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Through Machine Learning Models Diagnosis of Medical Conditions in Patients

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Abstract

A variety of patient care and intelligent health systems can benefit from the implementation of artificial intelligence as a tool to aid caregivers. Machine learning and deep learning are two types of AI that are increasingly being used in the medical industry. Artificial intelligence methods require a large amount of clinical data from a range of imaging modalities for correct disease diagnosis. In addition, AI has greatly enhanced the quality of hospital stays, allowing patients to be released sooner and complete their recoveries at home. This article aims to provide the information on the field of AI subset i.e., machine learning-based disease detection with information that will aid them in making better decision making. This helps the researchers to classify the medical conditions in patients with a prominent dataset.

1. Introduction

Artificial intelligence (AI) in medicine researchers focus on creating algorithms and methods for assessing a system behavior to evaluate if a condition has been correctly diagnosed. A medical diagnosis is the process of determining the root cause (or reasons) ofa patient symptoms and indicators. When trying to make a diagnosis, the doctor will typically look to the patient medical history and physical exam as starting points [1]. There are a wide variety of elusive symptoms and signs that make it impossible to diagnose without the assistance of a trained medicalprofessional. As a result of a lack of trained medical personnel, emerging nations like Bangladesh and India struggle to meet the medical demands of their whole populations [2]. In addition, persons with lower incomes often struggle to afford the medical testing necessary for an accurate diagnosis.

Due to human error, over diagnosing a patient is not a common practice. Individual healthand the economy may suffer from an overabundance of diagnoses [3]. The majority of people will obtain a false diagnosis at some point in their lives, according to a study published in 2015 by the National Academies of Science, Engineering, and Medicine [4]. Several factors can lead to a misdiagnosis, including a lack of pertinent symptoms (which may be so subtle they go undetected), the manifestation of a very rare disease, or the physician inability to even consider the possibility of the ailment.

Machine learning (ML) is used in a wide variety of fields, from healthcare to cutting- edge technology. Medical diagnosis is one of several sectors where ML is finding significant use. Several researchers and medical professionals have shown that machine learning-based disease diagnostics (MLBDD) is effective [5]. Traditional methods of diagnosis are time-consuming, expensive, and often include the involvement of a medical professional. Unlike traditional techniques of diagnosis, which are constrained by the capabilities of the individual practitioner, ML-based systems are not affected by human fatigue. That could lead to the formulation of a plan for disease diagnosis in the context of an unexpectedly large patient population. Baseball-like batting-average-decision-discovery (MLBDD) systems [6] are built using medical data such images and tables of numbers.
ML is a branch of AI that relies on pre-existing data sets to train algorithms [7]. Oftentimes, it is very challenging to achieve the same outcome without resorting to well-established mathematical functions. For instance, ML can be used to make it much easier to spot cancer cells in a microscope image. The photographs alone rarely provide enough information to accomplish this. Furthermore, the most recent study showed that MLBDD accuracy is above 90%. This is especially true when deep learning, a type of machine learning, is taken into account.

Many diseases and disorders may be diagnosed with ML in the future. Some of these include Alzheimer, heart failure, breast cancer, and pneumonia. Medical professionals increasingly turn to machine learning (ML) algorithms to make accurate diagnoses. This demonstrates the technology potential benefits in the medical field.

Just a few examples of the many challenging areas that need to be treated in a summary include the recent successes in machine learning, such as unbalanced data and interpretation in medical domains [8]. This study focuses on the distinct applications of ML in disease diagnosis in the medical field stating the issues associated with ML in disease diagnosis. To better understand the present direction, methods, and obstacles of ML in disease diagnosis, this review was produced. First, we'll go over a variety of ML/DL approaches, as well as specific architectural frameworks, for identifying and assessing health problems.

This article aims to provide current and future researchers in the field of machine learning- based disease detection with information that will aid them in making better decision about which ML/DL approaches to adopt. As a result, it will be easier to identify and classify disorders.

2. Role of AI in Detection of Diseases

AI is the study of how machines can learn, including things like image recognition and pattern recognition in highly novel settings. Data collection, analysis, and sharing in the healthcare industry are all being affected by the growing use of AI.

The conventional AI aims at preparing a system as being similar to creating a rough sketch of its eventual layout. If the customer has a secure grasp on the framework architecture, they will have a greater comprehension of the constraints that it imposes.

The disease detection model uses real-world machines and deep learning classification algorithms to ascertain the components that lead to the onset of disease. Data collected from the real world must be routinely updated and organised before computing can take care of it. While it is understandable that sometimes real-world data would have errors in the actual metrics used, this does not meanthat these mistakes can be ignored or ignored. Thus, information preparation takes the raw data and cleans it up by cycling it, removing the errors and sparing it from a second round of examination.

While the data is being pre-processed, it undergoes a series of operations. During data cleaning, many methods are used to get rid of old or irrelevant information. For example, increases the quantity of information available, while omitting commas and other cryptic symbols, decreases it. Information refers to the process of integrating data from several sources. Any discrepancies are then promptly addressed by updating the data.

- ***Information Alteration***: Depending on the computation being carried out, the data in this sequence may undergo a process known as information alteration, in which case the data will be standardised in a manner that is consistent throughout. When it comes to implementing information standardisation, there are a few different approaches to choose from (Nasser et al. 2019). The use of this method is common in data mining-related computations. Since error-free data is a prerequisite for successful data mining, this is the case. The improved and shared information benefits both parties.
- ***Dimensionality Reduction***: Dimension reduction aims to make data more manageable by reducing their overall number of dimensions.
- ***Data Collection***: Information collecting is divided down into manageable chunks, such as creating indexes and double-checking them for accuracy. Information acquired in the planning stage is used in the analysis of data samples. Most of the time, the information from the trials is re- extracted from the same database that was utilised for the initial research and pilot tests. Model preprocessing is followed by a brief phase in which the framework is validated.
- ***Systematic model***: In order to anticipate disease, a systematic model is utilised to compute the likelihood of a specific occurrence function given commitment parameters. It can infer the user mental state from external signals and past actions.

3. ML based Disease Diagnosis

More scientists and doctors are using ML techniques to enhance their prognostic abilities. The media has paid a lot of attention to ML-based disease diagnostics (MLBDD) in the recent years, and the study discusses a few of them here. Here, for instance, we gave more credence to studies that focused on the identification of COVID-19 disease using ML. Diseases such as coronary artery disease, breast cancer, kidney disease, Alzheimer disease, Parkinson disease, and corona virus 19 are briefly discussed.

Heart Disease

ML techniques are widely used in research and clinical applications for cardiac illness diagnosis. Ansari et al. [9] created a heart disease diagnosis using fuzzy. The system has an approximate accuracy of 89%. This method will function in a variety of circumstances, including multiclass classification, huge data processing, and unequal class distribution, is one of the study most glaring flaws. Furthermore, the validity of the model is not justified, despite its recent widespread promotion in the field of medicine. With this outreach, we hope to help users who aren't trained in the medical field become familiar with the methodology.

When attempting to identify aberrant cardiac sounds, Rubin et al. [10] relied on techniques based on deep convolutional neural networks. Through tweaks to the loss function, the researchers in this study increased the training dataset sensitivity while maintaining its specificity. In 2016, they submitted their proposed model to PhysioNet computing competition. For the competition as a whole, their final prediction placed second with a specificity of 0.95 and a sensitivity of 0.73.

Meanwhile, in a distinct but related trend, there has been a rise in recent years in the use of deep learning (DL) algorithms for the diagnosis of heart disease. For instance, Miao et al. [11] presented a deep learning (DL) method for diagnosing foetal heart problems from a cardiotocographic pattern in 2018. The 2018 study was released to the public. The developed approach classifies infertile patients according to their unique anatomical traits. The F-score for their preliminary computational results is 0.85, the accuracy is 88.02, and the precision is 85.01. The authors of that study put a premium on dropout mechanisms to prevent overfitting. That why they extended the training session significantly.

Despite the increasing popularity of machine learning applications for heart illness diagnosis, no research has yet tackled the difficulties of multiclass classification in the presence of imbalanced data. It is common for a model to lose explanatory power towards the last step of prediction.

Kidney Ailments

Renal disease refers to any ailment that negatively impacts the kidneys. Lack of treatment for chronic renal disease might lead to kidney failure. Since these two technologies have recently advanced, it is possible that certain countries will be able to reap the benefits of AI based renal disease diagnoses in the not-too-distant future. On publicly available datasets, Charleonnan et al. [12] found that classifiers achieved higher accuracy. The authors compared MLPperformance to that of other machine learning algorithms (RPART, SVM, and LOGR) and found that MLP had the highest successrate (98.1% of the time) in detecting chronickidney disease. This was found with the helpof the CKD dataset, which was also used by.

Breast Cancer

Researchers have speculated that a ML study would help with the decades-long issue of early breast cancer detection. Fuzzy logic was used by Miranda and Felipe [13] on a computer-assisted breast cancer diagnostic technique. Fuzzy logic is favoured over conventional machine learning techniques because it can mimic the behaviour of a seasoned radiologist with minimal computational overhead. Users select parameters, such as tumour size, shape, and density, to determine the type of cancer.

It was estimated that their proposed model was accurate 83.34% of the time. By taking roughly the same amount of images in each

circumstance, the authors were able to provide more reliable and objective results. A confusion matrix showing how well each model predicts its classes would be helpful. In its place, there is a total lack of sound.

Zheng et al. [14] reported hybrid methods for detecting breast cancer. Support Vector Machine (SVM) and K-means clustering (KMC) are the foundations of these methods. Using the Wisconsin Diagnostic Breast Cancer (WDBC) dataset, they proposed a model with an accuracy of 97.38%. As a result, they were able to significantly cut down on the dimensionality issue. There are a total of 32 attributes in the dataset, and they may be broken down into 10 categories. This is due to the possibility of missing values in the dataset. The Wisconsin Breast Cancer (WBC) research served as the source data. After looking at a number of different ML methods, they determined that SVM had the highest accuracy (97.13%). Repeating an experiment with data from a different source may produce different findings. Furthermore, it is possible to gain a more accurate estimate of the most successful ML model by supplementing experimental findings with ground truth data. What a nice bonus!

Experiments on the popular WBC and breast cancer datasets using NB, DT (J48), and sequential minimal optimization (SMO) to evaluate which ML algorithms yield the best results. The goal of these tests is to identify the most effective ML algorithms. What fascinating about this work is that it prioritised addressing issues with data imbalance by employing resampling data labelling processes. In comparison to the other two classifiers, the SMO algorithms performed better than 95% of the time on both datasets. When compared to the other two classifiers, this was the case. However, they frequently used resampling procedures to lower the imbalance ratio, which may have lowered data diversity. These three machine learning methods may not perform as well when applied to a data set whose values are not uniform or distributed in the same way.

To determine optimal values for the KNN algorithm parameters, Assegie [15] employed a grid search strategy. According to the findings of their research, adjusting the model parameters significantly affected the predicted outcome. They demonstrated that slight adjustments to the parameters of KNN, which by default provided an accuracy of 90%, could increase that to 94.35.Using a backpropagation neural network, the prospect of identifying breast cancer included 9 features were examined in all, and the WBC dataset was used for the study. Overall, the results were found to be 99.27% accurate. The WBCD and WDBI datasets were used in the creation of a shallow artificial neural network model for breast cancer tumour categorization. Without any human intervention in feature selection or algorithm tuning, the suggested model was found to have a 99.85% accuracy rate in tumour classification.

A strategy to constructANN by utilising the WBC dataset for breast cancer detection. Multilayer perceptron (MLP), Jordan-Elman network (JN), modular network (MN), generalised feedforward network (GFN), self- organizing feature map (SOFM), SVM, probabilistic network, etc. Unfortunately, this study is not as easily interpretable as many others due to its failure to identify which traits are most significant throughout the prediction stage. As a result, it cannot perform these functions, as they were not intended.

Diabetes

The number of individuals with diabetes is anticipated to increase from its current 382 million to 629 million by 2045, as reported by the International Diabetes Federation. (IDF). Detecting patients with diabetes is possible with ML-based methods that have been widely presented in a number of studies. In order to categorise people with diabetes mellitus, Kandhasamy and Balamurali [16] looked into many different machine learning classifiers. This could be seen as a flaw in the completed work. So, it shouldn't be shocking to get 100% accuracy with a smaller, more manageable dataset. Neither the impact of the algorithms on the final prognosis nor the accessibility of the results to a non-specialist audience are discussed in this paper. Using several different types of machine learning, Naz and Ahuja [17] dug into the publicly available PIMA datasets. Findings from their study suggest that DL is reliable for diagnosing diabetes in its earliest stages (ithas a sensitivity of 98.07%. The PIMA dataset has been studied more extensively than any other major dataset. Because of this, it feasible to easily run intricate and straightforward ML-based algorithms. Therefore, it is not surprising that the PIMA Indian dataset allows for higher accuracy. Furthermore, the research does not investigate how well the model may perform when applied to an asymmetric dataset or one that is missing a substantial quantity of data, nor does it address problems surrounding the model interpretability. Not all output data will be as high-quality as the PIMA Indian dataset in terms of labelling, categorization, and preprocessing. Within the medical community, this is common knowledge.

Every time a sizable chunk of data is missing from a multiclass classification dataset, it is crucial to examine the algorithmsused by the CDSS for their fairness, unbiasedness, dependability, and interpretability.

Ashiquzzaman et al. [18] devised the use of DL and found that using dropout approaches considerably improved performance and mitigated overfitting issues. However, overusing the dropout technique lengthens the duration of instruction. It is unclear whether or not their proposed model is suitable for computational purposes because they neglected to take them into account throughout their investigation.

Parkinson's Disease

A disorder like Parkinson disease that has received extensive coverage in the medical literature over the years is a good illustration of this. This condition causes chronic nervepain that worsens over time. There is some evidence that the loss of dopamine-producing neurons or their destruction can impair basic cognitive and motor functions in specificregions of the brain. ML has sparked the creation of numerous other strategies. Using the KNN, SVM, NB, and RF algorithms, Sriram et al. [19] created cutting-edge diagnostic tools for Parkinson illness. The computational findings demonstrate that RF performs best (90.26%), while NB performs worst (69.23%) among all of the other algorithms considered. The deep CNN-based model proposed for identifying Parkinson disease achieved nearly 100% accuracy on both the training and testing sets. In spite of its lack of clinical experience, the model was able to attain this level of accuracy. Nonetheless, overfitting issues were not reported in this study. It is difficult to draw firm conclusions about the ultimate classification and regression from the experimental data, as is now the norm, especially in CDSS.

With the hope of discovering whether or not decision support systems can spot brain tumours and Parkinson disease, Warjurkar and Ridhorkar [20] undertook an extensive study in this area. Boosted logistic regression was shown to be the best effective method for identifying people with Parkinson disease by the research team. According toestablished standards, its accuracy is at 97.15%. However, when it came to tumour segmentation, the Markov random technique yielded the highest accuracy (97.4%).

COVID-19

When it comes to threats to human existence, the next SARS-CoV-2 pandemic (COVID-19) is by far the most serious. Despite efforts to speed up vaccine delivery in response to the worldwide emergency, the vast majority of people remained without access to the vaccine for the duration of the disaster. The recently identified COVID-19 Omicron strain is a major reason for alarm because of its high transmission rates and resistance to vaccinations.

Screening methods that are more accurate and efficient were also developed thanks to some of the studie use of much larger datasets. In order to achieve their results, Brunese et al. [21] relied on a total of 6505 images. Out of these images, 3 003 were classified as showing symptoms associated with COVID-19, while 3 520 were classified as showing symptoms in other patients.

Alzheimer's Disease

Alzheimer disease is a degenerative brain disorder that often manifests with a delayed onset and steady decline in symptoms over time. Of those with a dementia diagnosis, Alzheimer disease accounts for 60-70% of cases. Cognitive decline is a hallmark of Alzheimer disease, and it can manifest in a variety of ways. Many patients are given a prognosis of only three to nine years after diagnosis, due to the inevitable deterioration of their bodily systems. However, getting a proper diagnosis quickly could help you avoid complications and begin the road to recovery much sooner. The use of machine learning and deep learning to detect Alzheimer patients has been demonstrated over the course of several years. By combining SVMwith DT, they were able to create a model that could accurately identify Alzheimerpatients 83% of the time.

Multiple diagnostic algorithms have been implemented and evaluated, contributing to the progress of ML-based Alzheimer disease diagnosis. The accuracy of Logistic Regression (LR), Support Vector Machines (SVM), Decision Trees (DT), ensembles of Random Forests (RF), and Boosting Adaboost varies between 78.95% and 84.21%. In comparison to other existing algorithms, CNN performance in image processing is substantially higher. Therefore, several scientists have turned to a convolutional neural network (CNN) based method for diagnosing Alzheimer.

4. Challenges

Although the incorporation of AI into the disease-diagnosis process has already had a major impact, researchers still confront a number of obstacles.

Limited Data size

The absence of sufficient data to effectively train the model was the main obstacle faced by the bulk of the research. The limited size of the training set prevents us from drawing any firm conclusions about the efficacy of the proposed solutions. The performance of a trained model can suffer if too few data points are used in the process, whereas using a high number of data points can boost training results.

High dimensionality

Another problem that can come from working with cancer research data is its high dimensionality. When there are many more qualities than there are cases, as we show there is, the dimensionality is high. However, this issue can be resolved by employing any of

5. Conclusions

The success of the treatment plan and the patient continuing health depend on a correct diagnosis. Artificial intelligence (AI) is a huge and diversified discipline made up of data, algorithms, analytics, deep learning, neural networks, and insights that is constantly expanding and altering in order to meet the needs of the healthcare business and the people who utilise its services. This research highlights the need for AI to be used in healthcare, particularly for early disease detection.

There are still many challenges in the field of reliable clinical diagnostics that need to be overcome and enhanced before new diseases and disorders may be treated effectively. Despite great strides in the past few years, this remains a problem. Medical professionals agree that several obstacles must be addressed before AI may be used in conjunction with disease diagnosis in humans. Because of their scepticism that AI can reliably predict the onset and progression of disease, many medical practitioners have been slow to embrace AI-based remedies. It takes a lot of effort to train AI-based systems to improve their predictive ability when it comes to making medical diagnoses. Any future research on AI must account for the issue just drawn if it is to foster a collaborative working relationship between AI and medical experts. If early disease detection is the goal, then disease datasets located all over the world should be combined into a single training model using a decentralised federated learning approach.

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