Artificial intelligence in Medical Diagnosis

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Highlights

- Machine Learning is a very useful solution not only to facilitate analysis but also to save time.
- In this paper, basic concepts of the medical field and machine learning will be described.
- We will show how data analytics can help in the healthcare process.
- We will present some challenges that must be carefully studied to obtain effective solutions in medical diagnosis.

ABSTRACT

Researchers have created software to aid doctors in making decisions without directly consulting specialists due to advancements in computer technology. Software development uses many aspects of the human intellect, including logic, decision-making, experiential learning, and many others. Although the idea of artificial intelligence is not new, computer science has acknowledged it as new technology. It has been used in various fields, including industry, business, healthcare, and education. The potential of artificial intelligence approaches is examined in this research, focusing on machine learning-based medical applications—additionally, a proposed paradigm for machine learning-based medical diagnosis and prediction.

Keywords: Medical, Artificial intelligence, Healthcare, Intelligent Medical

1. INTRODUCTION

Precision medicine and health care are anticipated to benefit from artificial intelligence (AI). [1,2] The clinical and biomedical research groups are rapidly embracing this approach to create diagnostic and prognostication tools and enhance healthcare delivery efficiency. Unprecedented discoveries are being made, and those produced have received regulatory approval and entered common medical practice. [3,4,5] The curriculum for medical schools, graduate medical education, and other teaching programs inside academic hospitals across the United States and the rest of the world, however, has not yet grasped the need to educate students and trainees on this growing technology. Several expert opinions have pointed to the benefits and limitations of using ML in medicine [1,2,6,7,8,9,10]. Still, the aspect related to formally educating the younger generation of medical professionals has not been openly discussed.

1.1. Decision support in healthcare settings

Healthcare decision assistance is not an entirely new field. The potential of computer-based systems to aid healthcare professionals in decision-making has been studied for over 50 years. Several prototypes and real solutions have been implemented in the field. An algorithm created by a computer could be useful in many decisions. The identification of an illness based on medical images or signals is arguably the most typical example. This task involves classification (diseased vs. healthy case or disease A vs. disease B). The users, in this instance, are medical experts (e.g., medical doctors or radiologists). Other frequent decision-making tasks include risk assessment (the likelihood of contracting a disease or experiencing unfavorable events), forecasting hospital resource requirements and treatment outcomes, assisting with the planning of interventions (making surgery or treatment plans), or tracking a patient's condition over time to determine whether a treatment was successful or not. Many research papers have been published in the literature, ranging from modeling and expert systems techniques to statistical pattern recognition to completely data-driven (AI/ML) approaches. The following overview works are available: [30] for a full examination of the case of statistical modeling and prediction approaches; [31] for a focus more on clinical contexts; and [32] for a thorough survey of more current trends and outlooks, particularly considering advancements in AI.

Numerous phases make up the processing chain that underpins decision support tools from the perspective of data science. These include techniques that extract and choose features, deal with missing or invalid data, increase the signal-to-noise ratio, and validate input data at the "early sections" of the chain. They are often followed by more advanced classification or regression techniques that give the user the "final output." This study attempts to judge the system's performance, or the "final output," reliably and impartially.

We focus primarily on evaluating the results of supervised classification and regression algorithms because they are a crucial component of most decision support systems used in healthcare. Unsupervised methods, like clustering techniques, are frequently more relevant to exploratory research at the early stages, which typically involves visualization. This is a crucial step in solving the issue at hand, but it's frequently not as necessary to precisely quantify 'success' in terms of numbers.

1.2. Further acceptance criteria for decision support in healthcare

It should be highlighted that several other factors, in addition to performance in general, affect whether an algorithm is successfully adopted in clinical practice. Among the criteria are performance metrics like (classification) accuracy, sensitivity, specificity, and others.

- The approaches' usability by end users, which may be patients or healthcare professionals.
- Simplicity of integration into current workflows and processes.
- Compatibility and simplicity of interaction with current IT standards and infrastructures.
- Resilience (e.g., handling missing and bad data, which is particularly important with health data).
- The results' capacity to be explained and understood (black box solutions are not suitable for decision support in healthcare, in particular); and
- Concrete evidence of an impact, as demonstrated by cost-effectiveness, clinical utility, quantifiable productivity gains, or effects on quality of life.

Due to the performance measures' critical involvement in processes like diagnosis, risk assessment, and treatment planning, we have chosen to concentrate on them in this study. The other criteria, however, are just as significant and would benefit from their explanation in other tutorials.

1.3. Intelligent medical technologies

The general public has embraced intelligent medical technologies (i.e., AI-powered) in part because they enable the 4P model of medicine (Predictive, Preventive, Personalized, and Participatory) and, consequently, patient autonomy in previously impossible ways (33); smartphones, for example, are increasingly being used to fill out and distribute an electronic personal health record (34), monitor vital functions with biosensors (35), and assist in reaching op. The emergence of augmented medicine, or the application of modern medical technology to enhance various facets of clinical practice, is made possible by developing intelligent medical technologies. The Food and Drug Administration (FDA) has approved several AI-based algorithms in the last ten years; as a result, they could be used. Several other digital tools, such as surgical navigation systems for computer-assisted surgery (37), virtuality-reality continuum tools for surgery, pain management, and mental diseases, as well as AI-based technologies, enable augmented medicine (38–40).

Even though the field of augmented medicine appears to be a success with patients, it can run into some opposition from medical professionals, especially doctors. To explain this phenomenon, four frequently cited explanations should be given. First, a clear lack of fundamental and ongoing education in this field leaves people unprepared for the possibilities of digital medicine (41). Second, early healthcare process digitization, which was very different from the promise of augmented medicine, was accompanied by a sharp increase in administrative burden, primarily associated with electronic health records (42), which is now recognized as one of the primary causes of physician burnout (43). Third, even though the consensus in the research is that AI will eventually supplement physician intelligence, there is growing concern about the possibility of AI replacing doctors (44). (45, 46). Fourth, the use of AI by doctors exposes them to potential legal repercussions because there is currently no global legal framework that establishes liability in the adoption or rejection of algorithm recommendations (47).

1.4. Machine Learning

The scientific field of machine learning focuses on how computers learn from data. [11,12] It develops at the nexus of computer science's concentration on effective computing techniques and statistics' quest to infer relationships from data. The computational difficulties of creating statistical models from enormous data sets, which might contain billions or trillions of data points, motivate this union of mathematics and computer science. Computer learning processes can be divided into supervised and unsupervised learning categories. In my opinion, the difference between learning activities that physicians can already accomplish well and learning tasks where physicians have only had limited success can be helpful when thinking about how machine learning might inform the practice of medicine. We may examine various fields of medicine that have benefited from machine learning techniques or could gain from them by keeping these broad categories in mind.

1.4.1. Supervised Learning

The first objective of supervised learning is to predict a known output or target. Recurrent supervised learning problems include handwriting recognition (such as recognizing handwritten digits), classifying images of objects (e.g., is this a cat or a dog?), and document classification (e.g., is this a clinical trial about heart failure or a financial report?). Individual competitors in machine learning competitions are judged on their performance on common data sets. Notably, each of these activities is something a skilled person can complete. Therefore the computer frequently tries to mimic human performance. Classification, which requires deciding which subgroups best describe a new instance of data, and prediction, which includes estimating an unknown parameter, are the main objectives of supervised learning (such as the temperature in San Francisco tomorrow afternoon).

These techniques are used to classify the data set.

1) Supervised learning: Based on a training set of examples with appropriate targets, algorithms respond correctly to all possible inputs. Supervised learning is another term for studying models. Regression and classification are two examples of supervised learning.

Classification: It provides a Yes/No prediction, such as "Does this cookie satisfy our quality standards?" or "Is this tumor cancerous?"

Regression: It provides the "How much" and "how many" answers.

2) Unsupervised learning: No targets or correct replies are given. The unsupervised learning technique attempts to identify patterns of similarity among the input data and then uses these patterns to classify the data. This also goes by the name of the density estimate. Clustering is a component of unsupervised learning [20]. Creating clusters based on similarities is known as clustering.

3) Semi-supervised learning: This supervised learning technique falls under semi-supervised education. Unlabeled data were also used in this approach for training purposes (generally, a minimum amount of labeled data with a huge amount of unlabeled data). Unsupervised learning (learning from unlabeled data) and supervised learning are separated by semi-supervised learning (labeled data).

4) Reinforcement learning: Behaviorist psychology supports this type of learning. The algorithm informs the user when the response is incorrect but does not tell them how to fix it. Before it discovers the correct solution, it must investigate and test many options. Another name for it is "learning with a critic." It does not suggest any upgrades. Reinforcement learning differs from supervised learning in that accurate input and output sets are not offered, nor are sub-optimal actions précised. Moreover, it focuses on online performance.

5) Evolutionary Learning: This biological evolution learning can be viewed as a learning process. Biological organisms are modified to increase their chances of survival and procreation. We can utilize this model in a computer by employing the fitness concept to determine how accurate the solution is [20].

6) Deep learning: A group of algorithms form the foundation of this discipline of machine learning. These learning techniques simulate high-level abstraction in data. It employs a deep graph with multiple processing layers incorporating linear and nonlinear transformations.

What are some instances of supervised learning in the medical field? Perhaps the most frequent example that a cardiologist observes is the automated interpretation of the ECG, which uses pattern recognition to choose from a small number of diagnoses (i.e., a classification task). Automatic lung nodule detection from a chest x-ray would be an example of supervised learning in radiology. In both instances, the computer accurately approaches what a skilled doctor can already achieve.

Risk estimation frequently makes use of supervised learning. The Framingham Risk Score [13] for coronary heart disease may be the most widely applied example of supervised learning in the medical field. These risk models are used in all areas of medicine, including administering antithrombotic treatment in atrial fibrillation [14] and placing automated implanted defibrillators in hypertrophic cardiomyopathy. [15] The machine is discovering new relationships in risk modeling that are not immediately obvious to people rather than roughly approximating medical skills.

1.4.2. Unsupervised Learning

Unsupervised learning, in comparison, does not produce any predictable results. Instead, we're searching the data for naturally existing patterns or clusters. The worth of such groups learned through unsupervised learning is frequently assessed by how well they perform in subsequent supervised learning tasks (i.e., are these new patterns valuable in some way?), which is more difficult to appraise.

When might these techniques be applied in medicine? The precision-medicine initiative is perhaps the most compelling opportunity. [16] A rising movement exists to characterize disease according to pathophysiologic pathways because of the intrinsic variability in most common diseases. This could lead to new therapeutic avenues. But it won't be simple to pinpoint these pathways for complex multifactorial disorders. Let's consider how unsupervised learning might be used in cardiac disease to achieve that aim, using a diverse disorder like myocarditis as an example. One can start with a sizable sample of people with unexplained acute systolic cardiac failure that appear to be similar. Then, myocardial biopsies can be performed on them using a method like immunostaining; one can determine the cellular makeup of each sample. A count of T cells, neutrophils, macrophages, eosinophils, etc., would be one example. Then, one may check to see if there are any trends in the composition of the cells that might point to a mechanism and offer potential treatments. Similar research, however, focused on genetics and helped to identify an eosinophilic subtype of asthma, which responds specifically to a novel treatment that targets the cytokine interleukin-13 secreted by eosinophils. [18] We are solely interested in finding patterns in the data, in contrast to supervised learning, where results are expected. Treating this as a supervised learning task, such as creating a model of myocarditis mortality and categorizing patients based on risk, may completely overlook such subgroups, preventing the discovery of new disease pathways.

2. Literature survey

Algorithms for machine and deep learning are expanding quickly in the dynamic field of medicine. Much work is currently being done to improve medical applications using these algorithms to identify flaws in disease detection systems that could lead to extremely unclear medicinal treatments. Medical professionals often use machines and deep learning algorithms to forecast early disease symptoms. Convolutional networks, in particular, part of deep learning approaches, have quickly evolved a way of their own for studying medicine. It makes predictions using supervised or unsupervised algorithms using a particular standard dataset. We examine the principles of deep learning and machine learning in medical imaging. These increase accuracy in medical imaging by extracting the pertinent patterns for the condition.

These methods support the decision-making process as well. This survey aims to demonstrate how machine learning and deep learning methods are applied to medical photos. We wanted to give academics a summary of the techniques now used in medical imaging, point out the benefits and pitfalls of these algorithms, and talk about potential future possibilities. Machine and deep learning offer an exemplary method for creating classification and autonomous decision-making for analyzing multidimensional medical data. This study surveys machine learning and deep learning techniques used in medical imaging to diagnose various disorders. It considers the collection of these algorithms that may be applied to illness research and automated decision-making [19].

In a study, Vembandasamy et al. [21] used the Naive Bayes algorithm to diagnose cardiac illness. Naive Bayes makes use of the Bayes theorem. Naive Bayes has a strong independence assumption as a result. The data came from one of the top research centers for diabetes in Chennai. There are 500 patients in the data collection. Weka is employed as a tool, and classification is carried out using a 70% Percentage Split. Naive Bayes provides an accuracy of 86.419%.

Chaurasia and Pal [22] have recommended using data mining techniques to identify heart disease. For mining purposes, the WEKA data mining tool is employed, which includes several machine learning techniques. For this viewpoint, Naive Bayes, J48, and bagging are employed. Seventy-six attributes comprise the heart disease data set provided by the UCI machine learning lab. Only 11 criteria are used in the prediction process. 82.31% accuracy is provided via naive Bayes. J48 provides 84.35% accuracy. The accuracy of Bagging is 85.03%. On this data set, bagging delivers a higher categorization rate.

Parthiban and Srivatsa [23] attempted to diagnose cardiac problems in diabetic individuals by utilizing machine learning techniques. WEKA is used to apply the Naive Bayes and SVM algorithms. Five hundred patients' worth of data from Chennai's Research Institute is utilized. There are 142 persons with the condition, and 358 patients do not have it. The Naive Bayes algorithm yields an accuracy rate of 74%. The maximum accuracy, 94.60, is provided by SVM.

Tan et al. proposed.'s a hybrid strategy [24] that combines the effectiveness of the wrapper approach with the two machine-learning techniques, Genetic Algorithm (G.A) and Support Vector Machine (SVM). The data mining tools LIBSVM, and WEKA are employed in this investigation. For this project, five data sets are selected from the UC Irvine machine learning repository: iris, diabetes illness, breast cancer disease, heart disease, and hepatitis disease. Heart disease accuracy has increased to 84.07% after using a hybrid GA and SVM technique. For the diabetic data set, 78.26% accuracy was attained. For breast cancer, the accuracy is 76.20%. Hepatitis disease results in correctness of 86.12%.

Iyer et al. [25].'s work used decision trees and Naive Bayes to forecast the development of diabetic illness. When insulin is produced insufficiently or is used improperly, diseases develop. Diabetes data from the Pima Indian population were used in this study. Several tests were run with the WEKA data mining tool. This data set's percentage split (70:30) predicts more accurately than cross-validation. Using Cross Validation and Percentage Split, J48 exhibits accuracy of 74.8698% and 76.9565%, respectively. By employing PS, Naive Bayes displays 79.5652% accuracy. Algorithms that use % split testing display the highest levels of accuracy.

Sen and Dash [26] have discussed meta-learning techniques for diabetic condition diagnosis. Diabetes among Pima Indians is the subject of the data set that the machine learning lab acquired at UCI. The analysis is performed with WEKA. To determine if a patient has diabetes or not, algorithms like CART, Adaboost, Logiboost, and grading learning are utilized. Experimental findings are compared to determine if the classification is right or erroneous. The accuracy of CART is 78.646%. The Adaboost achieves 77.864% accuracy. The accuracy rate provided by Logiboost is 77.479%. The classification accuracy rate for grading is 66.406%. CART has a misclassification rate of 21.354% and the best accuracy of 78.646%, with a lower misclassification rate than other approaches.

The experimental work of Kumari and Chitra [27] aims to forecast the development of diabetic illness. SVM is a machine learning approach that the researcher is using in this experiment. In SVM, the RBF kernel is utilized for classification. The University of California, Irvine's machine learning lab offers data collection on diabetes in Pima Indians. To experiment, MATLAB 2010a is used. SVM provides an accuracy of 78%.

It has been recommended by Sarwar and Sharma [28] to use Naive Bayes to predict Type-2 diabetes. There are three forms of diabetes. Type-1 diabetes, Type-2 diabetes, and gestational diabetes fall under this category. Insulin resistance is the cause of type 2 diabetes. The data set includes 415 cases, and for variety's sake, information was obtained from various Indian societal subgroups. The model is developed using MATLAB and a SQL server. Naive Bayes predicts correctly 95% of the time.

Ephzibah [29] has developed a model for identifying diabetes. The proposed model combines fuzzy logic with GA. It is employed to improve classification accuracy and choose the optimal subset of characteristics. The dataset for the experiment is taken from the UCI Machine Learning Laboratory and has eight attributes and 769 examples. Implementation is performed using MATLAB. Only three of the top characteristics or traits are chosen using a genetic algorithm. The fuzzy logic classifier uses these three features, which offer 87% accuracy. The cost has been reduced by almost 50%.

3. Discussion

For example, whole-slide pathology [50], X-ray [51], diabetes [52, 53], breast cancer [54], heart [55], time series [56], medicinal plants [57], stock market [58], stroke [59], etc., have all been successfully analysed using medical images and deep learning [48]. Machine learning-based big data analysis offers several benefits for assimilating and assessing massive amounts of complex healthcare data. However, to effectively employ machine learning techniques in healthcare, several challenges, including their ethical application and clinical execution, must be taken into account.

Machine learning has several advantages over conventional biostatistical approaches, including flexibility and scalability. As a result, it may be used for various tasks, including risk stratification, diagnosis and classification, and survival forecasts. The capability of machine learning algorithms to analyze many data sources, including free-text notes from clinicians, laboratory results, demographic data, and imaging data, and incorporate them into forecasts for disease risk, diagnosis, prognosis, and appropriate treatments, is another benefit. Despite these benefits, machine learning in healthcare delivery poses special difficulties that call for data pre-processing, model training, and system improvement about the relevant clinical issue. Ethical considerations, such as medico-legal ramifications, clinicians' familiarity with machine learning techniques, and data protection and security, are also very important. This Review discusses some of the benefits and challenges of big data and machine learning in health care.

4. Conclusion

The paper gives a historical, current-state-of-the-art, and outlook on some potential future trends in this area of applied artificial intelligence sector of the development of intelligent data analysis in medicine. The study instead highlights several subareas and directions that, in my opinion, appear to be crucial for using machine learning in medical diagnostics but do not aim to present an exhaustive review. In This paper emphasized the historical study's naïve Bayesian classifier, neural networks, and decision trees. This study compared a few algorithms from machine learning as they are used to perform various diagnostic tasks in medicine.

Author Contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

Conflict of Interest

The authors declare that the research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

REFERENCES

[1] Obermeyer, Z. & Emanuel, E. J. Predicting the future - big data, machine learning, and clinical medicine. N. Engl. J. Med. 375, 1216–1219 (2016).
[2] Darcy, A. M., Louie, A. K. & Roberts, L. W. Machine learning and the profession of medicine. JAMA 315, 551–552 (2016).
[3] Gulshan, V. et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA 316, 2402–2410 (2016).
[4] Ting, D. S. W. et al. Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes. JAMA 318, 2211–2223 (2017).
[5] FDA permits marketing of artificial intelligence-based device to detect certain diabetes-related eye problems, https://www.fda.gov/NewsEvents/Newsroom/PressAnnouncements/ucm604357.htm (2018).
[6] Chen, J. H. & Asch, S. M. Machine learning and prediction in medicine - beyond the peak of inflated expectations. N. Engl. J. Med. 376, 2507–2509 (2017).
[7] AI diagnostics need attention. Nature 555, 285 (2018) https://www.ncbi.nlm.nih.gov/pubmed/29542717.
[8] Obermeyer, Z. & Lee, T. H. Lost in thought - the limits of the human mind and the future of medicine. N. Engl. J. Med. 377, 1209–1211 (2017).
[9] Beam, A. L. & Kohane, I. S. Big data and machine learning in health care. JAMA https://doi.org/10.1001/jama.2017.18391 (2018).
[10] Cabitza, F., Rasoini, R. & Gensini, G. F. Unintended consequences of machine learning in medicine. JAMA 318, 517–518 (2017).
[11] Hastie T, Tibshirani R, Friedman J. The Elements of Statistical Learning. New York, NY: Springer Science & Business Media; 2009.CrossrefGoogle Scholar
[12] Abu-Mostafa YS, Magdon-Ismail M, Lin HT. Learning From Data. AMLbook.com; 2012. Google Scholar
[13] Kannel WB, Doyle JT, McNamara PM, Quickenton P, Gordon T. Precursors of sudden coronary death. Factors related to the incidence of sudden death.Circulation. 1975; 51:606–613.LinkGoogle Scholar
[14] Lip GY, Nieuwlaat R, Pisters R, Lane DA, Crijns HJ. Refining clinical risk stratification for predicting stroke and thromboembolism in atrial fibrillation using a novel risk factor-based approach: the Euro Heart Survey on atrial fibrillation.Chest. 2010; 137:263–272. doi: 10.1378/chest.09-1584.CrossrefMedlineGoogle Scholar
[15] O'Mahony C, Jichi F, Pavlou M, Monserrat L, Anastasakis A, Rapezzi C, Biagini E, Gimeno JR, Limongelli G, McKenna WJ, Omar RZ, Elliott PM; Hypertrophic Cardiomyopathy Outcomes Investigators. A novel clinical risk prediction model for sudden cardiac death in hypertrophic cardiomyopathy (HCM risk-SCD).Eur Heart J. 2014; 35:2010–2020. doi: 10.1093/eurheartj/eht439.CrossrefMedlineGoogle Scholar
[16] National Research Council (US) Committee on a Framework for Developing a New Taxonomy of Disease. Toward Precision Medicine: Building a Knowledge Network for Biomedical Research and a New Taxonomy of Disease. Washington, DC: National Academies Press; 2011.Google Scholar
[17] Woodruff PG, Modrek B, Choy DF, Jia G, Abbas AR, Ellwanger A, Koth LL, Arron JR, Fahy JV. T-helper type 2-driven inflammation defines major subphenotypes of asthma.Am J Respir Crit Care Med. 2009; 180:388–395. doi: 10.1164/rccm.200903-0392OC.CrossrefMedlineGoogle Scholar

[18] Corren J, Lemanske RF, Hanania NA, Korenblat PE, Parsey MV, Arron JR, Harris JM, Scheerens H, Wu LC, Su Z, Mosesova S, Eisner MD, Bohen SP, Matthews JG. Lebrikizumab treatment in adults with asthma.N Engl J Med. 2011; 365:1088–1098. doi: 10.1056/NEJMoa1106469.CrossrefMedlineGoogle Scholar.
[19] Latif, J., Xiao, C., Imran, A., & Tu, S. (2019, January). Medical imaging using machine learning and deep learning algorithms: a review. In 2019 2nd International conference on computing, mathematics and engineering technologies (iCoMET) (pp. 1-5). IEEE.
[20] Marshland, S. (2009) Machine Learning an Algorithmic Perspective. CRC Press, New Zealand, 6-7. [Citation Time(s):2]
[21] Vembandasamy, K., Sasipriya, R. and Deepa, E. (2015) Heart Diseases Detection Using Naive Bayes Algorithm. IJISET-International Journal of Innovative Science, Engineering & Technology, 2, 441-444. [Citation Time(s):1]
[22] Chaurasia, V. and Pal, S. (2013) Data Mining Approach to Detect Heart Disease. International Journal of Advanced Computer Science and Information Technology (IJACSIT), 2, 56-66. [Citation Time(s):1]
[23] Parthiban, G. and Srivatsa, S.K. (2012) Applying Machine Learning Methods in Diagnosing Heart Disease for Diabetic Patients. International Journal of Applied Information Systems (IJAIS), 3, 25-30. [Citation Time(s):1]
[24] Tan, K.C., Teoh, E.J., Yu, Q. and Goh, K.C. (2009) A Hybrid Evolutionary Algorithm for Attribute Selection in Data Mining. Journal of Expert System with Applications, 36, 8616-8630.
[25] https://doi.org/10.1016/j.eswa.2008.10.013 [Citation Time(s):1]
[26] Iyer, A., Jeyalatha, S. and Sumbaly, R. (2015) Diagnosis of Diabetes Using Classification Mining Techniques. International Journal of Data Mining & Knowledge Management Process (IJDKP), 5, 1-14.
[27] https://doi.org/10.5121/ijdkp.2015.5101 [Citation Time(s):1]
[28] Sen, S.K. and Dash, S. (2014) Application of Meta Learning Algorithms for the Prediction of Diabetes Disease. International Journal of Advance Research in Computer Science and Management Studies, 2, 396-401. [Citation Time(s):1]
[29] Kumari, V.A. and Chitra, R. (2013) Classification of Diabetes Disease Using Support Vector Machine. International Journal of Engineering Research and Applications (IJERA), 3, 1797-1801. [Citation Time(s):1]
[30] Sarwar, A. and Sharma, V. (2012) Intelligent Naive Bayes Approach to Diagnose Diabetes Type-2. Special Issue of International Journal of Computer Applications (0975-8887) on Issues and Challenges in Networking, Intelligence and Computing Technologies-ICNICT 2012, 3, 14-16. [Citation Time(s):1]
[31] Ephzibah, E.P. (2011) Cost Effective Approach on Feature Selection using Genetic Algorithms and Fuzzy Logic for Diabetes Diagnosis. International Journal on Soft Computing (IJSC), 2, 1-10.
[32] https://doi.org/10.5121/ijsc.2011.2101 [Citation Time(s):1]
[33] E. Steyerberg, Clinical Prediction Models: a Practical Approach to Development, Validation, and Updating
[34] 19, Springer-Verlag, Cham (2009)
[35] E.S. Berner (Ed.), Clinical Decision Support Systems: Theory and Practice, Health Informatics (2 edition), Springer-Verlag, New York (2007)
[36] Google Scholar
[37] E. Topol, Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again
[38] Basic Books (2019)
[39] Orth M, Averina M, Chatzipanagiotou S, Faure G, Haushofer A, Kusec V, et al. Opinion: redefining the role of the physician in laboratory medicine in the context of emerging technologies, personalised medicine and patient autonomy ('4P medicine'). J Clin Pathol. (2019) 72:191–7. doi: 10.1136/jclinpath-2017-204734
[40] Abdulnabi M, Al-Haiqi A, Kiah MLM, Zaidan AA, Zaidan BB, Hussain M. A distributed framework for health information exchange using smartphone technologies. J Biomed Informat. (2017) 69:230–50. doi: 10.1016/j.jbi.2017.04.013
[41] Topol EJ. A decade of digital medicine innovation. Sci Trans Med. (2019) 11:7610. doi: 10.1126/scitranslmed.aaw7610
[42] Morawski K, Ghazinouri R, Krumme A, Lauffenburger JC, Lu Z, Durfee E, et al. Association of a smartphone application with medication adherence and blood pressure control: the MedISAFE-BP randomized clinical trial. JAMA Int Med. (2018) 178:802–9. doi: 10.1001/jamainternmed.2018.0447
[43] Overley SC, Cho SK, Mehta AI, Arnold PM. Navigation and robotics in spinal surgery: where are we now? Neurosurgery. (2017) 80:S86–99. doi: 10.1093/neuros/nyw077

[44] Tepper OM, Rudy HL, Lefkowitz A, Weimer KA, Marks SM, Stern CS, et al. Mixed reality with HoloLens: where virtual reality meets augmented reality in the operating room. Plast Reconstruct Surg. (2017) 140:1066–70. doi: 10.1097/PRS.0000000000003802

[45] Mishkind MC, Norr AM, Katz AC, Reger GM. Review of virtual reality treatment in psychiatry: evidence versus current diffusion and use. Curr Psychiat Rep. (2017) 19:80. doi: 10.1007/s11920-017-0836-0

[46] Malloy KM, Milling LS. The effectiveness of virtual reality distraction for pain reduction: a systematic review. Clin Psychol Rev. (2010) 30:1011–8. doi: 10.1016/j.cpr.2010.07.001

[47] Haag M, Igel C, Fischer MR, German Medical Education Society (GMA) "Digitization-Technology-Assisted Learning and Teaching" joint working group "Technology-enhanced Teaching and Learning in Medicine (TeLL)" of the german association for medical informatics biometry and epidemiology (gmds) and the German Informatics Society (GI). Digital teaching and digital medicine: a national initiative is needed. GMS J Med Educ. (2018) 35:Doc43. doi: 10.3205/zma001189

[48] Chaiyachati KH, Shea JA, Asch DA, Liu M, Bellini LM, Dine CJ, et al. Assessment of inpatient time allocation among first-year internal medicine residents using time-motion observations. JAMA Int Med. (2019) 179:760–7. doi: 10.1001/jamainternmed.2019.0095

[49] West CP, Dyrbye LN, Shanafelt TD. Physician burnout: contributors, consequences and solutions. J Int Med. (2018) 283:516–29. doi: 10.1111/joim.12752

[50] Shah NR. Health care in 2030: will artificial intelligence replace physicians? Ann Int Med. (2019) 170:407–8. doi: 10.7326/M19-0344

[51] 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

[52] Verghese A, Shah NH, Harrington RA. What this computer needs is a physician: humanism and artificial intelligence. JAMA. (2018) 319:19–20. doi: 10.1001/jama.2017.19198

[53] Price WN, Gerke S, Cohen IG. Potential liability for physicians using artificial intelligence. JAMA. (2019) 322:1765–6. doi: 10.1001/jama.2019.15064.

[54] Abdollahi, J. A review of Deep learning methods in the study, prediction and management of COVID-19. 10 th International Conference on Innovation and Research in Engineering Science

[55] Abdollahi, J., Nouri-Moghaddam, B., & Ghazanfari, M. (2021). Deep Neural Network Based Ensemble learning Algorithms for the healthcare system (diagnosis of chronic diseases). arXiv preprint arXiv:2103.08182. https://doi.org/10.48550/arXiv.2103.08182

[56] Abdollahi, J., Davari, N., Panahi, Y., & Gardaneh, M. (2022). Detection of metastatic breast cancer from whole-slide pathology images using an ensemble deep-learning method. Archives of Breast Cancer.

[57] Abdollahi, J., & Mahmoudi, L. (2022, February). An Artificial Intelligence System for Detecting the Types of the Epidemic from X-rays: Artificial Intelligence System for Detecting the Types of the Epidemic from X-rays. In 2022 27th International Computer Conference, Computer Society of Iran (CSICC) (pp. 1-6). IEEE. DOI: 10.1109/CSICC55295.2022.9780523

[58] Abdollahi, J., Moghaddam, B. N., & Parvar, M. E. (2019). Improving diabetes diagnosis in smart health using genetic-based Ensemble learning algorithm. Approach to IoT Infrastructure. Future Gen Distrib Systems J, 1, 23-30.

[59] Abdollahi, J., Nouri-Moghaddam, B. Hybrid stacked ensemble combined with genetic algorithms for diabetes prediction. Iran J Comput Sci (2022). https://doi.org/10.1007/s42044-022-00100-1

[60] Abdollahi, J., Keshandehghan, A., Gardaneh, M., Panahi, Y., & Gardaneh, M. (2020). Accurate detection of breast cancer metastasis using a hybrid model of artificial intelligence algorithm. Archives of Breast Cancer, 22-28. https://doi.org/10.32768/abc.20207122-28

[61] Abdollahi, J., Nouri-Moghaddam, B. A hybrid method for heart disease diagnosis utilizing feature selection based ensemble classifier model generation. Iran J Comput Sci (2022). https://doi.org/10.1007/s42044-022-00104-x

[62] Abdollahi, J., Irani, A. J., & Nouri-Moghaddam, B. (2021). Modeling and forecasting Spread of COVID-19 epidemic in Iran until Sep 22, 2021, based on deep learning. arXiv preprint arXiv:2103.08178. https://doi.org/10.48550/arXiv.2103.08178

[63] Abdollahi, J. (2022, February). Identification of Medicinal Plants in Ardabil Using Deep learning: Identification of Medicinal Plants using Deep learning. In 2022 27th International Computer Conference, Computer Society of Iran (CSICC) (pp. 1-6). IEEE. DOI: 10.1109/CSICC55295.2022.9780493

[64] Abdollahi, J., & Mahmoudi, L. Investigation of artificial intelligence in stock market prediction studies. 10 th International Conference on Innovation and Research in Engineering Science

[65] Amani F, Abdollahi J, mohammadnia alireza, amani paniz, fattahzadeh-ardalani ghasem. Using Stacking methods based Genetic Algorithm to predict the time between symptom onset and hospital arrival in stroke patients and its related factors. JBE. 2022;8(1):8-23.