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Epileptic seizure detection using deep learning through min max scaler normalization

Deepa B
Research Scholar, Department of Computer Science, KSAWU, Vijayapur, Karnataka, India
Corresponding author email: deepa.bangarshetru@gmail.com

Ramesh K
Professor, Department of Computer Science, KSAWU, Vijayapur, Karnataka, India

***Abstract*---**Epileptic seizure detection and prediction are significantly sought-after research currently because robust algorithms are available. Machine learning and deep learning have allowed us to analyze brain signals with high accuracy. The brain signals collected using EEG (electroencephalogram) are complex and prone to noise. This paper describes a pre-processed dataset created using the famous CHB-MIT scalp EEG database. A deep learning model is trained and tested by applying the Bidirectional Long Short Term Memory (BiLSTM) algorithm through MinMaxScaler normalization on this pre-processed dataset. The results from this published dataset and model are promising in terms of accuracy, precision, and F1 score when compared with earlier research works. Accuracy is 99.55%, precision is 99.64%, and F1 score is 99.52% for the proposed model when the seizure activity data is considered for all the patients.

***Keywords*---**Bidirectional LSTM, Deep Learning, Epileptic seizures, MinMaxScaler Normalization.

Introduction

An epileptic seizure is a neurological disorder that affects many aged people worldwide. It is known to be the second most common brain disorder after stroke (J. Corsini *et. al.*, 2006). The seizures are detected by taking Electroencephalogram (EEG), a non-invasive technique to collect readings from the brain scalp. The readings are in the form of voltages in a few microvolts. These readings are collected according to an international standard 10-20 EEG placement, where the numbers 10 and 20 specify the spacing between electrodes to be 10% to 20%. As seen in figure 1, the placement of probes covers all parts of the scalp F- Frontal, T-Temporal, P-Parietal, and O-Occipital. This type of

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placement also ensures a fair distance between the electrodes and hence avoids interference.

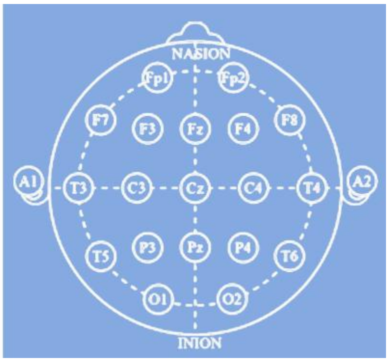

Figure 1. 10-20 EEG placement

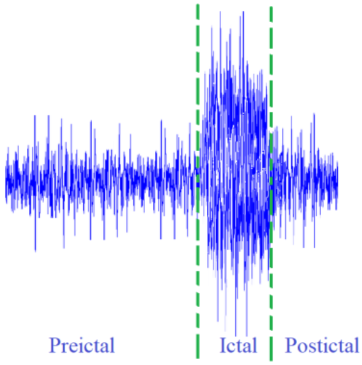

Figure 2. Sample EEG from a single

The readings are taken when the patient is in various conditions such as sleeping, awake, moving muscles, etc. The readings are analyzed and identified as seizures or non-seizures, as in figure 2. A preictal period is a time leading to an epileptic seizure, ictal is the period of seizure, and postictal is the state after the seizure. The data collected from EEG are often corrupted due to the non-uniform method of electrodes placement, discontinuity in the signals, and interference due to noise. Pre-processing is very much necessary for applying deep learning algorithms. Deep learning provides a valuable tool for working on large datasets as hand-engineering features is not an essential aspect (LeCun *et. al.* , 2015). EEG data is time-series data that can be used for training models using recurrent neural networks and other improved models.

The following four major steps are followed in epileptic seizures detection. The first step is the acquisition of data, the second is pre-processing the data, and the third step is extracting the features suitable for high accuracy detection. The fourth and final step is applying classifiers to detect the seizures accurately. Major research is done on feature extraction and using suitable classification models to detect seizures. The four steps can be summarized in figure 3.

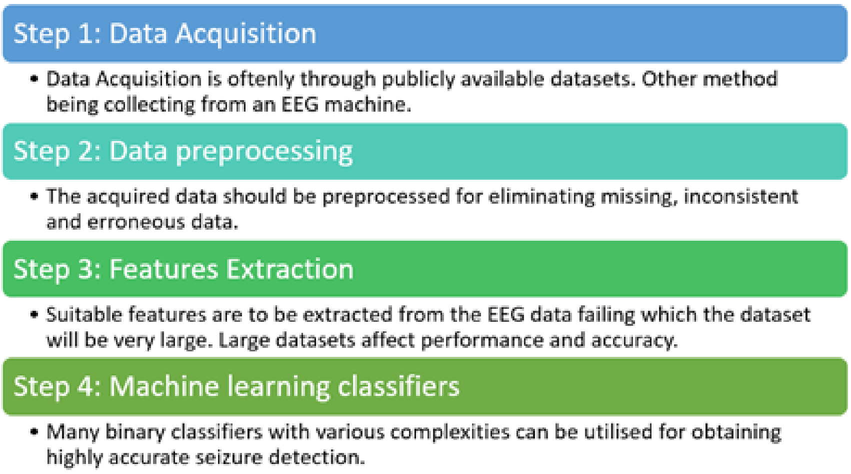

Figure 3. Steps is epileptic seizure detection

The four steps are very similar in all classification models. But applications involving analog signals such as EEG data need a particular and careful emphasis on data pre-processing and feature extraction steps (Maiorana *et. al.* , 2016).

Data Acquisition: Data is the most integral part of classification models; It should be acquired from reliable sources with good information. EEG data is stored in raw formats such as .edf and .eeg extensions. These formats can be converted to easily analyzable file formats such as .csv and .txt extensions.

Data Pre-processing: Data pre-processing is often done to fill in missing data, and remove outliers and erroneous values. The labels can also be encoded into numbers to facilitate feature extraction.

Feature Extraction: Extracting helpful features is a critical task in machine learning. For EEG signals, three broad categories are possible; one is the time domain, another frequency domain, and the third is the time-frequency domain.

Classifiers: Artificial Intelligence has gained widespread popularity in recent times. This popularity is due to the availability of ample computational power in both hardware and in the cloud. Many kinds of research are being carried out in the fields of machine learning and deep learning.
The major contributions of this paper are:

1. This paper introduces a pre-processed EEG dataset created using the very popular CHB-MIT Scalp EEG database. The dataset is published at IEEE Dataport.
2. The paper explores the application of MinMaxScaler normalization on the pre-processed dataset.
3. The paper analyses and compares results from applying RNN, LSTM, and Bidirectional LSTM on the pre-processed EEG dataset.

The paper is organized as follows: Section 2 gives an overview of the literature survey. Section 3 describes the dataset, Section 4 presents the proposed methodology, and Section 5 contains the results. The conclusion inferred from this work is discussed in Section 6, followed by future scope.

Literature Survey

Deep learning methods for epileptic seizure detection are a very new trend. The research works carried out earlier provide a thorough insight into the efficacy of using deep learning algorithms for seizure detection. The literature surveyed for this paper utilizes the CHB-MIT scalp EEG database containing 23 different patients' data and one repeat patient's data collected after some period.

The paper by Baocan Zhang et al. uses Convolutional Neural Networks (CNN) in deep transfer learning and provides an accuracy of 98.26 % (Baocan Zhang *et. al.*, 2020). The authors use Short Time Fourier Transform(STFT) to generate spectrum images as the input dataset. The data used for training is from 9 patients out of the total available 24 patients data. The paper by Akshay Sreekumar et al. uses the LSTM network and achieved a seizure detection accuracy of 97.4% (Sreekumar A *et. al.* , 2021). The training and testing are done for 5 hours of data from 5 patients using the transfer learning method. In the transfer learning method, the trained network is transfer learned to the next hour from the previous hour. The study by Ranjan Jana et al. uses CNN for classification and provides an accuracy of 94.33% by considering five patients (Ranjan Jana *et. al.* , 2019). Pool-based technique is used, and one minute of the signal which is most important from complete data, is utilized to improve the efficiency of prediction. The paper by Hisham Daoud and Magdy Bayoumi uses bidirectional LSTM to obtain an accuracy of 99.6% by considering data from 8 patients (H. Daoud and M. A. Bayoumi , 2019). The authors use Deep Convolutional AutoEncoder (DCAE) for the bidirectional LSTM model to achieve very high accuracy. The paper by Mohammad Khubeb Siddiqui et al. uses a machine learning technique called random forest on 17 patients' data and shows an accuracy of 98.81% (Mohammad Khubeb Siddiqui *et. al.* , 2020). The results from the research work of Chen-Sen Ouyang et al. is 86.5% accuracy (Chen-Sen Ouyang *et. al.* , 2019). The model uses Support Vector Machines on 11 patients' data out of 24 available patients datasets.

The paper by Ayesha Tooba Khan and Yusuf Uzzaman Khan describes the complex nature of EEG signals. The signals are highly susceptible to noise associated with the power line, skin potentials, and motion artifacts (Khan, A.T. *et. al.* , 2021). The study uses a quadratic classifier for training and testing all 24 patients' data individually, thus achieving an average accuracy of 86.58%. The research work by Satarupa et al. explores the application of a machine learning technique named Artificial Neural Network (Chakraborti, S *et. al.* , 2018). The dataset used consists of readings from two channels from a single female patient. This small dataset results in a training time of 15 seconds, providing an accuracy of 100%.

Dataset

The EEG datasets available for training and testing models are openly available or subscription-based. The availability of datasets has initiated a transition phase from the traditional error and trial aspect to patient-centric precision care (Shaikh, T.A *et. al.*, 2019). New researchers find it difficult to choose amongst the datasets. CHB-MIT scalp EEG dataset is very famous because it is large and annotated. The following subsections present the procedure employed in pre-processing the CHB-MIT scalp EEG database. The pre-processed dataset is published in IEEE Dataport. The earlier researchers have utilized few patients' data from the original EEG database in their research. The authors of this paper have used 68 whole minutes of epileptic seizure periods from all the patients and the preictal 68 whole minutes to summarize the dataset.

Pre-processed Dataset

CHB-MIT scalp EEG database by Ali Shoeb *et al.* and the EEG database, University of Bonn by Andrzejak *et al.* are the most sought after publicly available datasets (Ali Shoeeb, 2009)(R.G. Andrzejak *et. al.*, 2001). CHB-MIT database is preferred because it is large and annotated. This dataset contains EEG information from 24 patients recorded over 900 hours, containing 68 minutes of ictal data. The data is recorded at a sampling rate of 256 Hz. High sampling rate is an important parameter in EEG signals because brain signals during epileptic seizures and other brain abnormalities can be significantly higher than 100 Hz (Hughes JR *et. al.*, 2008). EEG signals are nonlinear, stochastic, and non-stationary (Z. Jiang *et. al.*, 2019). The data available in CHB-MIT database is heavily imbalanced and corrupted. The authors of this paper have followed the procedure in figure 4 to create a balanced pre-processed dataset.

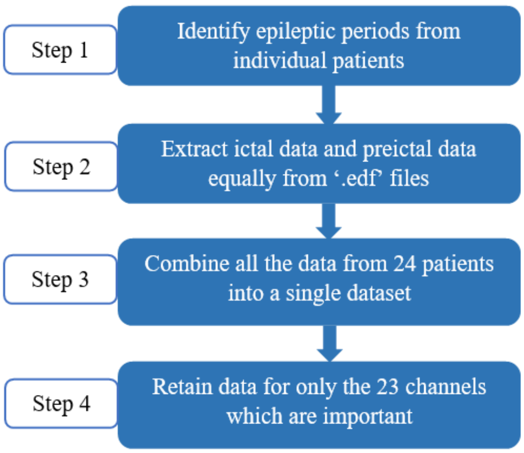

Figure 4. Steps in pre-processing the dataset

Step 1: CHB MIT scalp EEG database provides data at physionet in '.edf' European data format (Goldberger, A *et. al.*, 2000). The data is supported with information regarding epileptic periods, as shown in figure 5. The voltage levels from EEG electrodes are obtained from '.edf' files.

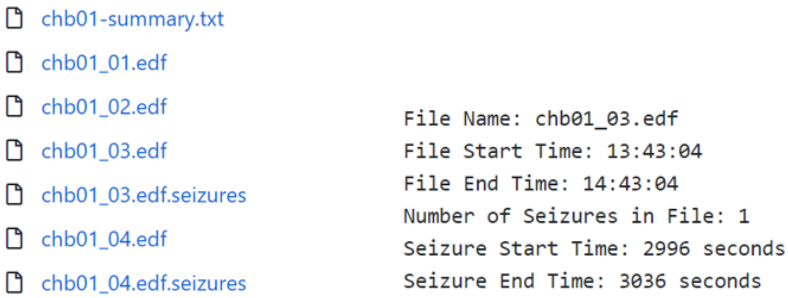

Figure 5. Sample epileptic period data

Step 2: The information regarding the ictal state and equal preictal state are collected from '.edf' files. Two files are kept separate for researchers to utilize data as required. This also helps in labeling.
Step 3: Careful analysis of the dataset yields duplicate and incorrect electrodes data. The EEG contains 96 channels of data, out of which 23 channels are essential. These 23 channels are to be retained.
Step 4: In the final step, the data from preictal and ictal states are labeled with 0 and 1, respectively. Both datasets are merged to provide final pre-processed data. The data is provided in five different files, two files with raw data for ictal and preictal data, two files with processed data containing 23 important channels as per 10-20 EEG placement system, and a final file with 136 minutes of combined ictal and preictal data with outcome indicated as '0' for preictal and '1' for ictal (Deepa B and Ramesh K, (2021). Data cleaning and data transformation are not done to help researchers choose appropriate methods based on the training and testing models. The authors of this paper have utilized data from all 24 patients.

Proposed Methodology

Various architectures of Recurrent Neural Networks such as LSTM and Bidirectional LSTM are evaluated to achieve high accuracy. This section describes the methodology followed to obtain results from training and testing the deep learning algorithms. The normalization technique, Recurrent Neural Network architectures, proposed model, and evaluation measures are described briefly.

MinMaxScaler normalization

Normalization is a technique to ensure that all data in the database have a similar range. This is extremely important when the data is unstructured and contains very different values. MinMaxScaler normalization is advantageous in high-dimensional data (Shaheen H *et. al.*, 2020). The values are in microvolts for EEG signals and vary largely from one channel to another channel. This variation creates problems in training a model. MinMaxScaler is a type of normalization which can scale all EEG signal values to have values from 0 to 1. Eq. (1) and Eq. (2) indicate the method of MinMaxScaler normalization.

$$X_{std} = \frac{(X - X.min)}{(X.max - X.min)} \qquad (1)$$

$$X_{scaled} = X_{std} * (X.max - X.min) + X.min \qquad (2)$$

In Eq. (1) and Eq. (2), min and max values are the minimum and maximum voltage values for the channel X under consideration. A channel will be made up of EEG voltage readings at 256Hz sampling rate. Eq. (1) and Eq. (2) provide the normalized values for the particular channel. The values are fit and transformed for all of the dataset and then used for training and testing.

Recurrent Neural Networks

Recurrent Neural Networks (RNN) in deep learning are very commonly used for natural language processing (NLP). This is because RNN models work better on time series data and hence are beneficial for EEG data too. Figure 6 provides a brief idea of the RNN layer.

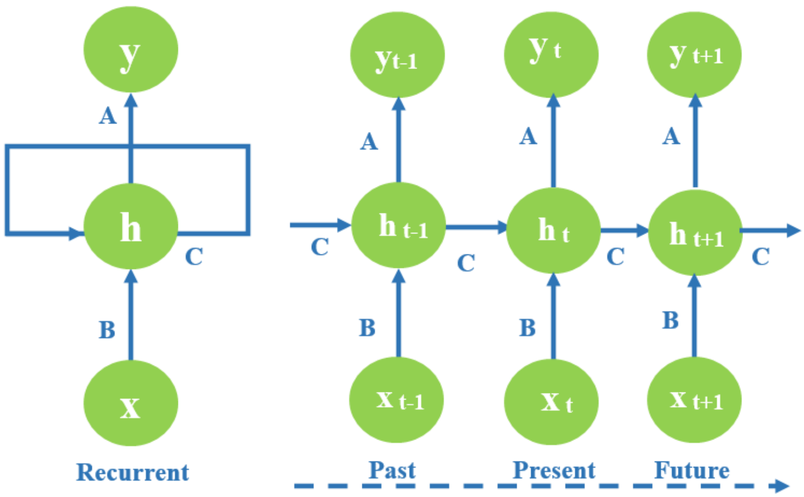

Figure 6. Recurrent Neural Network

The data is sequential, and hence the outputs from previous layers are fed to the network for improvement in performance. At any instant of time, the input is the combination of the present input and the previous input. The hidden layer of the present state is given as a function of the previous hidden state and present input.

$$h_t = f(h_{t-1}, x_t) \tag{3}$$

Eq. (3) represents the calculation of the present hidden layer as a function of the previous hidden layer and present inputs. A,B and C are parameters related to recurrent neural networks. RNN suffers from a vanishing gradient problem, where the importance of information loses value with time. This makes training a model with sequential data difficult. The problem is overcome with Long Short Term Memory (LSTM) networks. Instead of a single function, such as tanh in a neural network, LSTM uses four interacting neural network layers. Activations flow around in a loop by feedback connection (Chhachhiya D *et. al.*, 2019). Figure 7 shows the special version of RNN, which is the Long Short Term Memory (LSTM) cell.

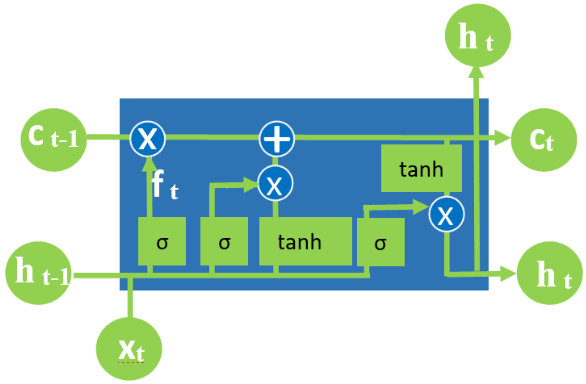

Figure 7. Long Short Term Memory cell

The four interconnected neural network layers decide what amount of information from the past and what amount of information from the present are to be left for determining the present output state.

$$f_t = \sigma(W_{fh}h_{t-1} + W_{fx}x_t + b_f) \quad (4)$$
$$i_t = \sigma(W_{ih}h_{t-1} + W_{ix}x_t + b_i) \quad (5)$$
$$o_t = \sigma(W_{oh}h_{t-1} + W_{ox}x_t + b_o) \quad (6)$$
$$\tilde{c}_t = \tanh(W_{ch}h_{t-1} + W_{cx}x_t + b_c) \quad (7)$$
$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t \quad (8)$$
$$h_t = o_t \circ \tanh(c_t) \quad (9)$$

i_t is the input state, c_t is the cell state, o_t is the output state, and h_t is the hidden state at the time instant t. W and b are weights and biases, respectively. Combinedly, Eq. (4) to Eq. (9) decide what amount of information which should be carried forward for efficient training of the model. Figure 8 shows Bidirectional LSTM, which is LSTM but operates from both directions, from the future to the past and from the past to the future.

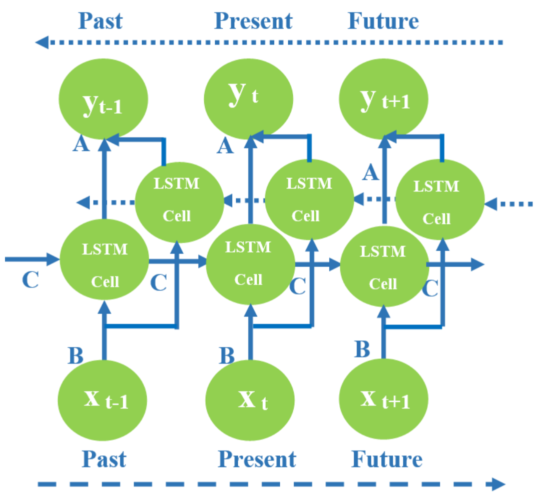

Figure 8. Bidirectional LSTM

Two models are trained in forward and reverse directions. The models are combined by a method called merging. Merging is done by either sum, multiply, average, or concatenation.

Proposed Bidirectional LSTM model with MinMaxScaler normalization

The training and testing are done as indicated in the flow diagram in figure 9. The activation functions and the number of units used in different hidden layers are indicated. The results and values of evaluation measures are discussed in the results section. Three layers of Bidirectional LSTM cells are used with 128 units, 64 units, and 32 units, respectively. Two dropout layers are used to avoid over-fitting the model.

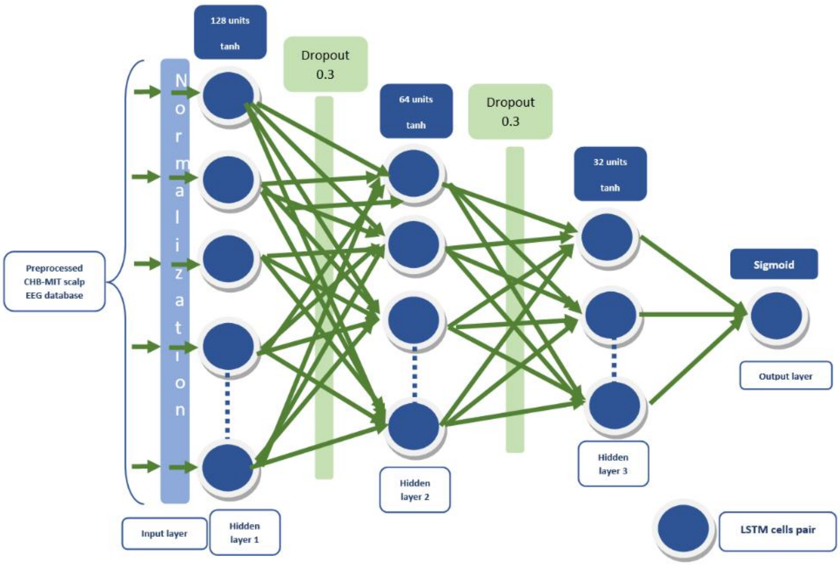

Figure 9. Training and Testing Methodology

Evaluation measures

The training and testing are done for all the 24 patients' data for 23 channels. This EEG data is collected from the pre-processed CHB-MIT scalp EEG dataset, which is published by the authors of this paper. The dataset is normalized using MinMaxScaler. RNN, LSTM, and Bidirectional LSTM models are trained and tested on the normalized dataset. Adam optimizer is used as it provides faster training because of combined benefits from gradient descent with momentum and root mean square propagation.

$$m_t = \beta m_{t-1} + (1-\beta)\left[\frac{\delta L}{\delta w_t}\right] \tag{10}$$

$$v_t = \beta v_{t-1} + (1-\beta) * \left[\frac{\delta L}{\delta w_t}\right]^2 \tag{11}$$

$$w_{t+1} = w_t - \widehat{m_t}\left(\frac{\alpha}{\sqrt{\widehat{v_t}} + \varepsilon}\right) \tag{12}$$

m_t = aggregate of gradients at time t [current] (initially, m_t = 0)

w_t = weights at time t
δL = derivative of Loss Function
δw_t = derivative of weights at time t
α = learning rate
v_t = sum of square of past gradients (initially, $v_t = 0$)
β = Moving average parameter
ϵ = A small positive constant

Eq. (10) is related to gradient descent with momentum, and Eq. (11) is related to the root mean square propagation algorithm. The combination of these helps in achieving global minima by adam optimizer quickly even though taking large enough steps. The loss function along with sigmoid activation, is the binary cross-entropy loss, which is helpful for binary classification tasks. Binary Cross Entropy is the negative average of the log of corrected predicted probabilities.

$$l(y, \hat{y}) = -[y\log(\hat{y}) + (1 - y)\log(1 - \hat{y})] \quad (13)$$

where $\hat{y}$ and y are the desired output and the calculated output, respectively, and $l(y, \hat{y})$ is the loss function.
Specificity, sensitivity, accuracy, precision, and F1 score of models are calculated as in equations (14) to (18). Specificity is a measure used to check the correctness of the model in detecting negative cases of epileptic seizures. Sensitivity is a measure to check the correctness of the model in detecting positive cases of epileptic seizures. Accuracy is the measure of correctness of the model in identifying positive and negative cases of epileptic seizures. Precision is an important measure in medical applications, which indicates the correctness of the model in identifying patients with the ailment. Higher precision indicates all patients with epileptic seizures are recognized as unhealthy. F1 score is a harmonic mean between precision and sensitivity.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (14)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (15)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (16)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (17)$$

$$\text{F1 score} = \frac{2\,(\text{Sensitivity}\cdot\text{Precision})}{\text{Precision}+\text{Sensitivity}} \quad (18)$$

where TN, TP, FN, and FP are the true negative, true positive, false negative, and false positive, respectively.

Results

This section has two subsections. The first subsection describes the analysis of results obtained by applying various deep learning algorithms to the pre-processed dataset through MinMaxScaler normalization. Bidirectional LSTM achieves the best accuracy, and this is compared with the results from earlier research in the second subsection.

Analysis

The results are obtained for RNN, LSTM, and Bidirectional LSTM models for the MinMaxScaler normalized pre-processed CHB-MIT dataset. Accuracy, Specificity, Sensitivity, Precision, and F1 score are plotted in figure 10. Training and testing datasets are divided into 80% and 20% of the total dataset. As noticed from the graph, bidirectional LSTM networks are better than LSTM networks and recurrent neural networks. The activation function for hidden layers initially had relu activation functions. Relu activation functions are replaced by tanh layers, which results in similar accuracy but lesser training time. The use of data from all 24 patients is computationally intensive. The accuracy obtained for RNN, LSTM, and Bidirectional LSTM are 78.26%, 81.19%, and 99.55%, respectively. It can be observed that Bidirectional LSTM provides the best results in seizure detection for the pre-processed CHB-MIT dataset published by the authors of this paper.

Figure 10. Results from RNN, LSTM, Bidirectional LSTM for the proposed dataset

Figure 10 shows the results from various models. The training time is considerably large for the proposed dataset, as all 24 patients are considered for training and testing. A whole of 23 channels multiplied by 136 minutes of data at a sampling frequency of 256Hz is utilized. Normalization helps map all values to a fixed range of 0 to 1. Various optimizers and activation functions are tested. The research provides promising results for adam optimizer, tanh activation function for hidden layers, and sigmoid function for binary classification at the output layer.

Comparison

The authors of this paper have utilized data from all the 24 patients rather than selecting a few as done by earlier researchers mentioned in the literature survey. The results are as in figure 11.

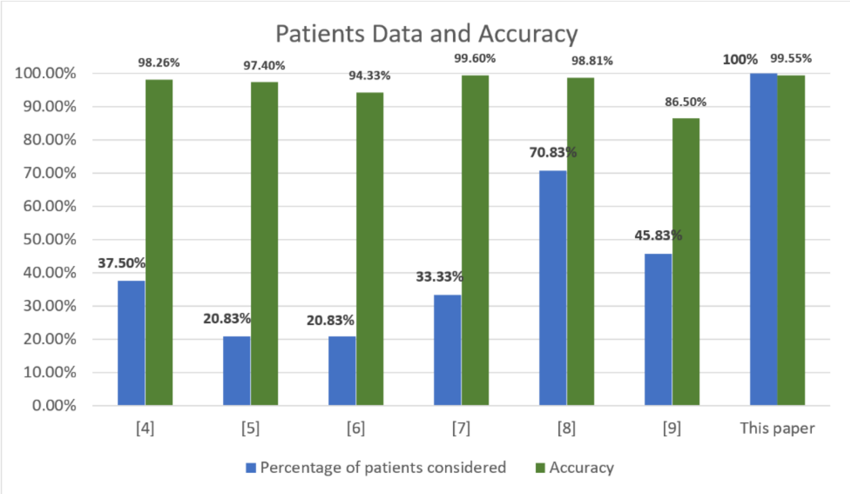

Figure 11. Graph for patients considered and accuracy

Figure 12 shows a graph comparing various algorithms used by different researchers and the results. It can be inferred that deep learning algorithms are suitable for processing large time-series data, such as EEG signals. Bidirectional LSTM is the best algorithm amongst all the algorithms as it works from two different directions. The accuracy of Bidirectional LSTM is very high even though using a large number of data points

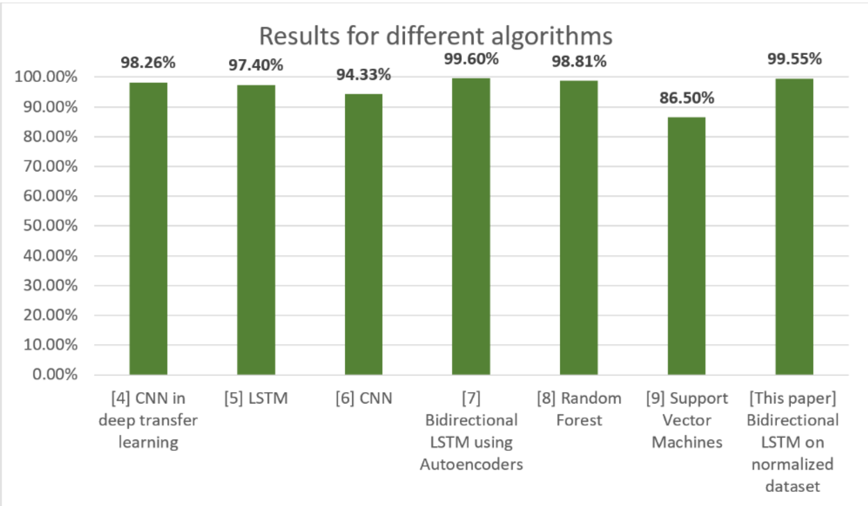

Figure 12. Accuracy for different algorithms

Conclusion

The authors of this paper have prepared a pre-processed CHB-MIT scalp EEG dataset utilizing data from all 24 patients from the CHB-MIT database. The prepared dataset contains 136 minutes of preictal and ictal data combined for 23 channels. The dataset is expected to be very helpful for researchers starting in the field of epileptic seizure detection using machine learning and deep learning algorithms. The dataset is applied with RNN, LSTM, and bidirectional LSTM networks with MinMaxScaler normalization technique. Bidirectional LSTM with three layers provides the best results for the MinMaxScaler normalized proposed dataset. The accuracy of 99.55% is promising compared with the earlier research.

Future Scope

The model's accuracy can be improved by utilizing complex architectures and applying MinMaxScaler normalization to individual patients' data. Novel deep learning models need to be cross-validated with datasets such as the University of Bonn, Germany EEG dataset, and other Indian patients' datasets. Cross-validated deep learning models will be effective in epileptic seizure detection across all ages and geographical locations. The future looks promising, and an effective deep learning model is expected to be deployed as an application that can be helpful to medical professionals.

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