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Applications of Deep Learning and Machine Learning in Healthcare Domain – A Literature Review

Beschi I S[1], Dr. S. Prakash Kumar[2]
[1]Research Scholar, PG & Department of Computer Science, Maruthupandiyar College (Affiliated to Bharathidasan University, Tiruchirappalli), Vallam, Thanjavur, Tamilnadu, India.
[2]Assistant Professor, PG & Department of Computer Science, Maruthupandiyar College (Affiliated to Bharathidasan University, Tiruchirappalli), Vallam, Thanjavur, Tamilnadu, India.

Abstract

In recent years, Artificial Intelligence (AI) has advanced rapidly in terms of software algorithms, hardware implementation, and implementations in a wide range of fields. The latest advances in AI applications in biomedicine, such as disease diagnostics, living assistance, biomedical information processing, and biomedical science, are summarised in this study. Brain-Computer Interfaces (BCIs), Arterial Spin Labeling (ASL) imaging, ASL-MRI, biomarkers, Natural Language Processing (NLP), and various algorithms all help to reduce errors and monitor disease progression. Computer-assisted diagnosis, decision support systems, expert systems, and software implementation can help doctors reduce intra- and inter-observer variability. In this paper, numerous researchers conduct a systematic literature review on the application and implementation of Machine Learning, Deep Learning, and Artificial Intelligence in the healthcare industry.

Keywords: Healthcare, Machine Learning, Deep Learning, Artificial Intelligence, Disease Severity, Survival prediction, Big data.

1. INTRODUCTION

Artificial intelligence (AI) [1] is classified as computer intelligence as opposed to human or other living species intelligence. AI is also the study of "intelligent robots," or any entity or system that can perceive and recognise its environment and take appropriate action to improve its chances of achieving its goals. AI also applies to cases in which computers can learn and analyse in the same way as humans do, and thereby assist in problem solving. Machine Learning (ML) is another name for this form of intelligence [2]. Manufacturing, transportation, and governance have all been transformed by Machine Learning (ML)/Deep Learning (DL) systems. DL has delivered state-of-the-art output in a variety of domains over the last few years, including computer vision, text analytics, and speech processing, among others. ML/DL algorithms have become inseparable from our daily lives as a result of their widespread use in different domains (e.g., social media). Healthcare is now being influenced by ML/DL algorithms, an area that has previously been immune to large-scale technological disruptions [3]. Recently, ML/DL techniques have demonstrated excellent results in a variety of tasks, including body organ identification from medical images, classification of interstitial lung diseases, lung nodule detection, medical image reconstruction, and brain tumour segmentation, to name a few [4]. Intelligent software is expected to assist radiologists and doctors in testing patients in the near future, and machine learning can revolutionise medical study and practise. Clinical medicine has emerged as a promising application field for ML/DL models, with human-level success in clinical pathology, radiology, ophthalmology, and dermatology already achieved [5].

The advancement of concomitantly advancing technologies like cloud/edge computing, mobile networking, and big data technology is also benefiting the potential of ML models for healthcare applications [6]. ML/DL can generate highly accurate predictive outcomes and promote human-centered intelligent solutions when used in conjunction with these technologies [7]. These innovations have the potential to revitalise the healthcare sector, as well as provide other benefits such as enabling remote healthcare systems for rural and low-income areas.

2. MACHINE LEARNING IN HEALTHCARE

The main stages of designing an ML-based healthcare system are depicted, followed by a brief description of the major forms of ML/DL that can be used in healthcare applications.

2.1 Un-Supervised Machine Learning

Unsupervised learning approaches are machine learning techniques that use unlabeled data. Clustering data points using a similarity metric and dimensionality reduction to project high-dimensional data to lower-dimensional subspaces are common examples of unsupervised learning methods (sometimes also referred to as feature selection). Unsupervised learning can also be used to identify anomalies, such as clustering [8]. Unsupervised learning approaches in healthcare include the use of Principal Component Analysis (PCA), a dimensionality reduction technique, to predict hepatitis disease [9] [56].

2.2 Supervised Machine Learning

Supervised learning approaches are those that use labelled training data to construct or map the relationship between the inputs and outputs [10]. The task is referred to as classification if the output is discrete, and regression if the output is continuous. The detection of various forms of lung diseases (nodules) and the identification of different body organs from medical photos are two classic examples of supervised learning approaches in healthcare. When the training data includes both labelled and unlabeled samples, ML methods can be neither supervised nor unsupervised. Semi-supervised learning methods are those that make use of such data [57] [58].

2.3 Semi-Supervised Machine Learning

When both labelled and unlabelled samples are available for training, such as a small amount of labelled data and a large amount of unlabelled data, semi-supervised learning methods are useful. Since obtaining sufficiently labelled data for model training is difficult in healthcare, semi-supervised learning techniques can be especially useful for a variety of healthcare applications.

2.4 Reinforcement Learning

Reinforcement Learning (RL) [11] is a class of methods that learn a policy function from a series of observations, behaviours, and rewards in response to actions performed over time. Many healthcare applications could benefit from RL, and it has recently been used for context-aware symptom checking for disease diagnosis.

3. APPLICATIONS OF MACHINE LEARNING IN HEALTHCARE

Healthcare services produce a vast volume of heterogeneous data and knowledge on a regular basis, making it impossible to interpret and process using "traditional methods." Machine learning and deep learning approaches aid in the accurate analysis of this data for actionable insights. Furthermore, there are a variety of data sources that can be used to supplement healthcare data, including genomics, medical data, social media data, and environmental data, among others [59] [60].

3.1 Applications of ML in Prognosis

In clinical practise, prognosis is the method of determining how a disease will progress. It also involves determining whether symptoms and signs associated with a particular illness can worsen, strengthen, or stay stable over time, as well as determining possible health problems, risks, ability to perform normal tasks, and survival odds. Multi-modal patient data, such as phenotypic, genetic, proteomic, pathology test results, and medical images, is obtained in the same way it is in a clinical setting, and this data can be used to enable ML models to help with disease prognosis, diagnosis, and treatment. For example, machine learning models have been used extensively to identify and classify various types of cancers, such as brain tumours and lung nodules. However, recent translational research efforts aimed at enabling personalised medicine have exploited the potential applications of ML for disease prognosis, i.e., prediction of disease symptoms, threats, survivability, and recurrence. However, personalised medicine is still in its infancy, and it will take a lot of work in adjacent fields like bioinformatics, solid validation methods, and demonstrably stable implementations of machine learning to have a big impact.

3.2 Applications of ML in Diagnosis

3.2.1 Electronic Health Records

On a regular basis, hospitals and other healthcare service providers generate a vast number of Electronic Health Records (EHRs), which are made up of organised and unstructured data and include a patient's full prescription history. For the extraction of clinical features to aid in the diagnosis process, ML-based approaches have been used [12].

3.2.2 ML in Medical Image Analysis

ML techniques are used in medical image processing [13] to obtain information from medical images obtained using various imaging modalities such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Ultrasound, and Positron Emission Tomography (PET), among others. These modalities provide vital functional and anatomical knowledge about various body organs, as well as assisting in the identification, localization, and diagnosis of abnormalities. The main goal of medical image processing is to help doctors and radiologists diagnose and prognosis diseases more quickly. Detection, classification, segmentation, retrieval, restoration, and image registration are some of the most common tasks in medical image processing.

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3.3 Applications of ML in Treatment

3.3.1 Image Interpretation

Medical images are often used in everyday clinical practise, and expert physicians and radiologists analyse and interpret these images. They write textual radiology reports about of body organ that was investigated in the conducted analysis to narrate the results about the images being studied. Writing such studies, however, can be difficult in some situations, such as for less qualified radiologists and healthcare professionals in rural areas where healthcare facilities are not up to par. For seasoned radiologists and pathologists, on the other hand, the method of writing high-quality reports may be cumbersome and time-consuming, which is compounded by the large number of patients who visit daily. As a result, a number of researchers have used Natural Language Processing (NLP) and machine learning (ML) techniques to try to solve this problem [14].

3.3.2 Real-time Health Monitoring

Critical patient monitoring in real time is critical and is an important part of the treatment process. People are becoming more interested in continuous health tracking using wearable devices, IoT cameras, and smartphones. Health data is obtained using a wearable tracker and smartphone in a standard environment of continuous health tracking, and then transmitted to the cloud for review using an ML/DL technique [15].

4. LITERATURE REVIEW

Almansour, Njoud Abdullah, et al [16] aimed to aid in the prevention of Chronic Kidney Disease (CKD) by using machine learning techniques to detect CKD early. Kidney diseases are illnesses that affect the kidney's ability to function normally. Efficient prediction techniques should be considered as the number of patients affected by CKD continues to rise. The authors used a dataset of 400 patients and 24 attributes related to chronic kidney disease diagnosis to test various machine learning classification algorithms. Artificial Neural Network (ANN) and Support Vector Machine (SVM) were used as classification techniques in this research (SVM). To conduct the experiments, the mean of the corresponding attributes was used to substitute all missing values in the dataset. Then, after tuning the parameters and running multiple experiments, the optimal parameters for the Artificial Neural Network (ANN) and Support Vector Machine (SVM) techniques were calculated. The best-obtained parameters and features were used to create the final versions of the two proposed techniques.

Belić, Minja, et al [17] aimed to provide a detailed, high-level overview of artificial intelligence applications in kinematic analysis of movement disorders, specifically Parkinson's Disease, using machine learning algorithms (PD). The authors searched online databases such as PubMed and Science Direct for papers published between January 2007 and January 2019, with a focus on the most recently published studies. Papers dealing with the use of machine learning algorithms for the diagnosis and evaluation of Parkinson's disease using data documenting upper and lower extremity motion were included in the quest. The authors provided an overview of 48 related studies published during the time span described, which look at the use of artificial intelligence for PD diagnostics, therapy evaluation, and progress prediction using body kinematics. Various machine learning algorithms yielded promising results, especially in the early detection of Parkinson's disease. The studies looked at the possibilities of gathering data from inexpensive and widely accessible devices.

Liang, Huiying, et al [18] showed that Machine Learning Classifiers (MLCs) can query Electronic Health Records (EHRs) in a way that is close to physicians' hypothetico-deductive reasoning and uncover correlations that have previously been missed by statistical methods. The proposed model used a deep learning-based automated natural language processing method to extract clinically meaningful data from EHRs. In diagnosing common childhood diseases, the proposed model demonstrates high diagnostic precision across multiple organ systems and is equivalent to experienced paediatricians. This study demonstrated the feasibility of using an AI-based system to help physicians deal with vast volumes of data, supplement diagnostic assessments, and provide clinical decision support in cases of diagnostic ambiguity or complexity.

Wu, Chieh-Chen, et al [19] The aim was to create a machine learning model to predict Fatty Liver Disease (FLD) that could help doctors classify high-risk patients, make a novel diagnosis, and prevent and treat the disease. FLD is a common health complication that has a high morbidity and mortality rate. Early detection of FLD patients, on the other hand, allows for the development of an effective prevention, early diagnosis, and treatment plan.

Jo, Taeho, Kwangsik Nho, and Andrew J. Saykin [20] performed a systematic review of publications for Alzheimer's disease diagnosis classification using deep learning methods and neuroimaging data (AD). Deep learning papers on AD published between January 2013 and July 2018 were found using PubMed and Google Scholar searches. The results were summarised after these papers were analysed, evaluated, and graded by algorithm and neuroimaging form. Four research used a mix of deep learning and conventional machine learning methods, while the other 12 used only deep learning approaches. Traditional machine learning for classification and Stacked Auto-Encoder (SAE) for feature selection provided accuracies of up to 98.8% for AD classification and 83.7 percent for predicting conversion from MCI, a prodromal stage of AD, to AD. Deep learning methods that use neuroimaging data without pre-processing for feature selection, such as Convolutional Neural Network (CNN) or Recurrent Neural Network (RNN), have achieved accuracies of up to 96.0 percent for AD classification and 84.2 percent for MCI conversion prediction. When multimodal neuroimaging and fluid biomarkers were combined, the best classification output was obtained. Deep learning approaches to diagnostic classification of Alzheimer's disease using multimodal neuroimaging data continue to advance in accuracy, and they appear to hold promise.

Ngiam, Kee Yuan, and Wei Khor [21] Machine learning, which makes use of capabilities like deep neural networks, is a powerful method for analysing vast volumes of complex health-care data in order to increase the quality and cost-effectiveness of health-care delivery. Machine learning can augment doctors' abilities by performing repetitive, standardised tasks with high accuracy, freeing up doctors' resources to focus on clinical conditions that are more complicated or require significant human interaction.

Kawakami, Eiryo, et al [22] aimed to use machine learning methods based on multiple biomarkers to create an ovarian cancer–specific predictive system for clinical level, histotype, residual tumour burden, and prognosis. In total, 334 patients with EOC and 101 patients with benign ovarian tumours were randomly assigned to "training" and "test" cohorts. Gradient Boosting Machine (GBM), Support Vector Machine (SVM), Random Forest (RF), Conditional RF (CRF), Naive Bayes, Neural Network, and Elastic Net were used to extract diagnostic and prognostic information from 32 parameters commonly available from pre-treatment peripheral blood tests and age using seven supervised machine learning classifiers.

Abdar, Moloud, et al [23] describe an advanced machine learning methodology for detecting Coronary Artery Disease (CAD) with high accuracy, and apply it to data from Iranian patients. The authors evaluated ten conventional machine learning algorithms first, then used the top three performers (three forms of SVM) in the rest of the analysis. A data pre-processing with normalisation was carried out to boost the efficiency of these algorithms. Furthermore, a genetic algorithm and particle swarm optimization, in combination with stratified 10-fold cross-validation, were used twice: for classifier parameter optimization and parallel feature selection.

Kwon, Joon-myoung, et al [24] The aim of this study was to create and test a deep-learning-based artificial intelligence algorithm for predicting AHF mortality (DAHF). DAHF outperformed current risk scores and machine-learning models in predicting in-hospital and long-term mortality in patients with AHF.

Kiely, David G., et al [25] The researchers wanted to see whether a predictive model focused on healthcare resource use could be used to screen large populations for patients with idiopathic pulmonary arterial hypertension. The Public Health Service in England's Hospital Episode Statistics, which provide near to maximum national coverage, is used as a measure of healthcare resource use. Data from the National Pulmonary Hypertension Service in Sheffield was compared to pre-diagnosis Hospital Episode Statistics records for patients with idiopathic pulmonary arterial hypertension. This study demonstrated how artificial intelligence could be used to screen for rare diseases like idiopathic pulmonary arterial hypertension using readily available real-world data. This algorithm will provide low-cost population-wide screening, allowing for earlier detection, higher diagnostic rates, and better patient outcomes. More research is needed to confirm this process.

Makino, Masaki, et al [26] Based on the Electronic Medical Records (EMR) of 64,059 diabetes patients, researchers created a new predictive model for Diabetic Kidney Diseases (DKD) using AI, processing natural language and longitudinal data with big data machine learning. Using a convolutional autoencoder, AI extracted raw features from the previous 6 months as the reference period and selected 24 factors to find time series trends relating to 6-month DKD aggravation. Using logistic regression analysis, AI built a predictive model with 3,073 features, including time series data. With a 71 percent accuracy rate, AI could predict DKD aggravation.

Shamai, Gil, et al [27] Morphological-Based Molecular Profiling (MBMP) is a machine learning model that was developed. A deep convolutional neural network was used to predict biomarker expression in examined tissues, and logistic regression was used to investigate associations between histomorphology and biomarker expression.

Ding, Yiming, et al [28] utilised The InceptionV3 architecture's convolutional neural network was trained on 90% of the ADNI data set and evaluated on the remaining 10%, as well as an independent test set, with results compared to radiologic readers. Sensitivity, specificity, Receiver Operating Characteristic (ROC), saliency diagram, and t-distributed stochastic neighbour embedding were used to evaluate the model. The authors created and validated a deep learning algorithm that predicts the final diagnosis of Alzheimer's Disease (AD), mild cognitive impairment, or neither at Fluorine 18 (18F) FluoroDeoxyGlucose (FDG) PET of the brain, and compared it to radiologic readers' results.

Shen, Jiayi, et al [29] aimed to conduct a systematic review of the literature, with an emphasis on performance comparisons between advanced AI and human clinicians, in order to include an up-to-date overview of the scope of AI's use in disease diagnosis. This review addressed the relationship between existing advanced AI development and clinicians in terms of disease diagnosis and, as a result, long-term clinical development. The authors used Scopus, PubMed, CINAHL, Web of Science, and the Cochrane Library to search for papers published between January 2000 and March 2019 that followed the Preferred Reporting Items for Systematic Reviews and Meta-Analysis. Only articles contrasting the medical performance of advanced AI and human experts were considered, based on the preset inclusion and exclusion criteria.

Seetharam, Karthik, Sirish Shrestha, and Partho P. Sengupta [30] Over the last year, it has been highlighted notable examples of machine learning use in echocardiography, nuclear cardiology, computed tomography, and magnetic resonance imaging. Machine Learning (ML) has made strides in cardiology in the last year, with some promising findings. Some studies have combined clinical and imaging data to improve the accuracy of these machine learning algorithms. The authors listed in this review have clearly shown that machine learning outperforms traditional approaches in terms of detecting obstructions and predicting significant adverse events.

Das, Arun, et al [31] presented a modular cloud-based teleophthalmology architecture for diagnosing Age-related Macular Disease (AMD) using the Internet of Medical Things (IoMT) (AMD). Patients wear a head-mounted camera (OphthoAI IoMT headset) to send their retinal fundus images to a safe and private cloud drive storage for customised disease severity identification and predictive progression analysis in the proposed architecture. The images will then be analysed by a proposed AMD-ResNet convolution neural network with 152 layers, which will classify and assess the magnitude of AMD disease.

Ting, Daniel Shu Wei, et al [32] provided a review of the state-of-the-art Deep Learning (DL) systems identified for ophthalmic applications, as well as future clinical deployment challenges and the way forward. Deep Learning (DL)-based Artificial Intelligence (AI) has generated a lot of interest around the world in recent years. While deep learning has been widely used in image recognition, speech recognition, and natural language processing, it is only now beginning to have an effect in healthcare. In ophthalmology, DL has been used to diagnose diabetic retinopathy and retinopathy of prematurity, as well as the glaucoma-like disc, macular oedema, and age-related macular degeneration, using fundus images, optical coherence tomography, and visual fields. Patients in primary care and community settings can benefit from using DL in ocular imaging in combination with telemedicine to screen, diagnose, and control major eye diseases.

Wong, Zoie SY, Jiaqi Zhou, and Qingpeng Zhang [33] aimed to highlight the benefits of using Artificial Intelligence (AI) methods to allow accurate disease-oriented monitoring and forecasting in this information age. Because of advancements in information and communications technology and the data collection mechanisms currently in place, the amount of data collected from public health monitoring has risen significantly since the turn of the century.

Myszczynska, Monika A., et al [34] Machine learning can help with early detection and understanding of medical images, as well as the creation and advancement of new therapies, according to the discussion. The automated derivation of actionable insights from multiple high-dimensional sources of data, each of which provides a different view on disease, is a unifying theme of machine learning applications.

Banerjee, Abhirup, et al [35] aimed to distinguish SARS-CoV-2 positive patients from full blood counts using machine learning, an Artificial Neural Network (ANN), and a simple statistical test without knowing the patients' symptoms or histories. The researchers discovered that using full blood counts, a random forest, shallow learning, and a versatile ANN model, they could accurately predict SARS-CoV-2 patients on regular wards (AUC = 93-94%) and those not admitted to hospital or in the community (AUC = 80-86%). The Area Under the Receiver Operating Characteristics Curve (AUC) is a model efficiency metric. Furthermore, for patients in the group, a simple linear combination of four blood counts will yield an AUC of 85%. Platelets, leukocytes, eosinophils, basophils, and lymphocytes are all lower in normalised data from SARS-CoV-2 positive patients, while monocytes are higher.

Huang, Shigao, et al [36] The paper outlines the benefits of AI in cancer diagnosis and prognosis based on a review of the literature. The authors looked at how AI can help with cancer diagnosis and prognosis, especially in terms of its unparalleled precision, which is higher than that of

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general statistical oncology applications. The authors also illustrated how these approaches are helping to advance the field. Finally, the advantages and disadvantages of using AI in clinical settings are addressed. As a result, the authors offered a fresh viewpoint on how AI can aid in cancer detection and prognosis, as well as continue to improve human health in the future.

Shen, Jiayi, et al [37] aimed to investigate the implementation of a high-performing AI algorithm in Gestational Diabetes Mellitus (GDM)diagnosis in an environment with less medical equipment and personnel, as well as the development of an app based on the AI algorithm. The authors also looked at how far our app could go if it were popular. GDM is a form of diabetes that can affect both mothers and their new-borns. Pregnant women in low- and middle-income areas or countries, on the other hand, often miss out on early health interventions at local medical facilities due to a lack of GDM diagnosis. Artificial Intelligence's (AI) excellent success in disease diagnosis in previous studies shows its potential applications in GDM diagnosis.

Santo, Briana A., Avi Z. Rosenberg, and Pinaki Sarder [38] Classic image processing and machine learning were used to prognosticate renal disease in the early days of digital pathology informatics. While this traditional approach had a lot of promise, advances in hardware technology have made artificial neural networks the preferred tool for machine vision in computational pathology. ANNs also aided the advancement of diagnostic and prognostic applications by allowing for the rapid and repeatable identification, characterization, and classification of kidney morphology. Furthermore, modern machine learning with ANNs has discovered novel biomarkers in kidney disease, showing the potential for machine vision to elucidate novel pathologic pathways beyond what is currently known in clinical practise.

Kaul, Vivek, Sarah Enslin, and Seth A. Gross [39] presents a brief historical overview of AI's evolution over the last few decades, as well as its recent introduction and advancement in medicine. There's also a quick rundown of the most important AI applications in gastroenterology and endoscopy.

Chu, Chui S., et al [40] The natural history of Oral Squamous Cell Carcinoma (OSCC) is complicated by progressive disease, which includes tumour recurrence in the same location and the growth of distant metastases. In order to provide individualised care plans and implement optimal patient follow-up and surveillance strategies, accurate tumour behaviour prediction is critical. In oncology research, machine learning algorithms can be used to enhance clinical outcome prediction. The development of a comprehensive clinicopathological database was aided by a retrospective study of 467 OSCC patients treated over a 19-year period. To attempt progressive disease outcome prediction, 34 prognostic features from the database were used to populate four machine learning algorithms: Linear Regression (LR), decision tree (DT), Support Vector Machine (SVM), and K-Nearest Neighbours (KNN) models. To minimise data dimensionality and highlight associated variables, bivariate analysis and Principal Component Analysis (PCA) were used. The predictive potential of the models was determined using the Receiver Operating Characteristic (ROC) and Area Under the Curve (AUC) calculations, which were used to validate them for precision, sensitivity, and specificity.

Kovačević, Živorad, et al [41] The results of applying Machine Learning (ML) techniques to the management of infant incubators in healthcare facilities were discussed. For the creation of the Expert system based on ML classifiers, a total of 140 samples were used. These samples were obtained between 2015 and 2017 as part of an ISO 17020 certified laboratory's annual inspections of incubators in healthcare facilities. Classifiers were developed and validated using dataset divisions 80–20. The following machine learning algorithms were tested: Nave Bayes (NB), Decision Tree (DT), Random Forest (RF), k-Nearest Neighbor (kNN), and Support Vector Machine (SVM). The performance of the various classifiers was compared, and the classifier based on the Decision Tree algorithm produced the highest accuracy (98.5%) among the other systems tested. The findings show that incorporating machine learning algorithms into MD management techniques benefits healthcare organisations not only in terms of improving the safety and efficiency of patient diagnosis and treatment, but also in terms of cost reduction and resource management.

Armstrong, Grayson W., and Alice C. Lorch [42] Because of the numerous multimodal imaging studies and clinical indicators available, ophthalmology is uniquely positioned to benefit from machine learning. As evidenced by the first FDA-approved AI algorithm for disease diagnosis being applied to DR screening, AI and machine learning have already begun to revolutionise computer-assisted diagnosis, screening, and prognostication of both anterior and posterior segment ophthalmic disease. These advancements would favour population-based screening services and telemedicine campaigns, as well as clinicians who use AI-based decision support systems.

Ahmed, Zeeshan, et al [43] aimed at advancing academic solutions in paving the way for a new data-centric age of exploration in healthcare by reviewing and addressing various published artificial intelligence and machine learning solutions, methods, and perspectives.

Castellazzi, Gloria, et al [44] The researchers wanted to see if different kinds of machine learning algorithms combined with advanced MRI features could help distinguish VD from AD, and if the established approach could help predict the prevalent disease in people who had an ambiguous profile of AD or VD. Artificial Neural Network (ANN), Support Vector Machine (SVM), and Adaptive Neuro-Fuzzy Inference System (ANFIS) were the three types of machine learning algorithms that were studied.

Aggrawal, Ritu, and Saurabh Pal [45] To pick the most appropriate features, the author proposes a sequential feature selection algorithm for detecting death events in heart disease patients during treatment. Linear Discriminant Analysis (LDA), Random Forest (RF), Gradient Boosting Classifier (GBC), Decision Tree (DT), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) are among the machine learning algorithms used.

Verma, Anurag Kumar, Saurabh Pal, and Surjeet Kumar [46] presented a new strategy for predicting various classes of skin disease that uses six different data mining classification techniques and then established an ensemble approach using bagging, AdaBoost, and gradient boosting classifiers techniques. In addition, the function value approach is used to pick 15 key features that play a key role in prediction. After selecting only 15 features from the original dataset, a subset of the original dataset is created to compare the effects of the six machine learning techniques and ensemble method on the entire dataset. The new subset of the original dataset derived from the feature selection method is compared to the ensemble method used on the skin disease dataset.

Battineni, Gopi, et al [47] Machine Learning (ML) predictive models in the diagnosis of chronic diseases were examined. Chronic diseases (CDs) account for a significant portion of global health expenditures. Patients with these diseases need lifelong care. Predictive models are now commonly used in the diagnosis and prediction of these diseases. The authors of this study looked at the most up-to-date methods for using ML models in the primary diagnosis of CD. Our document search was performed from the PubMed (Medline) and Cumulative Index to Nursing and Allied Health Literature (CINAHL) archives, and our research includes 453 papers published between 2015 and 2019.

Ström, Peter, et al [48] The aim was to create an Artificial Intelligence (AI) system that could diagnose, localise, and grade prostate cancer with clinically appropriate accuracy. An AI system can be equipped to diagnose and grade cancer in prostate needle biopsy samples with a level of accuracy comparable to that of international prostate pathology experts. By reducing the assessment of benign biopsies and automating the task of measuring cancer duration in positive biopsy cores, the clinical application could minimise pathology workload. An AI system capable of expert-level grading may provide a second opinion, help in grading standardisation, and provide pathology knowledge in areas where it is lacking.

Feeny, Albert K., et al [49] provided a basis for how one could conduct an ML study and provided literacy of Artificial Intelligence/ Machine Learning (AI/ML) methods to the inexperienced reader. The authors presented a scientific overview of some of the most widely used terminology, methods, and difficulties in AI/ML research, illustrating key points with recent studies in cardiac electrophysiology. Significant considerations and challenges for effective validation, implementation, and deployment of AI technologies in clinical practise were highlighted by the authors.

Hügle, Maria, et al [50] supervised learning, unsupervised learning, reinforcement learning, and deep learning are examples of machine learning subfields. The authors gave an overview of existing supervised learning approaches for e-diagnosis, disease identification, and medical image processing in rheumatology.

Thomsen, Kenneth, et al [51] conducted a comprehensive analysis of current literature, locating the literature through a PubMed database search. Screening and eligibility were evaluated by two physicians based on pre-determined inclusion and exclusion requirements. The authors provided an in-depth look at how artificial intelligence is being used in dermatology. In all eight categories, impressive results were recorded, but a head-to-head comparison proved difficult. The authors' identification of machine learning methods in a variety of dermatology fields demonstrates the diversity of machine learning.

Mayro, Eileen L., et al [52] Deep Learning (DL) is a subset of Artificial Intelligence (AI) that employs multilayer neural networks modelled after the mammalian visual cortex to synthesise images in ways that will revolutionise glaucoma research. To outperform ophthalmologists in disease detection, autonomous DL algorithms will maximise knowledge contained in digital fundus photographs and ocular coherence tomographs. As compared to traditional software packages, other unsupervised algorithms such as principal component analysis (axis learning) and archetypal analysis (corner learning) promote visual field perception and display great promise in detecting functional glaucoma progression and distinguishing it from non-glaucomatous shifts. Forecasting tools like the Kalman filter, which account for a variety of factors to set target intraocular pressure targets that maintain vision, may revolutionise glaucoma management. Activation maps created by deep learning algorithms processing glaucoma data have the potential to efficiently guide our attention to critical data elements embedded in high throughput data and improve our understanding of the glaucomatous process.

Farhadian, Maryam, Parisa Shokouhi, and Parviz Torkzaban [53] The aim was to create a decision-making support system based on a support vector machine (SVM) to diagnose various periodontal diseases. Data was obtained from 300 patients referred to Hamadan University of Medical Sciences' Periodontics department in the west of Iran. There were 160 cases of gingivitis, 60 cases of localised periodontitis, and 80 cases of generalised periodontitis among these patients. In the designed classification model, 11 input and output variables such as age, sex, smoking, gingival index, plaque index, and so on are used to display the individual's periodontal disease status. Using various kernel functions in the design of the SVM classification model revealed that the radial kernel function has the best results, with an overall correct classification accuracy of 88.7% and an overall Hypervolume Under Manifold (HUM) value of 0.912. The current study's findings show that the built classification model performs well in predicting periodontitis.

Ahn, Joseph C., et al [54] provided a detailed review of hepatology-focused AI studies, explored some of the obstacles to clinical acceptance and implementation, and suggested potential directions for the field

Ahmed, Hager, et al [55] presented a real-time method for predicting heart disease based on medical data sources that characterise a patient's current state of health. The proposed system's main aim is to find the best machine learning algorithm for predicting heart disease with high accuracy. To select important features from the dataset, two types of feature selection algorithms are used: univariate feature selection and Relief. The authors contrasted four types of machine learning algorithms with selected and complete features: Decision Tree, Support Vector Machine, Random Forest Classifier, and Logistic Regression Classifier. To improve accuracy, the authors combined hyperparameter tuning and cross-validation with machine learning. One of the proposed system's strongest features is its ability to effectively manage Twitter data streams containing patient data.

5. PROBLEM STATEMENT

Due to the growing complexity of diseases, treatment plans, and multiple patient population samples, accurately predicting survival rates in patients with diseases remains a challenge. Predictions that are accurate and well-validated may help with more personalised care and treatment, as well as better cancer control. In modern medical diagnostics, there is a clear rise in the use of classification-based approaches. At first glance, both of these classification-based methods seem to use a variety of and heterogeneous medical data, potentially inflating diagnostic efficiency. On the contrary, various recent advancements in computer science, data science, and machine learning (ML) aid in the reduction of diagnostic errors. Artificial intelligence methods for classification in medical studies provide a more informative knowledge-based background for disease prediction and prognosis to be checked more meticulously and quickly.

6. RESEARCH DIRECTION

With the expanded use of bioinformatics, computer science, statistics, and machine learning techniques, new knowledge-based diagnostic methods for disease detection are being developed rapidly. Aside from that, integrating and combining all of these approaches into a meaningful workflow is difficult. Machine Learning (ML) approaches have become more reliable and focused on the discovery of new enriched information about origin, classification, prognosis, and therapy as a result of the widespread implementation and application of these methods in medical studies.

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