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REVIEW ARTICLE

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Reviewing the Impact of Machine Learning on Disease Diagnosis and Prognosis: A Comprehensive Analysis

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Abstract:

Aim: This study aimed to explore how machine learning algorithms can enhance medical diagnostics through the analysis of illness imagery and patient data, assessing their effectiveness and potential to improve diagnostic accuracy and early disease detection.

Background: This study highlights the critical role of machine learning in healthcare, particularly in medical diagnostics. By leveraging advanced algorithms to analyse medical data and images, machine learning enhances disease detection and diagnosis, contributing significantly to improved patient outcomes and the advancement of precision medicine.

Objective: The objective of this study was to thoroughly analyse and evaluate the efficacy of machine learning algorithms in medical diagnostics, focusing on their application in interpreting illness images and patient data. The goal was to ascertain the algorithms' accuracy in disease diagnosis and prognosis, aiming to demonstrate their potential in revolutionizing healthcare through improved diagnostic precision and early disease detection.

Methods: A systematic approach has been used in this study to evaluate machine learning algorithms' effectiveness in diagnosing diseases from medical images and data. It involved selecting pertinent datasets, applying and comparing models, like SVM and K-nearest neighbors, and assessing their diagnostic accuracy and performance, aiming to identify the most effective methodologies in medical diagnostics.

Results: The results have highlighted the varying accuracy of machine learning algorithms in medical diagnostics, with a focus on the performance of models, such as SVM and K-nearest neighbors. A comparative analysis has illustrated the differential effectiveness of these algorithms across various diseases and datasets, underscoring their potential to enhance healthcare diagnostics.

Conclusion: The study has concluded that machine learning algorithms have significantly improved medical diagnostics, offering varied effectiveness across different conditions. Their potential to revolutionize healthcare is evident, with enhanced diagnostic accuracy and efficiency. Ongoing research and clinical application are essential to harness these technologies' full benefits.

Keywords: Machine learning, Algorithms, Disease diagnosis, Image-based disorders, Human , Disease , Health system.

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1. INTRODUCTION

Machine Learning (ML) is a subfield of Artificial Intelligence (AI) that leverages algorithms to acquire knowledge from data. It is characterised by its ability to autonomously enhance its performance by making modifications during the learning process [1, 2]. Machine Learning (ML) has shown its effectiveness in a wide range of domains, including but not limited to robotics, education, travel, and health care. Machine Learning (ML) techniques are mostly used in the healthcare field with the objective of illness diagnosis. Machine learning procedures were acquainted with the field of medical care during the 1970s, harmonizing with the foundation of the global magazine Artificial Intelligence in Medication in 1980 [3].

The scientific and technological field of Artificial Intelligence (AI) is a branch of computer science that aims to create systems capable of performing tasks that normally require human intelligence. These tasks can range from recognizing speech to making decisions, translating languages, and detecting patterns. AI systems are based on algorithms and models that provide them with the capability to learn from data and respond as if they were actually making decisions [4, 5]. Machine Learning (ML), on the other hand, falls under the broader category of AI; it emphasizes algorithms and statistical models that enable computers to execute tasks without specific instructions. Instead, such systems acquire knowledge and generate predictions or decisions through the use of data. Machine learning involves algorithms that are trained with substantial volumes of data, which progressively tune their parameters leading to better accuracy without any involvement of human beings [6, 7].

AI and ML are intrinsically related. AI is the overarching concept of achieving autonomous machine functionality, and ML acts as the resource for creating the techniques that power these AI systems. By studying data to make sense of patterns, ML algorithms continue evolving, learning with each iteration to perform better and faster at tasks traditionally carried out by humans. This self-learnability is what makes AI systems more intelligent over time; thus, ML is central to AI progress because it helps transform AI technology into reality. Thus, ML does not stand alone under the umbrella of AI, but is also a kind of engine or source code that drives such intellectual capabilities beyond human perception [8, 9].

The clinical picture of chronic pain is a complex and stubborn entity that claims millions of lives around the world, causing heavy casualties on one's quality of life. Unlike acute pain that is typically intended to serve as a short-term warning sign of physical damage or illness, chronic pain endures for several months or, more often, years. Sometimes it might continue long after the wound has healed. Possible reasons for its development are numerous, including arthritis, nerve damage, back injuries, fibromyalgia, and ailments, such as migraines and diabetes [10].

The union of Artificial Intelligence (AI) and Machine Learning (ML) with chronic pain control as their platform describes a radical forward stride in medicine. When huge quantities of information need to be analyzed, AI and ML algorithms are very good at detecting latent patterns that might not be noticeable at first glance by human observers, such as patient records or imaging. This skill is particularly important for chronic pain because this condition is intricate and most often defies direct diagnostic techniques. By using AI and ML, medical specialists can offer exact diagnoses and custom-designed treatment strategies leading to better results for individuals suffering from chronic pain [11].

Both of these advancements have not only improved the efficiency of medical diagnostics, but also provided better resource distribution, particularly in regions where health facilities are scarce. In this way, AI and ML have not been merely added to existing medical procedures, but they have completely changed the way chronic pain is dealt with, giving hope for more effective care for patients and increased productivity. By situating AI within the specific context of pain management, researchers and practitioners can gain a nuanced understanding of how these technologies can be harnessed to improve diagnostic accuracy, personalize treatment plans, and enhance patient outcomes [12]. In a domain where precision and individualized care are paramount, AI's potential to analyse vast datasets, identify patterns, and predict patient responses offers a transformative avenue for advancing pain treatment. Moreover, integrating discussions of AI into the narrative of pain management can encourage innovation and interdisciplinary collaboration in tackling one of the most challenging and pervasive medical issues [13].

In the sphere of pain management, the main goal of this paper was to cover all aspects of applying machine learning algorithms. Based on an extensive literature review, this research aimed to demonstrate how diverse ML techniques are currently employed for mining data related to patient records and medical imaging. Such an analysis can be applied to improve the diagnostic procedures implemented in relation to painful disorders, such as cancer, within the healthcare industry [14]. Furthermore, the article has elaborated on the transformative capability of machine learning and pointed out that it can play a major part in completely reinventing the diagnostic procedures and treatment approaches employed for pain disorders. This study has not just evaluated how well these algorithms work, but also evaluated their effect on the effectiveness and efficiency of strategies used in pain management, opening up an avenue for better customized care with a more prompt response [15].

2. MACHINE LEARNING IN DISEASE DIAGNOSIS

2.1. The Method/process of using ML in the Clinical Diagnosis of a Disease

Machine learning methods, as depicted in Fig. (**1**), play a pivotal role in the diagnosis of a range of disorders, including cancer, diabetes, and heart and skin diseases. These techniques enhance the diagnostic process by significantly improving speed, accuracy, and reliability. Among the various machine learning approaches, decision trees are lauded for their simplicity and intuitiveness. However, more sophisticated methods, like Support Vector Machine (SVM) and Artificial Neural Networks (ANN), are increasingly preferred due to their enhanced predictive capabilities [16, 17].

Furthermore, the utility of machine learning extends beyond traditional diagnosis, impacting fields, such as proteomics and genomics. For instance, machine learning algorithms are instrumental in predicting protein functions and gene expression, offering insights that are not reliant on the protein's sequence or structure. This independence from traditional homology-based methods represents a significant advancement in machine learning, driving research efforts toward developing innovative strategies for protein function prediction. Such advancements underscore the broader trend of leveraging machine learning to achieve more accurate and efficient outcomes in various biomedical applications [18, 19].

The process of medical diagnosis is a difficult effort that is generally known as an empirical activity, but it is little understood as a cognitive task [20]. Therefore, despite the seeming complexity of the process, diagnosis utilising a computer, or more specifically, using ML in this instance, is broken down into several stages. Data collection is the initial stage in the process of illness diagnosis. This data could come in a variety of formats, such as clinical data from a medical interview, demographic information, imaging data, speech data, patient history data, or even heart sounds [21, 22]. This list is not exhaustive. Processing is the next step that must be employed. In this stage, the data are prepared; for example, dealing with missing values, reducing the dimensionality of the data, and addressing noisy data are all done in that phase. The next step is to determine the target variable as well as the predictors. After that, one of those models is trained using this data by having it fed into it. After the model has been educated, it may subsequently be used for diagnostic work [23, 24].

3. MACHINE LEARNING TECHNIQUES OR ALGORITHMS IN DISEASE DIAGNOSIS AND PROGNOSIS

To detect the diseases, a variety of algorithms based on machine learning are applied. The majority of them are given below.

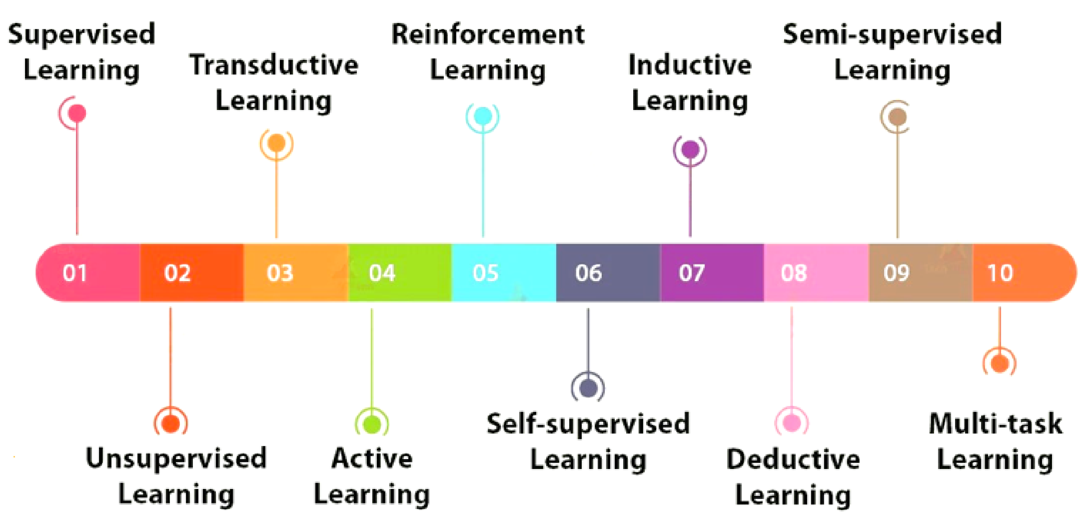

FIg. (1). Types of ML.

3.1. K Nearest Neighbors (KNN) Algorithm

The K-nearest Neighbors (KNN) algorithm is a popular and straightforward machine learning model that is often used for tasks, such as classification, pattern recognition, and regression. The K-nearest Neighbors (KNN) algorithm identifies neighboring data items by calculating the Euclidean distance between them. The method in question is often used in the context of classification and regression issues [25]. The constant k, as set by the user, plays a crucial role in identifying comparable feature instances to the new case. By using k, all relevant examples within the same category may be identified and analyzed to determine the new case's characteristics [26]. Hence, the selection of the K value has utmost importance since it might potentially result in overfitting of the system when K is too small. There are several restrictions, notably the suboptimal performance shown in scenarios when the training dataset is big. The computational expense is substantial due to the need to calculate the distances between all training samples and each query instance [27].

3.2. K-means Clustering Algorithm

The unsupervised learning method known as K-means is frequently used for clustering data based on nearest neighbors. According to their commonalities, the data can be clustered into K categories. For this procedure to be effective, the value of K, an integer, must be known. Since K-means can determine the most likely cluster for new data by analyzing the distribution of distances among them, it has become the most popular clustering method [28]. After randomly picking K cluster centroids, each data point is then reassigned to the center of the cluster that is physically closest to it. K-means suffers from the influence of its centroid in some situations, making it more susceptible to noise and outliers.

The K-means method is advantageous due to its ease of implementation, intuitive nature, and low computational overhead. It may be challenging to estimate K values, which is a potential drawback of this approach. Round clusters are less effective. A visual representation of the K-means method is provided in Fig. (**2**). Two categories of goods exist in the first stage. As a result, they end up with two hubs. With the help of the centroid, the original clusters in the different datasets can be reconstructed. Clusters are optimized by repeating this process [29].

4. MACHINE LEARNING-BASED DISEASE DIAGNOSIS (MLBDD)

Machine Learning (ML) techniques are widely used by both academics and practitioners for illness diagnosis. This section provides an overview of several Machine Learning-based Disease Diagnostics (MLBDD) techniques that have garnered significant interest due to their significance and gravity. This discourse quickly addresses severe ailments, including heart disease, renal illness, breast cancer, diabetes, Parkinson's disease, Alzheimer's disease, and COVID-19 [30]. Conversely, other diseases are concisely mentioned under the category of “other disease.”

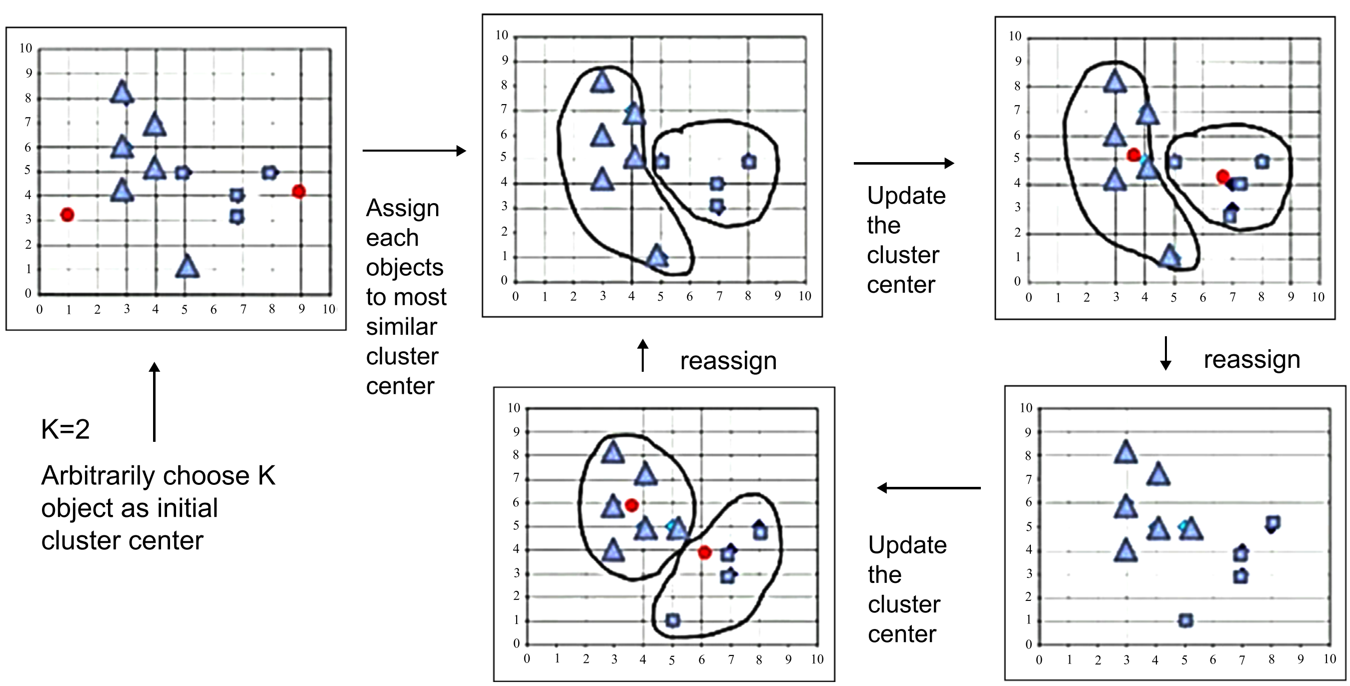

FIg. (2). The procedure of clustering with K-means.

4.1. Heart Disease

Most research institutions and medical practices today use Machine Learning (ML)-based diagnostic methods for heart disease [31]. For instance, a study [32] demonstrated a neuro-fuzzy integrated systems-based automated coronary heart disease detection system. This method is around 89% effective in most situations. The study had significant gaps in its description of the suggested method's performance under varying conditions, such as multiclass classification, massive data processing, and unequal class distribution. As a corollary, there is little evidence to support the accuracy of claims made about the model, despite the fact that such claims are increasingly promoted in the medical domains, mostly for the benefit of users outside of the medical domains. This is done so that consumers who are not medical professionals can comprehend the process. The authors of a study [33] used methods based on deep convolutional neural networks to identify abnormal heart sounds. For the 2016 PhysioNet computing competition, the model was put through its paces. They came in second place overall with a final forecast precision of 0.96 and a recall of 94.5.

4.2. Kidney Disease

Nephropathy and kidney damage are both included in the broader category of kidney disease, also known as renal disease. Those who have been diagnosed with renal disease and are not given immediate treatment are at an increased risk of developing renal failure if their renal functional capacity decreases. About 10% of the world's population suffers from Chronic Kidney Disease (CKD), and due to a lack of adequate treatment, CKD contributes significantly to global mortality rates. Recent advances in Machine Learning (ML) and Deep Learning (DL) may offer hope to countries with less access to diagnostic testing for renal illness. Several Machine Learning (ML) approaches, including K-nearest Neighbor (KNN), Support Vector Machine (SVM), Logistic Regression (LR), and decision tree classifiers, were evaluated using publicly accessible datasets in a study [34]. Accuracy rates of 98.1%, 98.3%, 96.55%, and 94.8% were achieved with these methods. In 2022, Garai *et al*. [35] conducted studies with a similar objective. Using a dataset named Chronic Kidney Disease (CKD) that had been utilized in a prior work, the researchers conducted an experiment to assess numerous machine learning algorithms, such as Recursive Partitioning and Regression Trees (RPART), SVM, Logistic Regression (LOGR), and Multi-layer Perception (MLP). According to the findings, MLP's accuracy in recognizing cases of chronic renal disease was the greatest at 98.1%. In order to determine whether or not chronic renal illness is present [36], a wide variety of data from many sources has been employed. Accuracy levels between 87% and 99% were attained by the suggested model, called the Heterogeneous Modified Artificial Neural Network (HMANN).

4.3. Breast Cancer

Numerous academics within the medical domain have put up the proposition of utilizing Machine Learning (ML) techniques for the purpose of breast cancer analysis, with the aim of addressing the challenge of early-stage detection. A study [37] suggested computer-aided diagnostic techniques for breast cancer classification using fuzzy logic. One notable benefit of fuzzy logic in comparison to traditional machine learning approaches is its ability to reduce computing complexity while emulating the thinking and approach of an expert radiologist. An algorithm develops cancer classification based on the user's preferred method when given input criteria, including contour, form, and density. Goswami's (2022) model showed around 83.34% accuracy rate. An even number of images were employed in the experiment, which resulted in better precision and consistency. A study [38] presented a set of hybrid techniques combining K-means Clustering (KMC) and Support Vector Machine (SVM) for the diagnosis of breast cancer. Applying the proposed model to the Wisconsin Diagnostic Breast Cancer (WDBC) dataset resulted in an accuracy of 97.38%, greatly reducing the difficulties associated with dimensions (Table **1**).

4.4. Diabetes

More than 382 million people worldwide have diabetes, and that number is anticipated to climb to 629 million by 2045 [43], as reported by the International Diabetes Federation (IDF). Numerous papers have been written about utilising ML techniques to diagnose diabetes. To identify individuals with diabetes mellitus, various Machine Learning (ML) models, including J48 Decision Tree, KNN, Random Forest (RF), and Support Vector Machine (SVM), have been examined [44]. Both the KNN (K = 1) and RF models have performed nearly optimally in the experiment with the UCI Diabetes dataset. The study has limitations due to the fact that it was conducted using a modified diabetes dataset having only eight features that can be split into two categories. Thus, it should come as no surprise that a less stringent collection may be entirely reliable. No consideration has been given to how the algorithms might have influenced the forecast or how a layperson might have interpreted the result. A diagnostic tool, Clinical Decision Support System (CDSS), was created to assist in diabetes diagnosis [45]. Support Vector Machine (SVM), Random Forest (RF), and a deep Convolutional Neural Network (CNN) were used to accomplish this. With an accuracy of 83.67%, RF outperformed all other algorithms, including SVM (65.38%) and Deep Learning (DL) (76.81%) (Table **2**).

Although the details of chronic pain development are not clear yet, it is hypothesized that these changes involve some alterations in the functioning of the nervous system resulting in its hypersensitivity towards pain signals. The said process is often called “central sensitization”, where even slight harm may trigger overwhelming pain. In addition to this, chronic pain can form a vicious cycle where the nervous system continuously becomes more and more efficient at sensing pain, lowering the threshold for what is considered painful. It is not easy to manage chronic pain, and in most cases, a comprehensive plan has to be established to tackle this issue.

Table 1. Studies on the diagnosis of breast cancer disease using machine learning.

Authors	Disease Discussed	ML Algorithm	Dataset	Performance Evaluation
R. Aggarwal, S. Tiwari, and V. Joshi (2022) [39]	Breast cancer	NB, BN, RF, and DT (C4.5)	BCSC	ROC: 0.937 (BN)
Abdel-Nasser M. *et al*. (2015) [40]	Classifying breast mass and density	SVM	Mini-MIAS, INBreast	Mini-MIAS: 99% accuracy, 0.9325 AUC
Sharma, S.; Khanna, P. (2015) [41]	Classifying vector characteristics as malignant or non-malignant	SVM	IRMA, DDSM	IRMA: 98.5% precision, 93.7% recall; DDSM: 96.2% precision, 96.5% recall
Sajid *et al*. (2023) [42]	Tumour size classification for breast cancer	LR-ANN	156 privately owned cases	Accuracy: 80.5%, precision: 83.6%, recall: 79.4%, and AUC: 0.855

Table 2. Studies on diabetes disease using machine learning.

Authors	Disease discussed	ML algorithm	Dataset	Performance Evaluation
Fitriyani, N.L. *et al*. (2019) [45]	Hypertension and diabetes	DPM	Privately owned	Accuracy: 96.74%
Fernández-Edreira, D. *et al*. (2021) [46]	Type 1 diabetes	RF	DIABIM-MUNE	AUC: 0.80
Ali, A.; Alrubei *et al*. (2020) [47]	Classification of diabetes	KNN	Privately owned 4900 samples	Accuracy: 99.9%
Tsao, H.Y.; Chan, P.Y.; Su, E.C.Y. (2018) [48]	Predicting diabetic retinopathy and identifying biomedical characteristics that can be interpreted	SVM, DT, ANN, and LR	Privately owned	SVM accuracy: 79.5%; AUC: 0.839

The course of treatment might consist of medications, like anti-inflammatory drugs or opioids, physical therapy, psychological counselling, or lifestyle modifications, such as exercise and stress control. Alternative treatments are on the rise today, including acupuncture, massage, and mindfulness meditation, making their way to address the problem. Chronic pain not only manifests itself through physical symptoms, but it also has a considerable impact on the emotional and mental health of an individual. This means that chronic pain patients tend to undergo anxiety, depression, as well as feelings of loneliness, which could even worsen their pain. It follows, therefore, that management should also involve psychological aspects so that a patient is helped in developing coping skills for a better quality of life.

5. HOW OUR FINDINGS CONTRIBUTE TO THE CLINICAL CONTEXT

Our research provides significant contributions to the clinical context by leveraging machine learning techniques in disease diagnosis and prognosis, marking a substantial advancement in clinical practice. Here is provided an in-depth look at the multifaceted ways our findings may enrich the clinical landscape:

5.1. Enhancing Early Disease Detection

A cornerstone of our research is the application of machine learning algorithms for the early detection of diseases. These algorithms demonstrate an exceptional ability to detect subtle pathological changes, surpassing traditional diagnostic methods in accuracy and efficiency. Such advanced detection is crucial, as it allows for early intervention, potentially halting disease progression and improving the success rate of treatments. Our findings highlight the pivotal role of machine learning in transforming early diagnostic processes, ultimately leading to significant improvements in patient outcomes.

5.2. Facilitating Personalized Medicine

Our investigation sheds light on how machine learning algorithms can decode complex data patterns to provide insights into disease trajectories, offering a more personalized understanding of patient health. This nuanced perspective enables clinicians to design tailored treatment plans, aligning with the principles of precision medicine. By integrating these insights into clinical practice, healthcare providers can offer more targeted therapies, enhancing the effectiveness of medical interventions and ensuring better health outcomes for patients.

5.3. Streamlining Clinical Workflows

Another critical aspect of our research is the potential of machine learning to enhance the efficiency of clinical workflows. By rapidly processing vast datasets, these algorithms can significantly reduce the time required for diagnostic processes, alleviating the workload on healthcare professionals and systems. This efficiency is crucial in healthcare settings where prompt decision-making can have a profound impact on patient care. Our findings underscore the value of machine learning in optimizing clinical operations, contributing to more efficient and effective healthcare delivery.

Overall, our research underscores the transformative potential of machine learning in the clinical realm. By enhancing early disease detection, enabling personalized treatment plans, and streamlining clinical workflows, our findings offer valuable insights and practical applications that can elevate the standard of care, leading to improved patient outcomes and a more efficient healthcare system. As we continue to explore the capabilities of these algorithms, their integration into clinical practice is poised to redefine healthcare paradigms, illustrating a significant leap forward in medical science.

6. APPLICATION OF MACHINE LEARNING IN RADIOLOGY

The application of Artificial Intelligence (AI) in radiology, a field increasingly referred to as “radiomics,” is transforming the landscape of medical imaging, diagnostics, and patient care. This burgeoning field leverages sophisticated AI algorithms, particularly machine learning and deep learning, to analyse, interpret, and enhance medical imaging data, leading to more precise, efficient, and predictive healthcare outcomes. Published literature underscores AI's pivotal role in enhancing radiological accuracy and efficiency. AI algorithms excel in detecting subtle patterns and anomalies in imaging data that might escape human observation. For instance, AI-powered tools can identify minute changes in imaging scans, such as CTs or MRIs, which can be early indicators of diseases, like cancer. Studies have demonstrated AI's ability to discern malignant from benign tumours with remarkable accuracy, often aligning with or surpassing expert radiologists' assessments.

AI's integration into radiology also extends to predictive analytics, a domain where these technologies forecast disease progression and patient outcomes by analyzing historical and real-time imaging data. For example, AI models can predict the likelihood of tumor growth or reduction in response to a particular treatment regimen, assisting clinicians in customizing patient care plans. Furthermore, AI contributes significantly to the efficiency of radiological practices. Automated image analysis reduces the time radiologists need to spend reviewing and interpreting scans, allowing for quicker diagnosis and treatment initiation. This efficiency is crucial in emergency settings or when dealing with high patient volumes, demonstrating AI's role in optimizing healthcare workflows.

The literature also highlights AI's potential in advancing personalized medicine within radiology. By integrating patient-specific data, including genetic information and past medical history, with imaging data, AI tools can offer tailored diagnostic insights, enhancing the personalization of healthcare. However, the deployment of AI in radiology is not without challenges. Issues, such as data privacy, algorithmic bias, and the need for substantial training datasets, are recurrent themes in scholarly discussions. Ensuring AI's ethical and equitable application in radiology requires ongoing research, regulation, and dialogue among stakeholders in the healthcare ecosystem.

7. COMPARISON OF MACHINE LEARNING ALGORITHMS, THEIR EVALUATION PROCEDURES, AND RESULTING OUTCOMES

In a series of studies published in 2023 [49], researchers have employed various machine learning algorithms to diagnose different diseases, showcasing the potential of these technologies in medical diagnostics. The authors have achieved high accuracy levels in hepatitis diagnosis using KNN, random forest, and naïve Bayes algorithms, demonstrating the applicability of these methods in identifying hepatitis viruses. Similarly, Gangadharan and colleagues [50] applied an ensemble of algorithms to heart disease diagnosis, finding that the combined approach outperformed individual classifiers in accuracy. Oumaima Terrada and team [51] utilized ANN, KNN, K-medoids, and K-mean algorithms for athero-sclerosis detection, achieving a system accuracy of 96%, which signifies a substantial enhancement in medical diagnostic support systems for the disease. In the realm of neurology, Gokalp Cinaree and Bulent Gursel Emiroglu [52] found SVM to be more accurate than other algorithms in diagnosing brain tumors. Arya’s team [53] applied SVM for diabetic eye diagnosis using thermal imaging, proposing a non-invasive and effective method. Lastly, Utomo Pujianto and colleagues [54] employed K-means and SVM for chronic kidney disease detection, achieving near-perfect accuracy, thus highlighting the effectiveness of the RBF kernel in SVM. These studies collectively underscore the diverse and impactful applications of machine learning in diagnosing a range of medical conditions.

8. CHALLENGES

Effectively training healthcare practitioners faces a myriad of challenges, encompassing technical, financial, and resource dimensions. On the technical front, seamless integration of training programs into existing healthcare systems poses a hurdle, necessitating compatibility with diverse platforms. The technological infrastructure demands, including the incorporation of learning management systems and simulation tools, present additional complexities. Moreover, ensuring the security and privacy of patient data during training processes requires robust technical solutions to comply with stringent healthcare regulations. Financial challenges also emerge prominently, with the need for substantial upfront investments in technology, content creation, and infrastructure. Ongoing operational costs for updates and maintenance further strain financial resources, often competing with the allocation of funds for patient care. Resource challenges, such as time constraints on practitioners, limited access to skilled trainers, and the availability of facilities and equipment for hands-on training, compound the intricacies of healthcare training. Addressing these multifaceted challenges necessitates strategic planning, collaboration between various stakeholders, and a commitment to continuous improvement, ensuring that healthcare practitioners receive effective and efficient training to enhance patient care outcomes.

We hope that both rookie and seasoned researchers and practitioners in MLBDD will find our review useful. There is a need for more investigation into the limits noted in the paper. The enhancement of information, including mathematical, all-out, and picture information may likewise be a focal point of future work in MLBDD, as might be multiclass characterization with exceptionally imbalanced information as well as profoundly missing information, clarification and translation of multiclass information grouping utilizing Explainable Artificial Intelligence (XAI), *etc*. Later on, research may be conducted with additional boundaries while building ML models. Proper selection of models might diminish the hour of execution, for example, CNN may turn out better for picture information, information could be normalized for impartial outcomes, profound learning and troupe models might be utilized, and patients with different infections might profit from synchronous findings.

CONCLUSION

The inclusion of Machine Learning (ML) in pain management is a major advance, most notably necessary for places, like India, where medical facilities are restricted and the doctor-patient ratio is extremely low. In the field of pain management, these algorithms are significant because they increase the detection and diagnosis of conditions related to pain in their early stages. This is especially helpful in situations when there are not many expert doctors or clinics offering proper treatment options. In such regions, ML algorithms can help to improve healthcare delivery as they automate repetitive diagnostic procedures, thus freeing physicians from unnecessary burdens on their time and energy. In conclusion, it can be seen that the introduction of machine learning in chronic pain management will not only assist physicians and improve patient outcomes by enabling better diagnostics and accurate treatment planning, but it will also contribute to the optimization of resource distribution, especially for marginalized areas.

LIST OF ABBREVIATIONS

ML	=	Machine learning
AI	=	Artificial intelligence
ANN	=	Artificial neural networks
SVM	=	Support vector machine

CONSENT FOR PUBLICATION

Not applicable.

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CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

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REFERENCES

[1] Ross A. Ligamentous knee joint instability: Association with chronic conditions of the knee and treatment with prolotherapy. The Open Pain J 2023; 16(1): e18763863267142.

[2] Holmboe ES, Durning SJ. Assessing clinical reasoning: Moving from *in vitro* to *in vivo*. Diagnosis (Berl) 2014; 1(1): 111-7. http://dx.doi.org/10.1515/dx-2013-0029 PMID: 29539977

[3] Taverner F J, Wylie N E, Lachlan DM. Hindquarter amputation as a successful treatment of chronic pain in an adolescent with PTEN hamartoma tumor syndrome. The Open Pain J 2023; 16(1): e187638632303310.

[4] Kononenko I. Machine learning for medical diagnosis: History, state of the art and perspective. Artif Intell Med 2001; 23(1): 89-109. http://dx.doi.org/10.1016/S0933-3657(01)00077-X PMID: 11470218

[5] Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. Adv Neural Inf Process Syst 2012; 2012: 1097-105.

[6] Prakash Anadya. Sample size estimation for a non-inferiority pain management trial. The Open Pain J 2023; 16: e187638632301260.

[7] Habib M, Faris M, Qaddoura R, Alomari M, Alomari A, Faris H. Toward an automatic quality assessment of voice-based telemedicine consultations: A deep learning approach. Sensors (Basel) 2021; 21(9): 3279. http://dx.doi.org/10.3390/s21093279 PMID: 34068602

[8] Massaro A, Galiano A, Scarafile D, *et al.* Telemedicine DSS-AI multi level platform for monoclonal gammopathy assistance. 2020 IEEE International Symposium on Medical Measurements and Applications (MeMeA). 01 June 2020 - 01 July 2020; Bari, Italy. 2020. http://dx.doi.org/10.1109/MeMeA49120.2020.9137224

[9] Niculescu MS, Florescu A, Pasca S. LabConcept—A new mobile healthcare platform for standardizing patient results in telemedicine. Appl Sci (Basel) 2021; 11(4): 1935. http://dx.doi.org/10.3390/app11041935

[10] Massaro A, Maritati V, Savino N, Galiano A. Neural networks for automated smart health platforms oriented on heart predictive diagnostic big data systems. Proceedings of the 2018 AEIT International Annual Conference. 16 December 2018; Bari, Italy. 2018. http://dx.doi.org/10.23919/AEIT.2018.8577362

[11] Sharma R, Goel T, Tanveer M, Lin CT, Murugan R. Deep learning based diagnosis and prognosis of Alzheimer's disease: A comprehensive review. IEEE Trans Cogn Dev Syst 2023; 15(3): 1123-38. http://dx.doi.org/10.1109/TCDS.2023.3254209

[12] Dhillon A, Singh A, Bhalla VK. A systematic review on biomarker identification for cancer diagnosis and prognosis in multi-omics: From computational needs to machine learning and deep learning. Arch Comput Methods Eng 2023; 30(2): 917-49. http://dx.doi.org/10.1007/s11831-022-09821-9

[13] Fatima M, Pasha M. Survey of machine learning algorithms for disease diagnostic. J Intell Learn Syst Appl 2017; 9(1): 1-16. http://dx.doi.org/10.4236/jilsa.2017.91001

[14] Tfarah E. Factors related to experiencing pain in patients affected by chronic inflammatory rheumatic disease during the COVID-19 pandemic. The Open Pain J 2022; 15: e187638632210060.

[15] Mhlanga D, Suleiman-Martos N, Mhlanga D. The role of artificial intelligence and machine learning amid the COVID-19 Pandemic: What lessons are we learning on 4IR and the sustainable development goals. Int J Environ Res Public Health 2022; 19(3): 1879. http://dx.doi.org/10.3390/ijerph19031879 PMID: 35162901

[16] Mitchell TM. Machine Learning. New York, NY, USA: McGraw-Hill 1997.

[17] Çınar M, Engin M, Engin E Z, Ziya Ateşçi Y. Early prostate cancer diagnosis by using artificial neural networks and support vector machines. Expert Syst Appl 2009; 36(3): 6357-61.

[18] Hassanien AE, Kim T. Breast cancer MRI diagnosis approach using support vector machine and pulse coupled neural networks. J Appl Log 2012; 10(4): 277-84. http://dx.doi.org/10.1016/j.jal.2012.07.003

[19] Nahar J, Imam T, Tickle KS, Shawkat Ali ABM, Chen YPP. Computational intelligence for microarray data and biomedical

image analysis for the early diagnosis of breast cancer. Expert Syst Appl 2012; 39(16): 12371-7.
http://dx.doi.org/10.1016/j.eswa.2012.04.045

[20] Ahmad MR, Datu MD, Hardiyanti R, Prasetyadhi J. Adductor Canal Block (ACB) provides Adequate Postoperative Analgesia in Patients Undergoing Total Knee Arthroplasty (TKA): Case report. The Open Pain J 2022; 15: e187638632206100.
http://dx.doi.org/10.2174/18763863-v15-e2206100

[21] Shilaskar S, Ghatol A. Feature selection for medical diagnosis : Evaluation for cardiovascular diseases. Expert Syst Appl 2013; 40(10): 4146-53.
http://dx.doi.org/10.1016/j.eswa.2013.01.032

[22] Chang C-L, Chen C-H. Applying decision tree and neural network to increase quality of dermatologic diagnosis. Expert Syst Appl 2009; 36(2): 4035-41.
http://dx.doi.org/10.1016/j.eswa.2008.03.007

[23] Azar AT, El-Metwally SM. Decision tree classifiers for automated medical diagnosis. Neural Comput Appl 2013; 23(7-8): 2387-403.
http://dx.doi.org/10.1007/s00521-012-1196-7

[24] Jin B, Tang YC, Zhang Y-Q. Support vector machines with genetic fuzzy feature transformation for biomedical data classification. Inf Sci 2007; 177(2): 476-89.
http://dx.doi.org/10.1016/j.ins.2006.03.015

[25] Mall S. Heart diagnosis using deep neural network. 3rd International Conference on Computational Intelligence and Knowledge Economy (ICCIKE 2023). 26 May 2023; Dubai, United Arab Emirates. 2023.

[26] Barros RC, Basgalupp MP, Freitas AA, de Carvalho ACPLF. Evolutionary design of decision-tree algorithms tailored to microarray gene expression data sets. IEEE Trans Evol Comput 2014; 18(6): 873-92.
http://dx.doi.org/10.1109/TEVC.2013.2291813

[27] Ahmadi H, Gholamzadeh M, Shahmoradi L, Nilashi M, Rashvand P. Diseases diagnosis using fuzzy logic methods: A systematic and meta-analysis review. Comput Methods Programs Biomed 2018; 161: 145-72.
http://dx.doi.org/10.1016/j.cmpb.2018.04.013 PMID: 29852957

[28] Davenport T, Kalakota R. The potential for artificial intelligence in healthcare. Future Healthc J 2019; 6(2): 94-8.
http://dx.doi.org/10.7861/futurehosp.6-2-94 PMID: 31363513

[29] Jordan MI, Mitchell TM. Machine learning: Trends, perspectives, and prospects. Science 2015; 349(6245): 255-60.
http://dx.doi.org/10.1126/science.aaa8415 PMID: 26185243

[30] Lin CT, Prasad M, Chung CH, *et al.* IoT-based wireless polysomnography intelligent system for sleep monitoring. IEEE Access 2017; 6: 404.

[31] Sarkar B, Ullah M, Sarkar M. Environmental and economic sustainability through innovative green products by remanufacturing. J Clean Prod 2022; 332: 129813.
http://dx.doi.org/10.1016/j.jclepro.2021.129813

[32] Al-Shawi SG, Alekhina NA, Aravindhan S, Thangavelu L, Kartamyshev NV, Zakieva RR. Synthesis of NiO Nanoparticles and Sulfur, and Nitrogen co Doped-Graphene Quantum Dots/ NiO Nanocomposites for Antibacterial Application. J Nanostructures 2021; 11(1)

[33] Chandrasekaran G, Karthikeyan PR, Kumar NS, Kumarasamy V. Test scheduling of System-on-Chip using Dragonfly and Ant Lion optimization algorithms. J Intell Fuzzy Syst 2021; 40(3): 4905-17.
http://dx.doi.org/10.3233/JIFS-201691

[34] Sarkar B, Debnath A, Chiu ASF, Ahmed W. Circular economy-driven two-stage supply chain management for nullifying waste. J Clean Prod 2021; 339(2): 130513.
http://dx.doi.org/10.1016/j.jclepro.2022.130513

[35] Garai A, Sarkar B. Economically independent reverse logistics of customer-centric closed-loop supply chain for herbal medicines and biofuel. J Clean Prod 2021; 334(7): 129977.
http://dx.doi.org/10.1016/j.jclepro.2021.129977

[36] Kumar S, Pathak SK, Singh J. A comprehensive study of XSS Attack and the digital forensic models to gather the evidence. ECS Trans 2022; 107(1): 7153-63.
http://dx.doi.org/10.1149/10701.7153ecst

[37] Goswami A, Sharma D, Mathuku H, *et al.* Change detection in remote sensing image data comparing algebraic and machine learning methods. Electronics (Basel) 2022; 11(3): 431.
http://dx.doi.org/10.3390/electronics11030431

[38] Sharan A. A new fuzzy logic based query expansion model for efficient information retrieval using relevance feedback approach.Neural Computing And Applications. Berlin, Germany: Springer 2017.

[39] Aggarwal R, Tiwari S, Joshi V. Exam proctoring classification using eye gaze detection. 2022 3rd International Conference on Smart Electronics and Communication (ICOSEC). 20-22 October 2022; Trichy, India. 2022.

[40] Abdel-Nasser M, Rashwan HA, Puig D, Moreno A. Analysis of tissue abnormality and breast density in mammographic images using a uniform local directional pattern. Expert Syst Appl 2015; 42(24): 9499-511.
http://dx.doi.org/10.1016/j.eswa.2015.07.072

[41] Sharma S, Khanna P. Computer-aided diagnosis of malignant mammograms using Zernike moments and SVM. J Digit Imaging 2015; 28(1): 77-90.
http://dx.doi.org/10.1007/s10278-014-9719-7 PMID: 25005867

[42] Sajid M, Rajak R. Capacitated vehicle routing problem using algebraic particle swarm optimization with simulated annealing algorithm.Artificial Intelligence in Cyber-Physical Systems. Boca Raton, Florida: CRC Press 2023.

[43] Naz H, Ahuja S. Deep learning approach for diabetes prediction using PIMA Indian dataset. J Diabetes Metab Disord 2020; 19(1): 391-403.
http://dx.doi.org/10.1007/s40200-020-00520-5 PMID: 32550190

[44] Yahyaoui A, Jamil A, Rasheed J, Yesiltepe M. A decision support system for diabetes prediction using machine learning and deep learning techniques. Proceedings of the 2019 1st International Informatics and Software Engineering Conference (UBMYK). 23 January 2020; Ankara, Turkey. 2019; pp. 1-4.
http://dx.doi.org/10.1109/UBMYK48245.2019.8965556

[45] Fitriyani NL, Syafrudin M, Alfian G, Rhee J. Development of disease prediction model based on ensemble learning approach for diabetes and hypertension. IEEE Access 2019; 7: 144777-89.
http://dx.doi.org/10.1109/ACCESS.2019.2945129

[46] Fernández-Edreira D, Liñares-Blanco J, Fernandez-Lozano C. Machine Learning analysis of the human infant gut microbiome identifies influential species in type 1 diabetes. Expert Syst Appl 2021; 185: 115648.
http://dx.doi.org/10.1016/j.eswa.2021.115648

[47] Ali A, Alrubei MAT, Hassan LFM, Al-Ja'afari MAM, Abdulwahed SH. Diabetes Diagnosis based on KNN. IIUM Eng J 2020; 21(1): 175-81.
http://dx.doi.org/10.31436/iiumej.v21i1.1206

[48] Tsao HY, Chan PY, Su ECY. Predicting diabetic retinopathy and identifying interpretable biomedical features using machine learning algorithms. BMC Bioinformatics 2018; 19(S9) (Suppl. 9): 283.
http://dx.doi.org/10.1186/s12859-018-2277-0 PMID: 30367589

[49] Singhal P, Gupta S. An integrated approach for analysis of electronic health records using blockchain and deep learning. Recent Adv Comp Sci Commun, Bentham Sci 2023; 16(9): 10.

[50] Gangadharan SMP, Dharani M, Thapliyal N, Yamsani N, Singh P. Comparative analysis of deep learning-based brain tumor prediction models using MRI scan. 2023 3rd International Conference on Innovative Sustainable Computational Technologies (CISCT).
http://dx.doi.org/10.1109/CISCT57197.2023.10351227

[51] Terrada O. Classification and prediction of atherosclerosis diseases using machine learning algorithms. 2019 5th International Conference on Optimization and Applications (ICOA). 03 June 2019; Kenitra, Morocco. 2019.

[52] Çınarer G. Classificatin of brain tumors by machine learning algorithms. 2019 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT).

11-13 October 2019; Ankara, Turkey. 2019.

[53] Arya C, Yamsani N, Kumar M, Singh P, Bhagat VK. A concise review Of MRI feature extraction and classification with Kernel functions. 2023 3rd International Conference on Innovative Sustainable Computational Technologies (CISCT). 08-09 September 2023; Dehradun, India. 2023. http://dx.doi.org/10.1109/CISCT57197.2023.10351471

[54] Pujianto U, A'yuni Ramadhani N, Prasetya Wibawa A. Support vector machine with purified k-means clusters for chronic kidney disease detection. 2018 2nd East Indonesia Conference on Computer and Information Technology (EIConCIT). 06-07 November 2018; Makassar, Indonesia. 2018. http://dx.doi.org/10.1109/EIConCIT.2018.8878511