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Heart Disease Prediction Model using Deep Learning Algorithms

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ABSTRACT

The second most common cause of mortality is heart disease. Heart-related illnesses require quick treatment from medical professionals. The requirement for the most recent wireless communication technology is enormous given the global medical technology industry's quick expansion and advancements, notably for the ongoing patient monitoring. Due to the increase in the number of unknown diseases like COVID, earlier disease diagnosis is one of the challenging scenarios for healthcare professionals like doctors and medical technicians, especially for a critical disease that requires immediate treatments. Some of the latest difficulties posed by medical practitioners and service providers in providing high-quality healthcare services opened the way for the implementation of innovative technologies like machine learning, the Internet of Things (IoT), artificial intelligence, and data analytics to improve clinical outcomes. Artificial intelligence is one of those technologies that provide fast solutions for medical diagnosis. This study's primary goal was to suggest a novel medical strategy for earlier illness diagnosis of cardiac problems that need urgent medical attention. This research suggests a deep learning method that helps medical professionals to expedite the diagnosis of patients who require urgent care. The experimental findings demonstrate that the proposed model delivers better result with the prediction accuracy of 91.48%. The model was compared with several existing deep learning models. Additionally, it was determined that the proposed prototype will be more suitable for early disease prediction, particularly for heart diseases and its related diseases.

Keywords: Artificial Intelligence, Disease, Heart, Deep Learning, Predictions, LSTM, Training Medical Domain and Testing.

INTRODUCTION

In the current pandemic situation, there are several undiagnosed diseases affects globally. The modern health care systems are the only solution for early disease diagnosis. [1] The effectiveness of treatment is greatly influenced by an early and accurate diagnosis that has an impact on infected

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individuals. For instance, undiagnosed patients with infectious disorders like Covid may spread the illness to other people. Some disorders, such as lung illnesses and heart disorders will have a significant impact on clinical outcomes since they require rapid treatment because a delayed diagnosis will put patients in a more hazardous situation. [2]. To efficiently monitor the provision of healthcare services, the majority of healthcare businesses are attempting to include the most recent ICT (Information and Communication Technology). ICT based technologies provides best services for the patients and the medical professionals within hospitals and clinics, but also to their work environments in the most efficient manner with minimal cost and the finest quality. The adoption of modern tools like Interne of Things(IoT), data analytics, deep learning algorithms provides the improved consequences in the disease diagnosis process. These modern tools provide an efficient way to overcome some of the recent challenges faced by medical professionals and service providers in delivering excellence medical services. The following figure 1 presents the heart disease ratio.

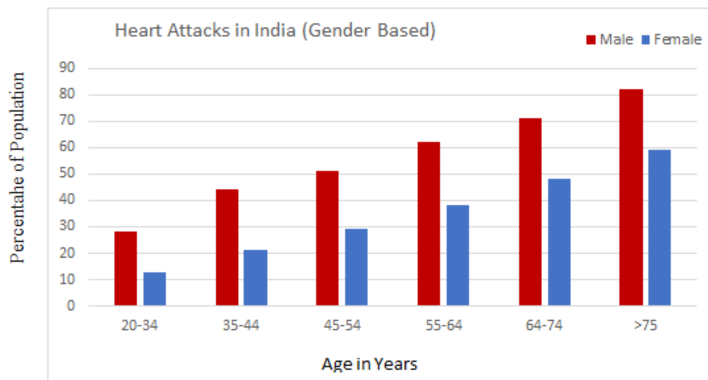

Figure 1 Heart Disuse ratio in India (2021)

IoT was the third most widely used expertise in the medical domain, according to the most recent medical survey results. Healthcare stakeholders now have the opportunity to effectively provide the best medical services using IoT technologies to overcome healthcare-related difficulties. IoT offers several advantages, including real-time monitoring systems, effective ways to gather medical data and analysis for the subsequent results: a) to more accurately assess the complexity and severity of a patient's medical issues; b) to develop contemporary treatment strategies, and c) to build decision support systems to evaluate medical professionals and processes for more accurate illness diagnosis. The analysis of high-dimensional biomedical data using the machine learning algorithms offers a sophisticated and automatic method that considerably enhances the efficiency of therapeutic analysis. The recent deep learning algorithms are applied in the medical domain that has a high reproducibility or accuracy when performing a task, that are crucial for medical management, particularly for detecting disorders. [3].

One of the most horrible diseases is cardiovascular disease, especially silent heart attacks, which strike suddenly and leave no time for treatment and are extremely challenging to identify. Building an effective method for detecting heart illness has become necessary due to the shortage of specialists and the rise in incidents of misdiagnosis. A range of medical data mining and machine learning techniques are being utilized to extract meaningful data on heart disease prediction. The desired results' precision, however, is insufficient.

Literature Survey

Early CHID detection is one of the essential components in treating heart related diseases. Finding and developing effective algorithms to carry out the CHD prediction task has been a major research priority. Techniques based on the machine learning have frequently been utilized to forecast CHD. Soni et al. used a free data mining program called Tanagra to test a number of algorithms on the Cleveland Heart Disease dataset, including K-Nearest Neighbors (KNN), Decision Tree (DT), Neural Network (NN) and Naive Bayes (NB). Thus, DT demonstrated the finest correctness of 89%, trailed by Naïve Bayes algorithm. [6]

The measurement lessening of high-dimensional facts has frequently employed PCA. In recent research, PCA has been utilized as a feature extractor to enhance classification performance. By utilizing PCA to reduce the Cleveland hearing disease dataset's data dimension from 10 to 6, the authors of [7] were intelligent to advance the performance of the SVM, NB, and DT algorithms. The Chi-square and PCA combination are demonstrated promising in CHD detection outcomes. Deep learning algorithms have been utilized to accurately detect and forecast disease in recent years.

The authors of [9] presented an enhanced approach to forecast heart disease by three dimensional U-net CNN deep learning technique. This model is applicable to various data sets under two backdrops with and without a centerline. The wavelet packet (WP) decomposition and SVM were used to classify 120 PCG signals from an internal dataset for HVD. Two classifications (Normal and HVDs) were used for the classification job, with a specificity of 96.67%. To more reliably assess cardiac illness, the authors of [11] suggested an IoT system that makes use of a modified deep convolutional neural network (MDCNN). Several parameters including the blood pressure and cardiogram of the patient was collected with the help of wearable device and ECG. The MDCNN was used to categorize device data that had been received into regular and abnormal conditions. By contrasting the proposed MDCNN with existing deep learning neural networks and logistic regression, the system's performance is evaluated. The outcomes demonstrate that the suggested model performs well when compared to other existing model. The author also presented the accuracy of the proposed work.

With data gathered from multiple sources, the authors of [12] presented a model using IoT technology and device supported mechanism to diagnose the people with heart disorders. Initially, the heart failure symptoms are collected from the patients using the smart phones and Bluetooth devices. The collected information is sent to the cloud database with the use of the gateway. Upon receiving the data, the patients will be divided into several categories based on the symptom set. With the help of the proposed decision making system, the patients are treated in an efficient manner. The results of the experience testing supported the high-level system's performance.

The author of [13] presented an automated diagnostic model for cardiac disease detection. After normalizing the data, the dataset will be divided into separate set for training and testing. The statistical model extracts the necessary features from the trained data. The trained dataset is used for testing the data. The results of the experience testing supported the high-level system's performance. The neural network approach was used to train the data with limited characteristics. Using the test

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data, the trained NN's performance was evaluated. The paper [14] presented a secured health-care model using block-chain technology. The block-chain was used to guarantee the confidentiality and openness of patient records, document accessibility, and the delivery procedure between benefactors and clients. The framework's empirical investigation was evaluated based on the communications or illegal acts of hostile IoT objects.

The author of [15] proposed disease diagnosis model for heart disease with the deep learning tools and heart disease dataset. They applied several feature assortment techniques, the cross-validation technique with several well-known machine learning algorithms, and performance assessment criteria for classifiers like classification accuracy, specificity, sensitivity, Matthews' correlation coefficient, and execution time. The suggested system provides flexible method to differentiate the patients with hearth diseases.

Research Methodology

The Kaggle dataset and real-time hospital data were utilized to create the study dataset. For analysis, two distinct datasets were employed. The first dataset (Kaggle Dataset) has 4500 records, and the second dataset was compiled from hospitals and medical centres with the use of specialized servers that are connected to various medical centres. The readings from wearable devices were taken for 1025 records in the second dataset.

3.1 Proposed Model

Several deep learning algorithms are evaluated to build the proposed model. The selected algorithms are Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), Multilayer perception (MP), Radial Basis Function Networks (RBFN) and Long Short Term Memory (LSTM).

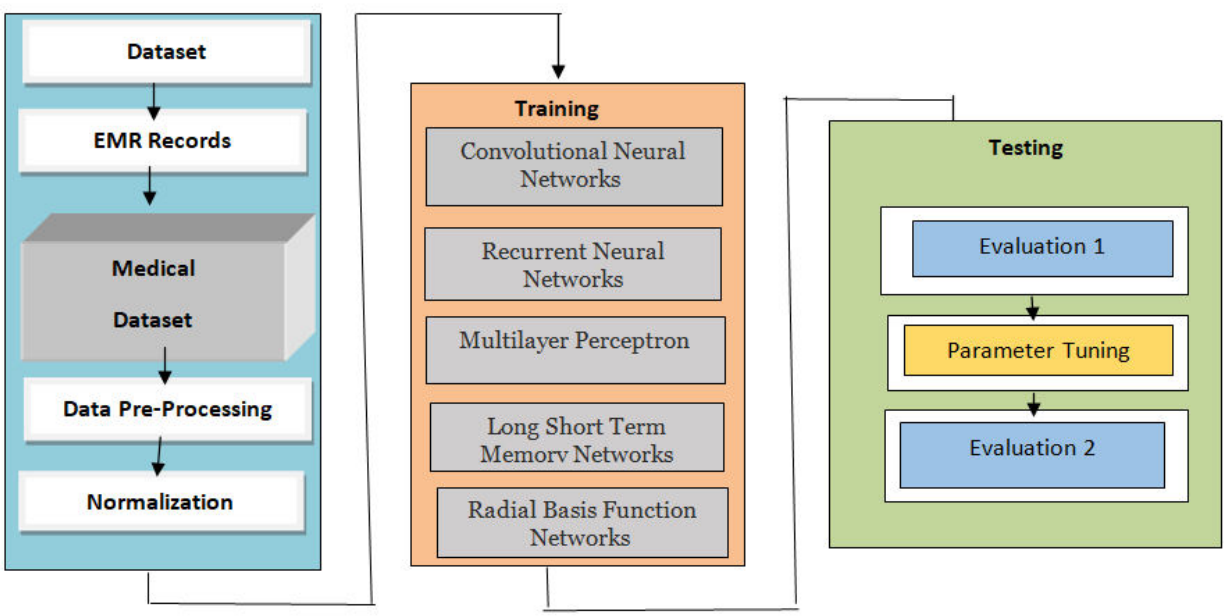

Figure 2 Proposed Model

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Deep Learning Models

4.1 Convolutional Neural Networks

ConvNets, often referred to as CNNs, are primarily made up of numerous layers and are used mainly for object detection and image processing. It was first known as LeNet and was developed by Yann LeCun in 1998. It was created back then to detect numerals and zip code characters. CNNs are widely used in anomaly detection, series forecasting, medical image processing, and satellite image identification. In order to do convolutional operations, CNNs process the data by putting it through several layers and extracting features. Rectified Linear Units (ReLUs), which are part of the convolutional layer, are used to correct the feature map. These feature maps are corrected in the following feed using the pooling layer. Pooling is often a down-sampled sampling procedure that decreases the dimensionality of the feature map. The final output is composed of 2-D arrays made up of linear, single, long, and continuous vectors that have been flattened in the map. The following layer, known as the Fully Connected Layer, creates a flattened matrix or 2-D array using the input from the Pooling Layer and classifies the image to give it a name [16].

4.2 Recurrent Neural Networks

Recurrent neural networks [17] are made up of a cycle of directed connections that enable the current phase of RNNs to utilize the input from the LSTMs. Because these inputs are so deeply ingrained, the LSTMs' capacity for memorization allows them to be temporarily stored in the internal memory. As a result, RNNs rely on the inputs that LSTMs preserve and operate in accordance with the synchronization phenomena of LSTMs. RNNs are mostly used for data translation to machines, time series analysis, handwritten data recognition, and captioning of images. When the time is defined as t, RNNs put output feeds at (t-1) time in accordance with the work strategy. At input time t+1, the output determined by t is then fed. Similar operations are carried out for all inputs, regardless of input length. RNNs have the additional property of storing historical data, thus even if the model size is expanded, the input size remains constant. RNNs resemble this when they are fully unfolded.

4.3 Multilayer Perceptron

The foundation of deep learning technology is MLPs [18]. It belongs to a group of feed-forward neural networks that have several perceptron-filled layers. These perceptrons each have a different activation function. Input and output layers in MLPs are also connected and have the same number of layers. Between these two strata, there is another layer that is still undiscovered. MLPs are primarily used to create voice and picture recognition software, as well as various kinds of translation software. Data is fed into the input layer to begin the operation of MLPs. The layer's neurons come together to create a graph that creates a link that only goes in one direction. It is discovered that there is weight for this input data between the secreted layer and the input layer. Activation functions are used to determine the node. The tanh function, sigmoid, and ReLUs are some of these activation mechanisms. In order to produce the required output from the given input set, MLPs are mostly utilised to train the models and determine what kind of co-relation the layers are serving.

4.4 Long short term Memory

Recurrent neural networks (RNNs) [19] with long-term dependent learning and adaptation capabilities are known as LSTMs. It can remember and recall information from the past for a longer

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time, and by default, this is its only behavior. Because LSTMs can hold onto memories or prior inputs, they are frequently utilized in time series predictions because they are built to retain information across time. This comparison is made due to their chain-like structure, which consists of four interconnected layers that communicate with one another in various ways. Along with time series prediction applications, they can be used to build voice recognizers, advance medicinal research, and create musical loops. The LSTM operate on a series of events. First of all, they have a tendency to forget superfluous information acquired in the preceding condition. They then selectively update a subset of the cell-state values before generating a subset of the cell-state as output. The diagram of how they work is below.

Experimental Setup

Utilizing specialized application software created to simulate some of the key characteristics of the system, Simulation is one of the methods for analyzing a numerous deep learning algorithms that mimic real-time applications. This study made use of Microsoft's ML.NET Open-Source and Cross-Platform deep learning tools. This approach was used to implement the deep learning algorithms. Additionally, it is best suited to train deep learning models for all types of health related applications, adding Artificial Inelegancy to any application.

5.1Evaluation Metrics

Performance metrics are vital component to evaluate the general enactment of deep learning algorithms. It is mainly used to monitor how successfully machine learning models were applied and worked on a particular dataset under various circumstances. Understanding the behavior of the model and making the required improvements depend on choosing the right metric. The metrics are displayed in the following table.

S.No	Metrics	Description
1	TP (True Positive)	It is the number of occurrences of stroke disease that are classified as true and are true.
2	TN (True Negative)	It's the number of cases of stroke disease that are classified as fake and are, in fact, false.
3	FN (False Negative)	It is the number of cases of stroke disease that are labeled as false but are true.
4	FP (False Positive)	It refers to the number of cases of stroke disease that are labeled as true but are false.

Table 1 Performance Metrics

A scientific modeling is the vital and important aspects to build the model for medical domain applications and to test the efficiency. These are crucial facts that must be appropriately evaluated for improved disease identification. The mathematical model that was employed to assess this result is described in this section.

Accuracy is the factor to determine the total number of predictions that the model got correct out of all the different kinds of predictions produced in categorization problems [18]. It is written as follows: The type of all procedural predictions (Yes and No) is in the denominator, while the proper forecasts (True Positive and True Negative) are the numerators.

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$$Accuracy = \frac{TP + TN}{(TP + FP + FN + TN)}$$

Precision [19] is one of the factors that ascertain the percentage of heart disease patients who have genuinely experienced a disease. The following are the predictable trueness (Patients who are anticipated to suffer from heart disease, denoted by FP and TP , and patients those who have already experienced a heart disease, denoted as TP) and the heart disease survivors:

$$Precision = \frac{TP}{TP + \mathrm{FP}}$$

Sensitivity/Recall [20]: It is a metric which indicates the proportion of heart patients that the procedure accurately identified as having the disease. The patient identified by the model as having heart disease is also TP, as are the true positives (patients who have heart disease are FN and TP). Since the Person had a heart disease in spite of the algorithm prediction, FN is specified as follows:

$$Sensitivity = \frac{TP}{TP + FN}$$

F1 Score: It is not required to compute both the precision and recall when building a prototype to address an organization problem [21]. Therefore, it would be ideal if it could obtain a normal score represented both Recall ® and Precision (P). One method for doing this is by taking the average of all of them. With P standing for precision and R for recall, the formula is (P + R) / 2. In other situations, though, It is not a fair option. It is spelled as follows:

$$F1\ Score = \frac{2 * Precision * Recall}{Precision + Recall}$$

Experimental Results

Parameter selection is one of the key aspects of any crucial medical applications; this study gives observations of cardiac illnesses based on parameters. Critical stroke-related disorders will not have a better solution than the most recent deep learning models. This study showed that models that solely employ medical imaging and only EGC imaging are unsuitable for making reliable forecasts of serious problems like heart-related ones. Even in this work, several classification methods are only employed with specified modifications for the classification of medical images. Recent research on heart problems has employed specialized modern deep learning models that solely provision ECG images. However, if these prototypes are employed with all possible parameters, then these models provides the best suited solution for applications that require high reliability.

6.1 Accuracy analysis based on Dataset

The accuracy outcomes of the dataset selection are displayed in the following figure. One dataset from the EMR and one dataset from real time, for example, are used. 450 records are chosen for first evaluations out of the dataset's 4500 total records. The graph unequivocally demonstrates that the Real-time Dataset offers greater accuracy than the EMR dataset. Modern medical data collection methods will provide patients with improved results in terms of essential medical applications such

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disorders associated with heart diseases.

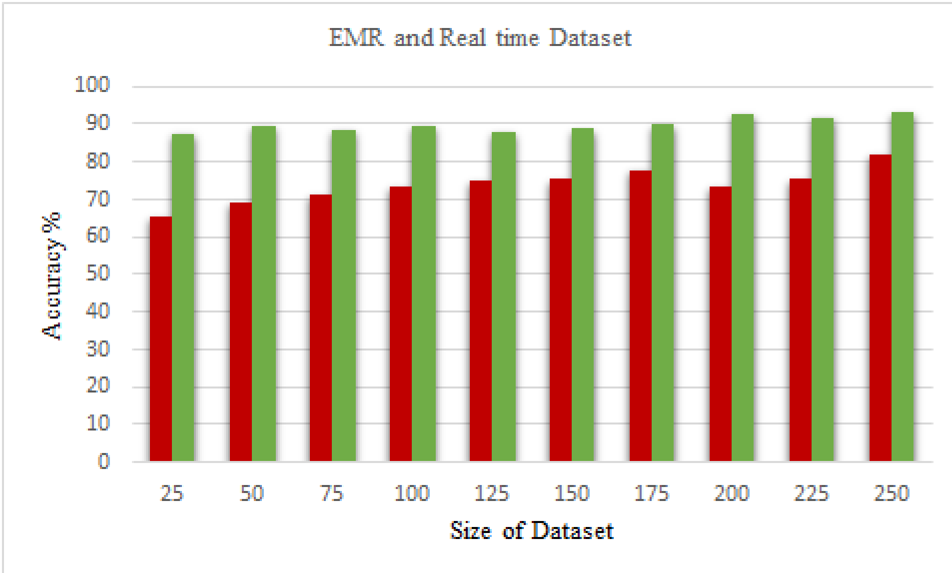
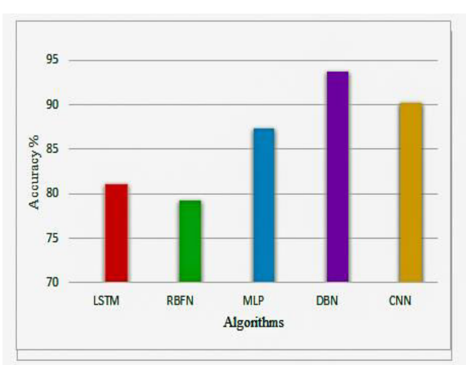


Figure 3 Accuracy based on dataset

6.2 Analysis based on the Deep learning Models

The numerous findings from the experiments conducted using the mathematical model that was described in the part before are reported in this section. The accuracy and outcomes of the deep learning models Convolutional Neural Networks, Recurrent Neural Networks, Multilayer Perceptron, Long Short Term Memory, and Radial Basis Function Networks are shown in the following Figure. When compared to other models, the experimental findings clearly demonstrate that the Long Short Term Memory model provides a better outcome with an accuracy of 92.23%. It also showed that the LSTM models were more appropriate for pathways for predicting heart-related diseases. Convolutional neural networks had an accuracy of 90.28%, recurrent neural networks had an accuracy of 81.17%, multilayer perceptron had an accuracy of 82.08, and recurrent neural networks had an accuracy of 77.21%. Figures a and b show the precision results obtained using deep learning models and the accuracy results obtained using dataset selection. In both situations, WBAN yields superior outcomes.



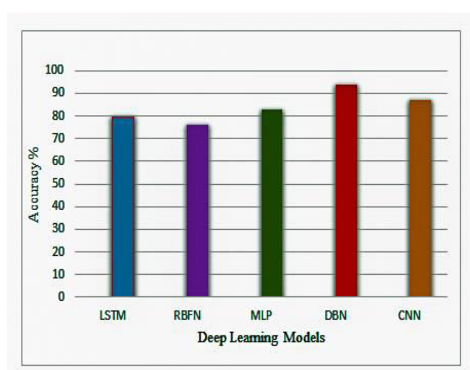


Figure 4 Accuracy based Deep Learning Models

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The outcomes based on the F1 Score and Recall Score are shown in the following figures (a and b). In all instances, DBN offers superior outcomes when compared to other models, which is encouraging for medical applications.

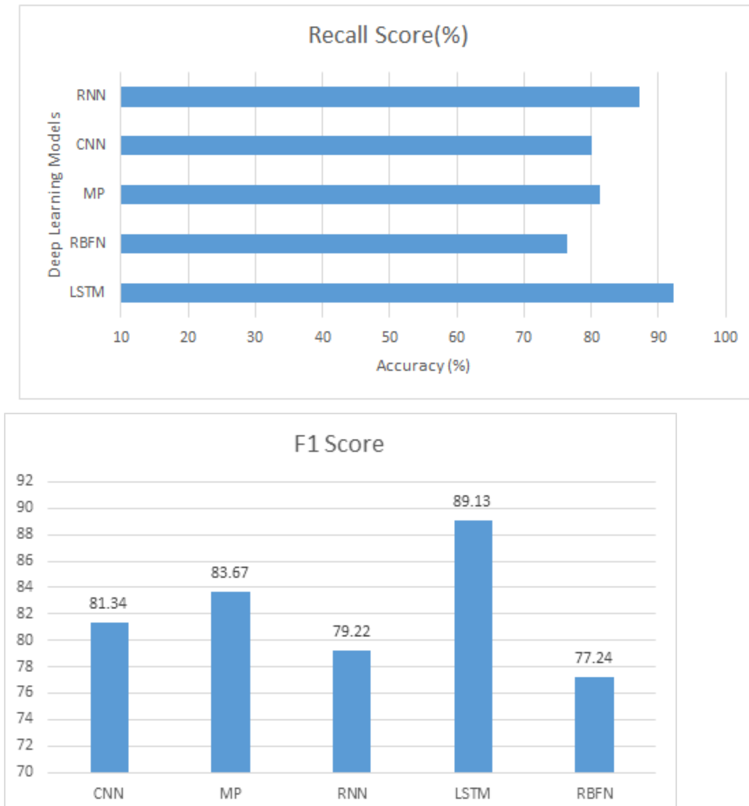

Figure 5 a) Recall Score b) F1 Score

6.3 Analysis based on Training Datasets

The following Figure presents the outcomes from a variety of data sets. In this work, the selected ranges for dataset (40 to 90). According to this investigation, the maximum value is reached for employed methods in the data training range of 75% to 80%. As the training size increases, only SVM shows an improvement in accuracy. On the other hand, the remaining algorithms deliver excellent outcomes and highest of 80% accuracy in the training domain. According to this research, a size range of 75% to 80% train data size is optimal for illness forecasting and obtaining accuracy, Recall, F1 Score and Precision. Additionally, it was also noted that the 50% Train data set has a higher likelihood of under-fitting. 90% of the Training Dataset is susceptible to over-fitting. As a result, any application for disease diagnosis benefits greatly from a data set with a training rate of between 75 and 80 percent.

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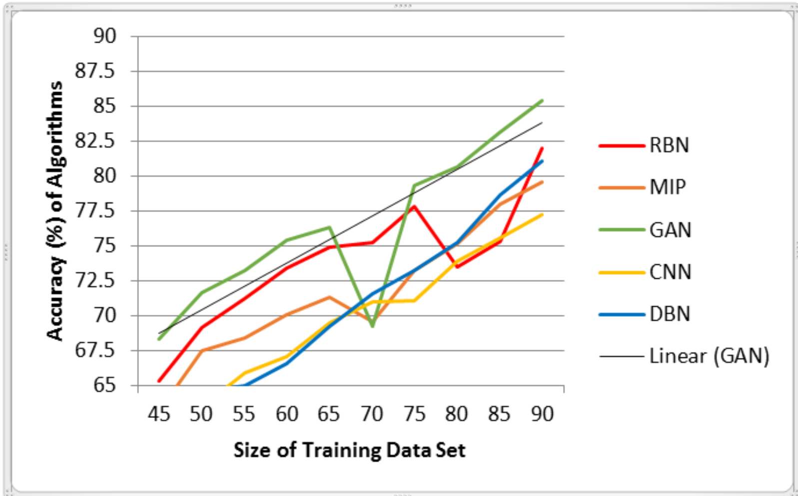

Figure 5 Accuracy based Training Dataset

Conclusion

One of the most significant health issues in the world is heart disease. Therefore, early management and prompt disease diagnosis are necessary to lower risk factors. The literature review revealed that enormous research has been done utilizing a different machine learning algorithm methodologies for the early diagnosis of strokes. The need to identify pertinent characteristics that could spot heart problems at a very early stage remains, though. In this study, well-known deep learning techniques were used. This research's key influence was the use of modern deep learning algorithm. The experimental outcomes demonstrate that the proposed model is well suited for heart disease predictions when compared to other existing models. The Long Short Term Memory model provides a better outcome with an accuracy of 92.23%. Another key finding from this proposed research is that an ideal training data set of 80% is needed for both accurate results and strong performances.

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