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E-Healthcare System for Stroke Management Using IoT and Machine Learning

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Abstract:

Machine learning is one of the hottest topics in e-healthcare and has a big social impact. It is challenging to build and develop an efficient and successful e-healthcare system without machine learning. Machine learning's primary function is to analyse healthcare data, which is gathered from various sources and can be both homogeneous and heterogeneous. Therefore, creating an effective machine learning algorithm that functions with both homogeneous and heterogeneous data is a difficult task. On the other hand, it is noted that a sizable number of health-related products, such as fitness bands, smart watches, and sensors, are being developed, and the majority of people use these items to track their own health. Each person's health data is also gathered by these devices, and a machine learning algorithm is integrated into the data to identify any strange patterns or behaviours. These gadgets capture any aberrant behaviour or pattern, and an alarm message is sent to the individual. Thus, machine learning (ML) presents a promising technique for cutting healthcare device costs and describing doctor-patient relationships at a higher level.

Keywords: E-healthcare, Sensor, Machine Learning.

1. INTRODUCTION

Nowadays, because of technological improvements, a lot of data is collected, particularly in the biomedical and healthcare domains. This data can be summed up as text, audio, images, and so on. Moreover, it is noted that the data is inherently unstructured [1] [2]. Therefore, it is a difficult task to separate pertinent and useful information from the massive amount of data that has been obtained [4]. It is also observed that early disease diagnosis considerably lowers the risk to human life. Regretfully, it is unable to effectively harvest pertinent data for wise decisions [6].On the other hand, data mining is a rapidly developing field that takes large amounts of unexplored data and uses it to extract information or meaningful patterns [8]. Depending on the type of data, the information that has been mined can be used to make various administrative decisions. Data mining's branch of machine learning studies several forms of learning techniques, including supervised, semi-supervised, and unsupervised learning [22]. Numerous researchers investigate machine learning's potential for accurate disease prediction in order to substantiate this claim. However, prompt and precise disease diagnosis is the most pressing necessity for healthcare. Thus, regression analysis of healthcare data concerning illness phases, decision-making, prediction, and upkeep of electronic health records is the duty of machine learning algorithms [3]. Additionally, it is anticipated that machine learning algorithms will be able to process both organised and unstructured data and produce diagnostic results that are more precise [10] [17]. Additionally, it is noted that ontology-based and multi-agent approaches have been created for efficient analysis of healthcare data. Multiple agents analyse the data in a multi-agent system to extract pertinent information and patterns [12]. On the other hand, ontology-based systems are made to extract useful rules from data using ontology [5] [16]. The purpose of the created remote monitoring systems is to offer health facilities to users who live far away.[18] [23].

2. RESEARCH OBJECTIVES

Researchers are currently interested in the healthcare profession because of the rapidly expanding healthcare data, the most up-to-date medical imaging and diagnostic equipment, the state-of-the-art medical facilities, etc. Automated diagnostic and imaging equipment generate vast amounts of medical data in the medical industry, which can be challenging to manage. Conversely, a variety of machine learning approaches are used to process medical data and arrive at accurate disease diagnoses. But it turns out that one of the main issues with making the right diagnosis is accuracy. In order to tackle the previously mentioned issue of disease diagnosis, this study investigates deep neural networks' capacity to manage unbalanced medical data. Additionally, the DL approach is used to identify the pertinent aspects for disease diagnosis. The contributions of this chapter are given as

- Creating a deep learning model that is optimised for precise stroke illness prediction.
- Using a genetic algorithm, the pertinent features for stroke prediction are identified.
- The stroke dataset is used to assess the effectiveness of the deep learning method optimised using genetic algorithms.

The organization of the remaining sections is as follows: Section 2 presents a challenge associated with security in the e-healthcare system, research motivation, goals, and contributions, and a detailed explanation of the research activity; in Section 3 identifies performance evaluation of the proposed system.; Section 4 presents the findings and discussion of the proposed model, and Section 5 concludes with a summary of the contributions to the research and future extensions.

3. SYSTEM DESIGN

Disease Overview

It has been noted that over 85% of strokes are classified as ischaemic strokes, which are a common type of stroke. It is caused by a clot or other obstruction in a brain blood artery. Thrombotic stroke and embolic stroke are two more subtypes of ischaemic stroke. Any area of the body can develop a clot, which is what defines an embolic stroke and prevents blood from flowing to the brain. On the other hand, a thrombotic stroke is characterised by a clot that restricts blood flow in an artery. It also has an impact on the brain's regular blood supply. Haemorrhagic stroke is caused by weak blood vessels. This kind of stroke, which occurs in 10-15% of cases, can be caused by blood vessel rupture, but it poses a greater hazard to human life than ischaemic stroke [7]. Subarachnoid haemorrhage and intracerebral bleeding are the two subclasses of hemorrhagic stroke. Mini-stroke is another term for transient ischaemic stroke. This stroke is caused by a transient obstruction and clot. Consequently, there may be transient damage to brain tissue [19]. It might also be interpreted as a warning sign for future strokes. In summary, stroke is one of the worst illnesses. Furthermore, since most doctors treat stroke patients using conventional methods, diagnosing and treating stroke is a difficult undertaking.

The lack of up-to-date diagnostic and monitoring techniques that can more accurately anticipate stroke patients makes it difficult to estimate the risk of stroke as well. Furthermore, the initial treatment for stroke patients is suggested, and the present state of the patient is ascertained based on their current behaviour. The likelihood that stroke victims will recover can also be improved by the availability of such technologies. However, using a tool with a high accuracy rate is a difficult undertaking, even though it can help stroke victims receive therapy.

Proposed Framework

The fundamental wavelet can be represented as Ψ (t), a temporal characteristic that can be further scaled to various translations. It is possible to scale the two-dimensional triadic wavelet into four pairs of mother wavelets using the BWT method. By comparing the intensity and textural features from the Spatial Grey Level Dependence Matrix, features are extracted based on the search for the corresponding cells or tissues that are affected by Ischaemic stroke cells. K-means clustering is used to put comparable pixels or voxels together based on their feature values once the features have been extracted. Using an iterative process, K-means clustering allocates each pixel or voxel to the cluster whose centroid is closest to it and represents the average of the cluster's feature values. The aforementioned method searches for characteristics that adhere to the standard metrics seen on medical photographs. Eight criteria—described in detail in the preceding chapter—are used to extract the characteristics. To improve feature extraction, the suggested model also adds colour properties. The functions mean, variance, skewness, kurtosis, and entropy are commonly used to describe the functions needed to extract the color-based properties [9].

Four hidden neurone layers and one output layer are included in the deep learning architecture to validate all of the network's operations. Highlighting the features necessary for segmentation and classification procedures comes next, following feature selection based on spatial properties and colour components. Since the characteristics chosen might not directly improve the classification, the suggested model has used a genetic algorithm for feature selection. Reducing the list of chosen features to a primary list is necessary to increase the classification accuracy. The new method, which uses a genetic algorithm to optimise the list of features, has been found to be superior to heuristic, depth first, breadth first, and linear programming techniques. Asymmetrical characteristics, boundaries, colours, diameters, contrast, correlation, energy, homogeneous intensities, mean, variance, standard deviation, skewness, kurtosis, and entropy attributes are among the general aspects. The genetic algorithm optimises the final list of features needed for accurate classification results out of all the features. [20].

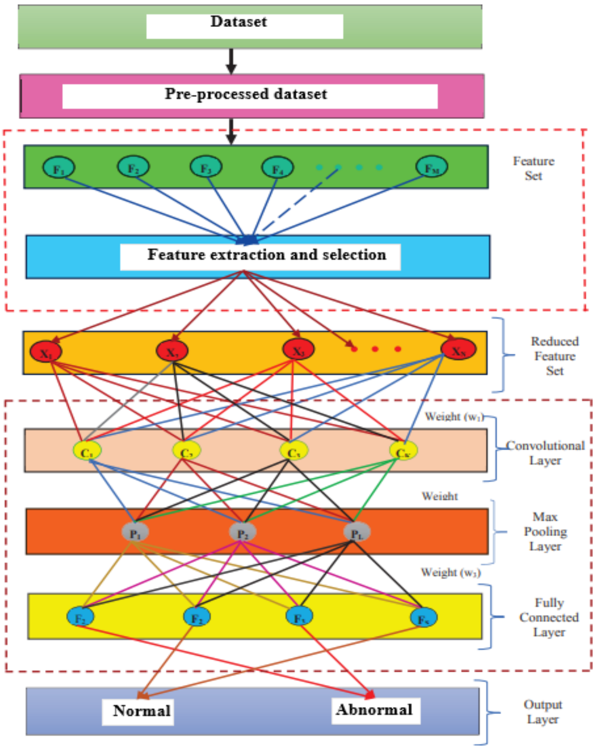

Figure 1: Proposed Framework

Genetic algorithm classification is a machine learning strategy that optimises feature selection, feature extraction, or model parameter tuning for classification tasks by utilising evolutionary computation approaches, namely genetic algorithms. Numerous classification tasks, including word classification, image classification, and other pattern recognition issues, can be classified using evolutionary algorithms. It provides an adaptable and flexible method for enhancing the process of feature selection or model parameter tweaking, and it can be especially helpful in scenarios when the search space is vast, intricate, or poorly understood.Numerous genetic algorithms have been implemented to enhance the segmentation and classification procedure, hence decreasing the quantity of features needed to identify the appropriate class or segment of ischaemic stroke. The quality results that the genetic algorithms guarantee are the only factors that affect the classifiers' performance. A genetic algorithm goes through several stages, such as determining the requirements for iterations, choosing the operators and functions, encoding the chromosomes, assessing the fitness levels of each function, and many other crucial parts that support the classification process. The structure of chromosomes is represented by the bit string when the genetic algorithm is applied in a binary search.Applying the fitness function to the entire population and determining if the bit strings are suitable for controlling the main population are the main tasks [11]. A chromosome is regarded as a primary characteristic that is necessary for classification when the bit string displays the value 1. The location and characteristics of the ischaemic stroke cells on the input medical image define the feature. The bit string's chromosomal values are used to rank the attributes, which determines the classification quality. The chromosomes with the greatest values following the fitness functions are regarded by genetic algorithms as the finest features for guaranteeing an appropriate classification [21]. To create the appropriate chromosomes for efficient processing, the remaining population will be iteratively processed using the same fitness functions that are subjected to crossover and mutation functions. The ideas underlying a genetic algorithm's operation, the actions needed in creating the population, fitness functions, and the procedures established to handle the optimisations necessary to create the fitness functions.

4. EXPERIMENTAL RESULTS AND DISCUSSION

The suggested deep learning model's experimental findings are shown in this section. The suggested model's simulation is also contrasted with well-known current methods and models. The suggested model's effectiveness is assessed through the application of three established performance metrics. These three performance metrics are recall, accuracy, and precision. The suggested DL model is implemented using the Matlab 2020a environment, and average results from thirty independent runs are shown. The stroke disease dataset is used to assess the suggested model's effectiveness. 43400 data objects with binary classes (Stroke and Healthy, i.e. no stroke) are included in the stroke disease dataset. A total of 42617 data objects are classified as healthy, or stroke-free. The remaining data items are members of the stroke class. In addition, there are a lot of missing values in the stroke dataset. There are many missing values in the dataset, and the mean value of each feature is used to swap these missing values. Ultimately, the stroke-affected patients are predicted using the DL model.

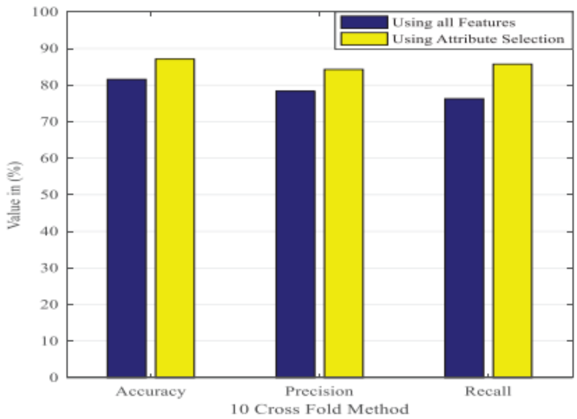

Figure 2: Simulation results of DL model

The experimental findings of the suggested BWT-GA optimised DNN model and DNN procedures employing the 50-50% training-testing and 10-cross fold methods are graphically shown in Figures 2-4. Plotting of these outcomes is done using the recall, accuracy, and precision factors. The simulation results for the DNN and BWT-GA optimised DNN models using the 10-cross fold method are shown in Figure 3.3. It is observed that compared to DNN models, the BWT-GA optimised DNN model archives greater accuracy, precision, and recall rates. Thus, it is also claimed that the feature weight technique greatly raises the DNN technique's prediction rate. The simulation results of the 50%-50% training-testing approach for DNN and BWT-GA optimised DNN models are shown in Figure 3. It is said once more that the BWT-GA optimised DNN model outperforms the DNN model in terms of performance. Based on the examination of Figures 3–4, it can be concluded that the ABC-FS optimised DNN model outperforms the DNN model when both training approaches are used (10–cross fold method and 50–50 training testing). The simulation results for the BWT-GA

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optimised DNN model employing accuracy, precision, and recall measures are shown in Figure 4 for the 10-cross fold method and the 50–50% training-testing methods. It is observed that the 10-cross fold approach outperforms the 50-50% training-testing approaches in terms of results. As a result, it is said that the 10-cross fold method is an important technique for modelling categorisation and prediction.

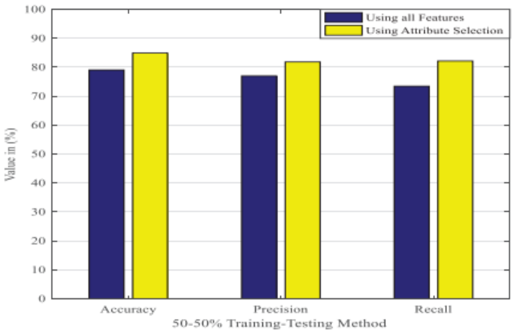

Figure 3: Simulation results of 50-50% training testing

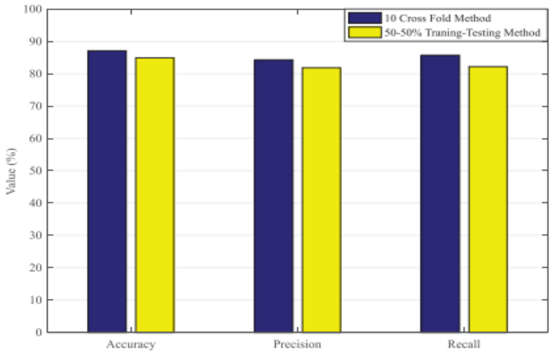

Figure 4:Comparison of simulation results of 10-cross fold and 50-50% training testing

Additionally, a comparison is made between the experimental outcomes of the suggested BWT-GA optimised DNN model and a number of machine learning approaches already in use.

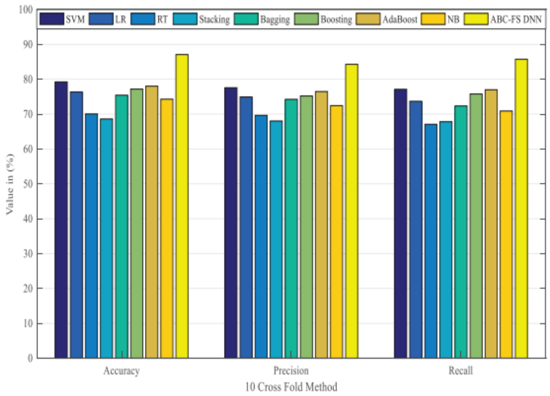

Figure 5:Simulation results of ABC-FS optimized DNN model and other machine learning techniques using accuracy, precision and recall parameters using 10-cross fold

Figures 5 and 6 use accuracy, precision, and recall characteristics to compare the performance of various machine learning techniques with the proposed BWT-GA optimised DNN model. The simulation results of the suggested BWT-GA optimised DNN model and further methods using the 10-cross fold method are shown in Figure 5. It is claimed that the suggested model performs better in terms of accuracy, precision, and recall rates than alternative methods. The simulation results of the proposed BWT-GA optimised DNN model and other methods utilising the 50%-50% training-testing strategy are shown in Figure 6.

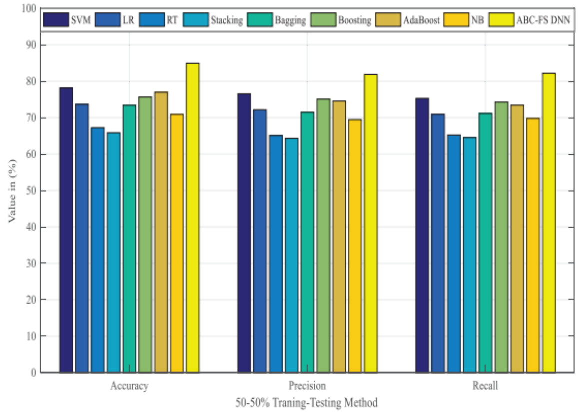

Figure 6: Simulation results of BWT-GA optimized DNN model and other machine learning techniques using accuracy, precision and recall parameters using 50-50% training-testing

It has been noted that the suggested model outperforms other methods currently in use in terms of accuracy, precision, and recall rates. As a result, it is claimed that the suggested model is one of the most accurate and efficient models for processing unbalanced data and predicting stroke patients. Additionally, it is asserted that the feature weighting technique increases the accuracy of predictions.

5. CONCLUSIONS

The capacity of a BWT-GA optimised DNN model to handle the imbalance stroke illness dataset is examined in the present section. This chapter's goal is to more precisely identify the stroke victims. In order to do this, the key features of stroke disease are identified using a feature weighting technique called BWT-GA. A DNN technique is then applied for the prediction job, resulting in a BWT-GA optimised DNN model. The proposed model's effectiveness is evaluated on 43600 patient records. It is discovered that stroke dataset also having missing value problem and this problem is repaired utilising mean value of each feature of stroke dataset. The efficacy of suggested model is tested by accuracy, precision and recall measurements. Additionally, two training techniques to train the prediction model, 50%-50% training-testing and 10-fold cross-folding are also taken into consideration. The suggested model's simulation results are compared to a number of well-liked, currently available machine learning models and methodologies. According to reports, the suggested BWT-GA optimised DNN model performs better than other methods already in use. In summary, the suggested BWT-GA optimised DNN provides a practical and efficient way to deal with imbalanced stroke data.

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