WB Saunders.
8. Baldominos A, Puello A, Oğul H, Aşuroğlu T, Colomo-Palacios R. Predicting Infections Using Computational Intelligence–A Systematic Review. IEEE Access. 2020 Feb 10;8:31083-102.
9. Murdoch TB, Detsky AS. The Inevitable Application of Big Data to Health Care. JAMA. 2013; 309 (13):1351–1352. DOI:10.1001/jama.2013.393
10. Yamauchi A, Ogawa Y, Maeda Y, Takeda K, Ichimasa K, Nakamura H, Yagawa Y, Toyoshima N, Ogata N, Kudo T, Hisayuki T. Artificial intelligence-assisted polyp detection for colonoscopy: initial experience. Gastroenterology. 2018;1:3.
11. Guo J, Li B. The application of medical artificial intelligence technology in rural areas of developing countries. Health equity. 2018 Aug 1;2(1):174-81.
12. Atasoy H, Greenwood BN, McCullough JS. The digitization of patient care: A review of the effects of electronic health records on health care quality and utilization. Annu Rev Public Health. 2018; 40:1. DOI: 10.1146/annurev-pub health-040218-044206.
13. Jiang F, Jiang Y, Zhi H, et al. Artificial intelligence in healthcare: past, present, and future. Stroke and Vascular Neurology 2017; 2: 230-43. DOI: 10.1136/svn-2017-000101
14. Haleem A, Javaid M. Haleem A, Javaid M. Industry 5.0 and its expected applications in medical field. Current Medicine Research and Practice. 2019; 9 (4), 167-169. DOI: 10.1016/j.cmrp.2019.07.002
15. Zhang Y, Yang J, Wang S, Dong Z, Phillips P. Pathological brain detection in MRI scanning via Hu moment invariants and machine learning. Journal of Experimental & Theoretical Artificial Intelligence. 2017 Mar 4;29(2):299-312.

16. Hashmi S. 'Coming of Age' of artificial intelligence: evolution of survivorship care through information technology. Bone Marrow Transplant. 2016; 51: 41–42. DOI: 10.1038/bmt.2015.271
17. Mintz Y, Brodie R. Introduction to artificial intelligence in medicine, Minimally Invasive Therapy & Allied Technologies 2019, 28:2, 73-81, DOI: 10.1080/13645706.2019.1575882.
18. Javaid M, Haleem A, Industry 4.0 applications in medical field: A brief review. Current Medicine Research and Practice. 2019; 9(3): 102-109. DOI: 10.1016/j.cmrp.2019.04.001
19. Kumar G, Kumar K, Sachdeva M. The use of artificial intelligence based techniques for intrusion detection: a review. Artificial Intelligence Review. 2010 Dec 1;34(4):369-87.
20. Smiti A. When machine learning meets medical world: Current status and future challenges. Computer Science Review. 2020 Aug 1;37:100280.
21. Zeng X, Luo G. Progressive sampling-based Bayesian optimization for efficient and automatic machine learning model selection. Health information science and systems. 2017 Dec 1;5(1):2.
22. Kinnings SL, Liu N, Tonge PJ, et al. A machine learning-based method to improve docking scoring functions and its application to drug repurposing. Journal of Chemical Information and Modeling 2011; 51:408–419. 28-51(2):408-19. DOI: 10.1021/ci100369f.
23. Ain QU, Aleksandrova A, Roessler FD, BallesterPJ. Machine-learning scoring functions to improve structure-based binding affinity prediction and virtual screening. Wiley Interdisciplinary Review Computational Molecular Science. 2015; 5(6):405-424. DOI: 10.1002/wcms.1225
24. Erickson BJ, Korfiatis P, Akkus Z, Kline TL. Machine Learning for Medical Imaging. Radiographics. 2017; 37(2):505-515. DOI: 10.1148/rg.2017160130
25. Li D, Madden A, Liu C, Ding Y, Qian L, Zhou E. Modelling online user behavior for medical knowledge learning. Industrial Management & Data Systems. 2018 May 14.
26. Varnek A, Baskin I. Machine learning methods for property prediction in chemoinformatic: Quo Vadis? Journal of Chemical Information and Modeling 2012, 52:1413–1437. DOI: 10.1021/ci200409x
27. Choy G, Khalilzadeh O, Michalski M, Do S, Samir AE, Pianykh OS, Geis JR, Pandharipande PV, Brink JA, Dreyer KJ. Current applications and future impact of machine learning in radiology. Radiology. 2018 Aug;288(2):318-28.
28. Roohi A, Faust K, Djuric U, Diamandis P. Unsupervised Machine Learning in Pathology: The Next Frontier. Surgical Pathology Clinics. 2020 Jun 1;13(2):349-58.
29. Saha J, Chowdhury C, Biswas S. Review of Machine Learning and Deep Learning Based Recommender Systems for Health Informatics. InDeep Learning Techniques for Biomedical and Health Informatics 2020 (pp. 101-126). Springer, Cham.
30. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nature medicine. 2019 Jan;25(1):44-56.
31. Boulos MN, Peng G, VoPham T. An overview of GeoAI applications in health and healthcare. International Journal of Health Geographics.2019; 18: 7. DoI: 10.1186/s12942-019-0171-2
32. Al-Turjman F, Nawaz MH, Ulusar UD. Intelligence in the Internet of medical things era: a systematic review of current and future trends. Computer Communications. 2020 Jan 15;150:644-60.
33. Bi WL, Hosny A, Schabath MB, Giger ML, Birkbak NJ, Mehrtash A, Allison T, Arnaout O, Abbosh C, Dunn IF, Mak RH. Artificial intelligence in cancer imaging: clinical challenges and applications. CA: a cancer journal for clinicians. 2019 Mar;69(2):127-57.
34. Shaban-Nejad A, Michalowski M, Buckeridge DL. Health intelligence: how artificial intelligence transforms population and personalized health.
35. Al-Turjman F, Zahmatkesh H, Mostarda L. Quantifying uncertainty in internet of medical things and big-data services using intelligence and deep learning. IEEE Access. 2019 Jul 29;7:115749-59.
36. Yang S, Zhou P, Duan K, Hossain MS, Alhamid MF. emHealth: towards emotion health through depression prediction and intelligent health recommender system. Mobile Networks and Applications. 2018 Apr 1;23(2):216-26.
37. Hussein AS, Omar WM, Li X, Ati M. Efficient chronic disease diagnosis prediction and recommendation system. In2012 IEEE-EMBS Conference on Biomedical Engineering and Sciences 2012 Dec 17 (pp. 209-214). IEEE.
38. Shoaib M, Bosch S, Incel OD, Scholten H, Havinga PJ. Complex human activity recognition using smartphone and wrist-worn motion sensors. Sensors. 2016 Apr;16(4):426.
39. Zhang S, Rowlands AV, Murray P, Hurst TL. Physical activity classification using the GENEA wrist-worn accelerometer.
40. Garcia-Ceja E, Brena RF, Carrasco-Jimenez JC, Garrido L. Long-term activity recognition from wristwatch accelerometer data. Sensors. 2014 Dec;14(12):22500-24.
41. LeCun Y, Bengio Y, Hinton G. Deep learning. nature. 2015 May;521(7553):436-44.
42. Acharya UR, Fujita H, Oh SL, Hagiwara Y, Tan JH, Adam M. Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals. Information Sciences. 2017 Nov 1;415:190-8.
43. So A, Hooshyar D, Park KW, Lim HS. Early diagnosis of dementia from clinical data by machine learning techniques. Applied Sciences. 2017 Jul;7(7):651.

44. Orru G, Pettersson-Yeo W, Marquand AF, Sartori G, Mechelli A. Using support vector machine to identify imaging biomarkers of neurological and psychiatric disease: a critical review. Neuroscience &Biobehavioral Reviews. 2012 Apr 1;36(4):1140-52.
45. Weakley A, Williams JA, Schmitter-Edgecombe M, Cook DJ. Neuropsychological test selection for cognitive impairment classification: a machine learning approach. Journal of clinical and experimental neuropsychology. 2015 Oct 21;37(9):899-916.
46. Payan A, Montana G. Predicting Alzheimer's disease: a neuroimaging study with 3D convolutional neural networks. arXiv preprint arXiv:1502.02506. 2015 Feb 9.
47. Chen R, Herskovits EH. Machine-learning techniques for building a diagnostic model for very mild dementia. Neuroimage. 2010 Aug 1;52(1):234-44.
48. Oliva-Felipe L, Barrué C, Cortés A, Wolverson E, Antomarini M, Landrin I, Votis K, Paliokas I, Cortés U. Health Recommender System design in the context of CAREGIVERSPRO-MMD Project. InProceedings of the 11th PErvasive Technologies Related to Assistive Environments Conference 2018 Jun 26 (pp. 462-469).
49. Tsang G, Xie X, Zhou SM. Harnessing the Power of Machine Learning in Dementia Informatics Research: Issues, Opportunities, and Challenges. IEEE Reviews in Biomedical Engineering. 2019 Mar 12;13:113-29.
50. Hosseini MP, Hosseini A, Ahi K. A Review on Machine Learning for EEG Signal Processing in Bioengineering. IEEE Reviews in Biomedical Engineering. 2020 Jan 28.
51. Rajaguru H, Prabhakar SK. Non linear ICA and logistic regression for classification of epilepsy from EEG signals. In2017 international conference of electronics, communication and aerospace technology (ICECA) 2017 Apr 20 (Vol. 1, pp. 577-580). IEEE.
52. Dora C, Biswal PK. Robust ECG artifact removal from EEG using continuous wavelet transformation and linear regression. In2016 International Conference on Signal Processing and Communications (SPCOM) 2016 Jun 12 (pp. 1-5). IEEE.
53. Murakami M, Nakatani S, Araki N, Konishi Y, Mabuchi K. Motion Discrimination from EEG Using Logistic Regression and Schmitt-Trigger-Type Threshold. In2015 IEEE International Conference on Systems, Man, and Cybernetics 2015 Oct 9 (pp. 2338-2342). IEEE.
54. Roy S, Kiral-Kornek I, Harrer S. Deep learning enabled automatic abnormal EEG identification. In2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) 2018 Jul 18 (pp. 2756-2759). IEEE.
55. Jalilifard A, Pizzolato EB, Islam MK. Emotion classification using single-channel scalp-EEG recording. In2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) 2016 Aug 16 (pp. 845-849). IEEE.
56. Huang Y, Yang J, Liao P, Pan J. Fusion of facial expressions and EEG for multimodal emotion recognition. Computational intelligence and neuroscience. 2017 Sep 19;2017.
57. Torabi A, Daliri MR, Sabzposhan SH. Diagnosis of multiple sclerosis from EEG signals using nonlinear methods. Australasian physical & engineering sciences in medicine. 2017 Dec 1;40(4):785-97.
58. Mumtaz W, Kamel N, Ali SS, Malik AS. An EEG-based functional connectivity measure for automatic detection of alcohol use disorder. Artificial intelligence in medicine. 2018 Jan 1;84:79-89.
59. Amin HU, Mumtaz W, Subhani AR, Saad MN, Malik AS. Classification of EEG signals based on pattern recognition approach. Frontiers in computational neuroscience. 2017 Nov 21;11:103.
60. Mumtaz W, Ali SS, Yasin MA, Malik AS. A machine learning framework involving EEG-based functional connectivity to diagnose major depressive disorder (MDD). Medical & biological engineering & computing. 2018 Feb 1;56(2):233-46.
61. Bigdely-Shamlo N, Vankov A, Ramirez RR, Makeig S. Brain activity-based image classification from rapid serial visual presentation. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2008 Aug 12;16(5):432-41.
62. Sharmila A, Geethanjali P. Effect of filtering with time domain features for the detection of epileptic seizure from EEG signals. Journal of medical engineering & technology. 2018 Apr 3;42(3):217-27.
63. Vijayakumar V, Case M, Shirinpour S, He B. Quantifying and characterizing tonic thermal pain across subjects from EEG data using random forest models. IEEE Transactions on Biomedical Engineering. 2017 Sep 25;64(12):2988-96.
64. Bloch E, Rotem T, Cohen J, Singer P, Aperstein Y. Machine learning models for analysis of vital signs dynamics: A case for sepsis onset prediction. Journal of healthcare engineering. 2019 Nov 3;2019.
65. Danner OK, Hendren S, Santiago E, Nye B, Abraham P. Physiologically-based, predictive analytics using the heart-rate-to-systolic-ratio significantly improves the timeliness and accuracy of sepsis prediction compared to SIRS. The American Journal of Surgery. 2017 Apr 1;213(4):617-21.
66. Lukaszewski RA, Yates AM, Jackson MC, Swingler K, Scherer JM, Simpson AJ, Sadler P, McQuillan P, Titball RW, Brooks TJ, Pearce MJ. Presymptomatic prediction of sepsis in intensive care unit patients. Clinical and Vaccine Immunology. 2008 Jul 1;15(7):1089-94.
67. Khoshnevisan F, Ivy J, Capan M, Arnold R, Huddleston J, Chi M. Recent temporal pattern mining for septic shock early prediction. In2018 IEEE International Conference on Healthcare Informatics (ICHI) 2018 Jun 4 (pp. 229-240). IEEE.

68. Ke C, Jin Y, Evans H, Lober B, Qian X, Liu J, Huang S. Prognostics of surgical site infections using dynamic health data. Journal of Biomedical Informatics. 2017 Jan 1;65:22-33.
69. Yao Y, Sun G, Matsui T, Hakozaki Y, van Waasen S, Schiek M. Multiple vital-sign-based infection screening outperforms thermography independent of the classification algorithm. IEEE transactions on biomedical engineering. 2015 Sep 17;63(5):1025-33.
70. Shankar PR, Kesari A, Shalini P, Kamalashree N, Bharadwaj C, Raj N, Srinivas S, Shivakumar M, Ulle AR, Tagadur NN. Predictive modeling of surgical site infections using sparse laboratory data. International Journal of Big Data and Analytics in Healthcare (IJBDAH). 2018 Jan 1;3(1):13-26.
71. Giuliano KK. Physiological monitoring for critically ill patients: testing a predictive model for the early detection of sepsis. American Journal of Critical Care. 2007 Mar;16(2):122-30.
72. Faggella D. Machine learning healthcare applications–2017 and beyond.
73. Chen CH. A hybrid intelligent model of analyzing clinical breast cancer data using clustering techniques with feature selection. Applied Soft Computing. 2014 Jul 1;20:4-14.
74. Eskofier BM, Lee SI, Daneault JF, Golabchi FN, Ferreira-Carvalho G, Vergara-Diaz G, Sapienza S, Costante G, Klucken J, Kautz T, Bonato P. Recent machine learning advancements in sensor-based mobility analysis: Deep learning for Parkinson's disease assessment. In2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) 2016 Aug 16 (pp. 655-658). IEEE.
75. Rello L, Romero E, Rauschenberger M, Ali A, Williams K, Bigham JP, White NC. Screening dyslexia for English using HCI measures and machine learning. InProceedings of the 2018 international conference on digital health 2018 Apr 23 (pp. 80-84).
76. Perera H, Shiratuddin MF, Wong KW, Fullarton K. EEG signal analysis of writing and typing between adults with dyslexia and normal controls. International Journal of Interactive Multimedia and Artificial Intelligence. 2018;5(1):62.
77. Hamid SS, Admodisastro N, Manshor N, Kamaruddin A, AbdGhani AA. Dyslexia adaptive learning model: student engagement prediction using machine learning approach. InInternational Conference on Soft Computing and Data Mining 2018 Feb 6 (pp. 372-384). Springer, Cham.
78. Lakretz Y, Chechik G, Friedmann N, Rosen-Zvi M. Probabilistic Graphical Models of Dyslexia. InProceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining 2015 Aug 10 (pp. 1919-1928).
79. Cui Z, Xia Z, Su M, Shu H, Gong G. Disrupted white matter connectivity underlying developmental dyslexia: a machine learning approach. Human brain mapping. 2016 Apr;37(4):1443-58.
80. Kariyawasam R, Nadeeshani M, Hamid T, Subasinghe I, Samarasinghe P, Ratnayake P. Pubudu: Deep Learning Based Screening And Intervention of Dyslexia, Dysgraphia And Dyscalculia. In2019 14th Conference on Industrial and Information Systems (ICIIS) 2019 Dec 18 (pp. 476-481). IEEE.
81. Khan RU, Cheng JL, Bee OY. Machine learning and Dyslexia: Diagnostic and classification system (DCS) for kids with learning disabilities. International Journal of Engineering & Technology. 2018;7(3.18):97-100.
82. Kaisar S. Developmental dyslexia detection using machine learning techniques: A survey. ICT Express. 2020 May 30.
83. Gray KR, Aljabar P, Heckemann RA, Hammers A, Rueckert D, Alzheimer's Disease Neuroimaging Initiative. Random forest-based similarity measures for multi-modal classification of Alzheimer's disease. NeuroImage. 2013 Jan 15;65:167-75.
84. Yu W, Na Z, Fengxia Y, Yanping G. Magnetic resonance imaging study of gray matter in schizophrenia based on XGBoost. Journal of Integrative Neuroscience. 2018 Dec 29;17(4):331-6.
85. Motwani M, Dey D, Berman DS, Germano G, Achenbach S, Al-Mallah MH, Andreini D, Budoff MJ, Cademartiri F, Callister TQ, Chang HJ. Machine learning for prediction of all-cause mortality in patients with suspected coronary artery disease: a 5-year multicentre prospective registry analysis. European heart journal. 2017 Feb 14;38(7):500-7.
86. van Rosendael AR, Maliakal G, Kolli KK, Beecy A, Al'Aref SJ, Dwivedi A, Singh G, Panday M, Kumar A, Ma X, Achenbach S. Maximization of the usage of coronary CTA derived plaque information using a machine learning based algorithm to improve risk stratification; insights from the CONFIRM registry. Journal of cardiovascular computed tomography. 2018 May 1;12(3):204-9.
87. Bebek O, Cavusoglu MC. Intelligent control algorithms for robotic-assisted beating heart surgery. IEEE Transactions on Robotics. 2007 Jun 25;23(3):468-80.
88. Wang TM, Tao Y, Liu H. Current researches and future development trend of intelligent robot: A review. International Journal of Automation and Computing. 2018 Oct 1;15(5):525-46.
89. Zhao B, Waterman RS, Urman RD, Gabriel RA. A machine learning approach to predicting case duration for robot-assisted surgery. Journal of medical systems. 2019 Feb 1;43(2):32.
90. Kooi T, Litjens G, Van Ginneken B, Gubern-Mérida A, Sánchez CI, Mann R, den Heeten A, Karssemeijer N. Large scale deep learning for computer aided detection of mammographic lesions. Medical image analysis. 2017 Jan 1;35:303-12.
91. Barbedo JG. Plant disease identification from individual lesions and spots using deep learning. Biosystems Engineering. 2019 Apr 1;180:96-107.

Pharmacophore, 10(4) 2020, Pages 139-149
92. Wang H, Jiang C, Bao K, Xu C. Recognition and clinical diagnosis of cervical cancer cells based on our improved lightweight deep network for pathological image. Journal of medical systems. 2019 Sep 1;43(9):301.
93. Sachs PB, Gassert G, Cain M, Rubinstein D, Davey M, Decoteau D. Imaging study protocol selection in the electronic medical record. Journal of the American College of Radiology. 2013 Mar 1;10(3):220-2.
94. Noorbakhsh-Sabet N, Zand R, Zhang Y, Abedi V. Artificial intelligence transforms the future of health care. The American journal of medicine. 2019 Jul 1;132(7):795-801.
95. He J, Baxter SL, Xu J, Xu J, Zhou X, Zhang K. The practical implementation of artificial intelligence technologies in medicine. Nature medicine. 2019 Jan;25(1):30-6.
96. Yu KH, Kohane IS. Framing the challenges of artificial intelligence in medicine. BMJ quality & safety. 2019 Mar 1;28(3):238-41.
97. Dilsizian SE, Siegel EL. Artificial intelligence in medicine and cardiac imaging: harnessing big data and advanced computing to provide personalized medical diagnosis and treatment. Current cardiology reports. 2014 Jan 1;16(1):441.
98. Pesapane F, Volonté C, Codari M, Sardanelli F. Artificial intelligence as a medical device in radiology: ethical and regulatory issues in Europe and the United States. Insights into imaging. 2018 Oct 1;9(5):745-53.
99. Vink JP, de Haan G. Comparison of machine learning techniques for target detection. Artificial Intelligence Review. 2015 Jan 1;43(1):125-39.
100. Ji SY, Smith R, Huynh T, Najarian K. A comparative analysis of multi-level computer-assisted decision making systems for traumatic injuries. BMC Medical Informatics and Decision Making. 2009 Dec 1;9(1):2.