# Epileptic Seizure Detection Using Deep BiLSTM With SVM Classifier For Indian Patients



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## ABSTRACT

Epileptic seizure is a neurological disorder that affects millions of people every year. This disorder causes uncontrolled movement of limbs and sometimes leads to unconsciousness. Medical professionals detect an epileptic seizure manually by observing the Electroencephalogram (EEG) readings. The readings are obtained from the patient's brain scalp using a noninvasive technique through an EEG machine. Deep learning algorithms are very helpful in precisely detecting the disorder during the initial stages as EEG data is huge and complex. This research aims at developing a hybrid deep learning model using deep Bidirectional Long Short Term Memory (BiLSTM) and Support Vector Machine(SVM). The model is trained and tested with the Indian patients' dataset created using data from SNMC, Bagalkot. The proposed model is fed with normalized values obtained by MinMaxScaler, a deep neural network is trained using three layers of BiLSTM, and classification is achieved using SVM. The proposed model achieved a very high accuracy of 95.56% and F1 score of 94.46%. Further, the same model is cross-validated with a famous, publicly available CHB-MIT scalp EEG database, and an accuracy of 92.85% and F1 score of 92.60% is achieved.

**Keywords**: Deep learning, Deep BiLSTM, SVM, Epileptic Seizure, MinMaxScaler normalization

**Abbreviations:**

| | |
|---|---|
| **BiLSTM** | Bidirectional Long Short Term Memory |
| **EEG** | Electroencephalogram |
| **CHB** | Children's Hospital Boston |
| **MIT** | Massachusetts Institute of Technology |
| **LSTM** | Long Short Term Memory |
| **RNN** | Recurrent Neural Networks |
| **SNMC** | S. Nijalingappa Medical College |
| **SVM** | Support Vector Machines |

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## 1. Introduction

Epileptic seizure detection is necessary as it helps patients and doctors take preventive measures in the initial stages. Seizures can last a few milliseconds duration up to a few minutes. Accurately distinguishing the brain signals as seizure and non-seizure activity is hard by manually observing EEG signals plotted on paper. The readings are acquired from a 10-20 EEG placement method where 10-20 indicates the separation between 2 electrodes should be 10% to 20%. This can be observed in figure 1.

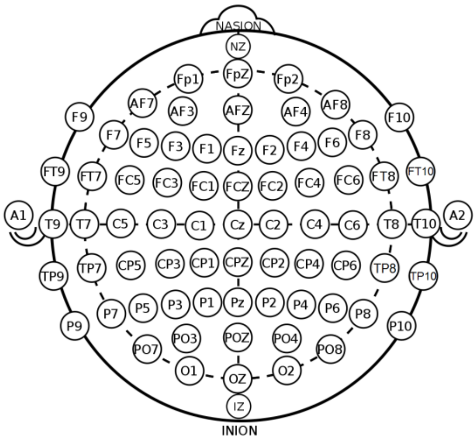


Figure 1: 10-20 EEG electrodes placement

Figure 2 shows a sample of EEG readings where seizure is observed as tall spikes on the y-axis. Preictal is the time duration leading to the seizure, ictal is the seizure duration and postictal is the state after seizure. The figure is obtained from a single channel named as 'C3-P3' indicating an electrode placement at C3 with reference to P3.

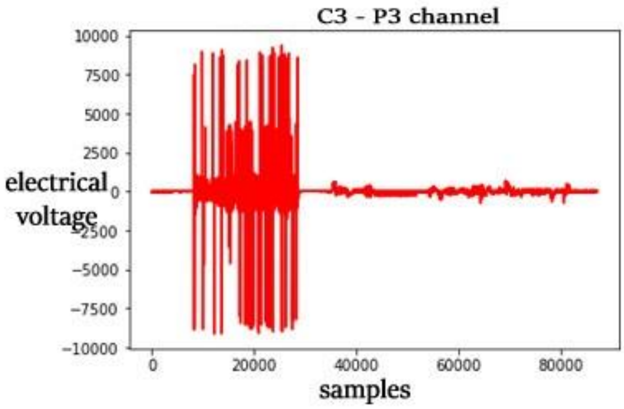


Figure 2: Seizure on C3-P3 channel

Much research has been carried out recently in epileptic seizure detection because of new deep learning algorithms that can strategically work on huge data, such as EEG. The state-of-the-art technologies available at researchers' disposal have helped researchers contribute immensely to the medical fraternity working on epileptic seizure patients' well-being. Deep learning models are famous because of their ability to handle time-series data of large duration. Two well-known publicly available datasets are CHB-MIT scalp EEG database [1] and the database from the University of Bonn, Germany [2]. Many researchers use these databases to train and test various machine learning and deep learning models. This research introduces a new dataset created using EEG data from patients at SNMC, Bagalkot [3]. The dataset is hosted in IEEE-Dataport, which can be accessed through Amazon S3 services or by downloading the files.

**Materials and Methods:** The discussions in the further reading are about dataset, algorithms, and comparison. Earlier research works on the area of epileptic seizure detection and prediction are discussed in section 2. The dataset description in Section 3 offers an insight into the new dataset regarding the methodology adopted to create the same and its use cases. Section 4 about deep learning algorithms explains training and testing deep BiLSTM with the SVM classification model. Section 4 further explains training and testing carried out for various categories of the new dataset, followed by cross-validation using CHB-MIT scalp EEG dataset. The fifth and final section provides a detailed analysis of the results obtained.

**Major contributions of this paper:** This research aims at introducing Indian patients' EEG dataset consisting of epileptic seizures. The dataset is published at IEEE Dataport. MinMaxScaler normalization is applied to the preprocessed dataset. A hybrid deep learning model made-up of three layers of BiLSTM and a classification method by SVM is used for training and testing. The model shows high accuracy and F1 Score on the proposed Indian dataset; it also holds good when cross-validated using the CHB-MIT scalp preprocessed dataset.

## 2. Literature survey

EEG datasets contain a large number of data points, and hence machine learning techniques prove less efficient. Epileptic seizure detection is researched recently using deep learning models because huge computing resources are available. The survey carried out for this paper reveals some of the significant research carried out over the years using CHB-MIT dataset. The dataset by University of Bonn, Germany, is small, and hence previous research work using this dataset is not analyzed.

Convolutional neural networks (CNN) are used in deep transfer learning in the Baocan Zhang et al. article, which offers an accuracy of 98.26% [4]. Out of the total 24 patients whose data are available, 9 patients' data were used for training. The LSTM network was used in the Akshay Sreekumar et al. research to achieve a seizure detection accuracy of 97.4 percent [5]. Using the transfer learning method, training and testing are conducted for 5 hours of data from 5 patients. The accuracy of the study by Ranjan Jana et al., which uses CNN for classification, is 94.33 percent [6]. Bidirectional LSTM is used in the study by Hisham Daoud and Magdy Bayoumi [7] to achieve an accuracy of 99.6%. The accuracy of the study by Mohammad Khubeb Siddiqui et al., which employs the machine learning technique random forest, is 98.81% [8]. The accuracy of the data obtained by Chen-Sen Ouyang et alresearch .'s utilising Support Vector Machines is 86.5 percent[9]. Ayesha Tooba Khan and Yusuf Uzzaman Khan's research explains the intricate nature of EEG waves. The signals are very sensitive to power line noise, skin potential noise, and motion artefact noise [10]. The study achieves an average accuracy of 86.58 percent by individually training and assessing the data from each of the 24 patients using a quadratic classifier. The study by Satarupa et al. investigates the use of the Artificial Neural Network machine learning technique [11]. Readings from two channels taken from a single female subject make up the dataset. With such a short dataset, training takes only 15 seconds, yet accuracy is 100%.

**Table 1** Review of traditional epileptic seizure classification models

| Author | Methodology | Features | Accuracy |
|---|---|---|---|
| **Baocan Zhang *et al.*** | Short Time Fourier Transform (STFT) | Short Time Fourier Transform(STFT) to generate spectrum images as the input dataset. | 98.26 % |
| **Akshay Sreekumar *et al.*** | Long Short Term Memory (LSTM) network | Transfer learning method is used where the trained network is transfer learned to the next hour from the previous hour. | 97.4% |
| **Ranjan Jana *et al.*** | Convolutional Neural Networks (CNN) | Pool-based technique is used, and one minute of the signal which is most | 94.33% |

| | | | |
|---|---|---|---|
| | | important from complete data is utilized. | |
| **Hisham Daoud and Magdy Bayoumi** | Bidirectional LSTM (BiLSTM) | Deep Convolutional AutoEncoder (DCAE) are used for the bidirectional LSTM model | 99.6% |
| **Mohammad Khubeb Siddiqui *et al.*** | Random Forest | An ensemble of decision trees which are coorelated are trained using 9 time domain features such as min, max, entropy etc. | 98.81% |
| **Chen-Sen Ouyang *et al.*** | Support Vector Machines | Five machine learning classifiers are tested by using positive zero crossing parameters in the signals. SVM provides the best accuracy. | 86.5% |



## 3. Dataset description

This research utilizes the new dataset created using EEG data from Indian patients at SNMC, Bagalkot. A total of 12 subjects between the age of 22 years to 66 years were observed. The dataset consists of data from 11 patients as data from 1 patient is corrupted. Table 2 indicates the details of data collected.

Table 2: Details of patients considered for preparing new dataset

| Patient Number | ID | Patient suffers Epileptic Seizure? | Duration of EEG (seconds) | Duration of seizure recorded on EEG (seconds) |
|---|---|---|---|---|
| **1** | 363 | Yes | 914s | 45s |
| **2** | 606 | Yes | 686s | Seizure not recorded during procedure |
| **3** | 2841 | No | 130s | |
| **4** | 2851 | No | 80s | |
| **5** | 2861 | No | 80s | |
| **6** | 2871 | No | 70s | |
| **7** | 2881 | No | 80s | |
| **8** | -- | -- | -- | .eeg file is corrupted |
| **9** | 605 | No | 865s | |
| **10** | 608 | No | 1014s | |
| **11** | 1306 | Yes | 864s | 125s |
| **12** | 1714 | No | 934s | |
| | | | Total: 5717s | Total: 170s |

As it can observed from Table 1, three patients suffer from epileptic seizure but seizures of two patients are recorded on EEG machine during the medical procedure. A total of 5717 seconds (approx. 1 hour 35 minutes) of EEG readings are available. A total of 170 seconds (2 minutes 50 seconds) of epileptic seizure activities are observed. The data is collected at 256Hz sampling rate for 16 channels indicating a dataset of 87040 rows by 16 columns. The dataset is balanced with positive and negative cases prevalence of 0.5 each meaning half number of rows are seizure data points, and remaining half are non-seizure data points.

The dataset is prepared in three categories by using the EEG data acquisition software. The categories are based on filtering.

Category 1: Raw data with no filters
Category 2: Raw dataset with bandpass filter from 1Hz to 70Hz
Category 3: Raw dataset with bandpass filter from 0Hz to 100Hz



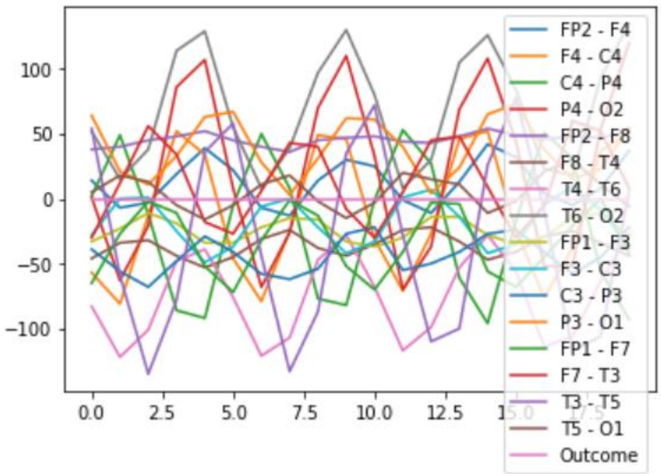


Figure 3: Category 1 dataset (No filter)

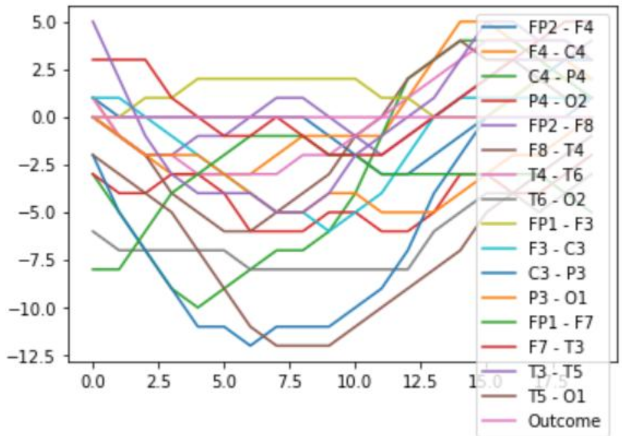


Figure 4: Category 2 dataset (1-70Hz)

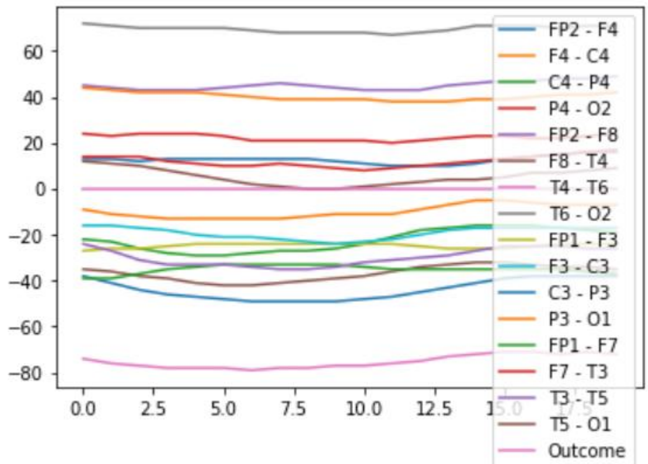


Figure 5: Category 3 dataset (0-100Hz)

Figure 3, 4, and 5 visualize the three categories with datapoints of first 15 rows with the help of graphs. Sampling rate indicates the faithful reconstruction of analog signals using discrete values. The rate of sampling should be always greater than or equal to Nyquist rate. This helps in preserving the structure of EEG signal [12]. Brain waves are classified into five predominant frequencies as

Gamma (γ), Beta (β), Delta (δ), Theta (Θ) and Alpha (α). Gamma having the highest frequency >35 Hz [13]. The proposed dataset is collected at a frequency of 256Hz. Seizure activities result in frequencies ranging from 70Hz to 100Hz. The algorithms used for this research work on time series data and amplitudes of datapoints. Thus three categories of dataset are trained and tested rigorously to identify the advantages and shortcomings of filtering the data.



gure 6 indicates the methodology used in creating the dataset. The original EEG readings in this dataset are recorded in .eeg file format. Different EEG machines use different file formats. The '.eeg' files are exported to .xlsx file format which contain various number of sheets based on the recorded duration. These .xlsx files contain timing information too. Three categories of database are prepared with no filtering and filters of 1Hz-70Hz and 0Hz-100Hz values. A balanced dataset is created consisting of 170 seconds of non seizure data and 170 seconds of seizure data. All files are uploaded and available at IEEE-Dataport.

## 4. Deep Learning Algorithms

The proposed dataset is used to train and test different deep learning models. Choosing machine learning or deep learning classifiers is the final and most crucial step in epileptic seizure detection. Use of classifier or combination of classifiers should be done based on a comprehensive evaluation of whether classification accuracy can be improved by diverse classifiers or by large diverse dataset [14]. Recurrent Neural Networks (RNN) are best suited for time series data such as EEG signals. The research carried out here works with three algorithms namely Recurrent Neural Networks(RNN), Long Short Term Memory(LSTM) and Bidirectional LSTM (BiLSTM).

RNN consists of three layers, input, hidden and output layers. In figure 7, A, B and C are the paramenters of the network. The hidden layer state is decided by the present input layer state and past hidden layer state. This can be expressed in an expression as,

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

where $h_t$ is the present hidden layer state

$h_{t-1}$ is the past hidden layer state

$x_t$ is the present input layer state

RNN suffer from vanishing gradient problem, where the importance of information decreases through time. This is overcome from using Long Short Term Memory Network(LSTM). The architecture of LSTM can be visualized as in figure 8.

The activations flow around the loop using four interacting layers [15]. The layers decide the amount of information to be carry forwarded for decision making process.

$$f_t = \sigma\left(W_{fh} h_{t-1} + W_{fx} x_t + b_f\right)(2)$$

$$i_t = \sigma(W_{ih} h_{t-1} + W_{ix} x_t + b_i)(3)$$

$$o_t = \sigma(W_{oh} h_{t-1} + W_{ox} x_t + b_o)(4)$$

$$\acute{c}_t = tanh(W_{ch} h_{t-1} + W_{cx} x_t + b_c)(5)$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \acute{c}_t(6)$$

$$h_t = o_t \circ tanh(c_t)(7)$$

$i_t$ 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.

Figure 9 illustrates the advanced version of LSTM i.e Bidirectional LSTM. Here the flow of information and training of neural networks occurs in both the directions, past to future and future to past.



dataset prepared is used for training and testing 4 different models. First RNN, second BiLSTM and finally 'Deep BiLSTM with SVM'. The best results are obtained for the fourth model amongst all and hence is taken as reference for cross validation which is discussed in next section. Figure 10 illustrates the method of training and testing employed for Deep BiLSTM and SVM classifier model. The preprocessed SNMC, Bagalkot dataset is normalized using MinMaxScaler normalization. MinMaxScaler normalization is beneficial in high-dimensional data[16]. MinMaxScaler is a normalization technique where all EEG signal values are scaled to range from 0 to 1. Eq. (8) and Eq. (9) indicate the steps in MinMaxScaler normalization.

$$X_{std} = \frac{(X - X.\min)}{(X.max - X.\min)} \quad (8)$$

$$X_{scaled} = X_{std} * (X.max - X.min) + X.min \quad (9)$$

In Eq. (8) and Eq. (9), min and max values are the minimum and maximum voltage values for the channel X under consideration. Three hidden layers of BiLSTM are used with a dropout of 0.3 in between layers to avoid overfitting. The classification at the last step is done using Support Vector Machine (SVM) classifier.

ss validation is the method of validating a model with respect to test cases which are unknown to the model. Prior to classification, the cross-validation stage is crucial since it gives a reliable indication of the classifier's performance [17]. The method is employed in different forms so as to get near real-world possible performance as possible. The model being cross validated in this research work is 'Deep BiLSTM with SVM' which is shown in figure 11. The validation is done in four ways. First by training and testing the model using SNMC dataset, second by training and testing using CHB-MIT dataset. The model is trained used CHB-MIT dataset and tested by SNMC dataset in the third procedure. And in the final procedure training is done by SNMC dataset and testing is done by CHB-MIT dataset. The following parameters are obtained to analyze the results in the next section.

Specificity, sensitivity, accuracy, precision, and F1 score of models are calculated as in equations (10) to (14). TN, TP, FN, and FP are the true negative, true positive, false negative, and false positive, respectively. Specificity is a metric used to assess how well a model detects instances of epileptic seizures that are not positive. Sensitivity is a metric used to evaluate how well a model can identify instances of positive epileptic seizures. The model's accuracy in differentiating between positive and negative cases of epileptic seizures is measured by accuracy. Precision is a crucial metric in medical applications since it shows how accurately the model identified patients with the illness. A higher level of precision means that all epileptic seizure patients are considered sick. The F1 score represents the harmonic mean of sensitivity and precision.

$$Sensitivity = \frac{TP}{TP + FN} \tag{10}$$

$$Specificity = \frac{TN}{TN + FP} \tag{11}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{12}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{13}$$

$$F1 \text{ score} = \frac{2\,(\text{Sensitivity} \cdot \text{Precision})}{\text{Precision} + \text{Sensitivity}} \tag{14}$$

## 5. Results and Discussion

The results are summarized using three tables. Table 3 shows results for purely SNMC, Bagalkot dataset. The performance metrics accuracy, precision, sensitivity, specificity and F1 score are obtained for three categories of SNMC, Bagalkot dataset using four models RNN, LSTM, BiLSTM and Deep BiLSTM + SVM. The best performance is observed from the proposed Deep BiLSTM + SVM model with 94.56% accuracy and 94.46% F1 score. All models performed best for unfiltered raw dataset amongst three categories.

Table 3 : Summary of results for SNMC, Bagalkot Dataset

| Algorithm | Dataset Category | Accuracy | Precision | Sensitivity | Specificity | F1 Score |
|---|---|---|---|---|---|---|
| **RNN** | No Filter | 84.11% | 81.51% | 80.69% | 80.69% | 84.04% |
| | 1 Hz - 70 Hz | 78.61% | 72.82% | 67.44% | 67.44% | 80.10% |
| | 0 Hz – 100 Hz | 82.33% | 80.53% | 80.10% | 80.10% | 82.04% |
| **LSTM** | No Filter | 89.46% | 85.33% | 84.10% | 84.10% | 89.59% |
| | 1 Hz - 70 Hz | 87.30% | 84.91% | 84.31% | 84.31% | 87.16% |
| | 0 Hz – 100 Hz | 88.63% | 85.82% | 85.24% | 85.24% | 88.54% |
| **BiLSTM** | No Filter | 91.36% | 88.40% | 87.96% | 87.96% | 91.28% |
| | 1 Hz - 70 Hz | 90.31% | 87.56% | 86.98% | 86.98% | 90.24% |
| | 0 Hz – 100 Hz | 90.13% | 88.38% | 88.22% | 88.22% | 89.89% |
| **Deep BiLSTM + SVM** | **No Filter** | **94.56%** | **93.87%** | **93.75%** | **93.75%** | **94.46%** |
| | 1 Hz - 70 Hz | 92.45% | 92.19% | 92.15% | 92.15% | 92.26% |
| | 0 Hz – 100 Hz | 93.35% | 94.93% | 95.08% | 95.08% | 93.01% |

Table 4 is the summary of cross validation results. The results are obtained by following the flowchart in figure 10. Training and testing split ratio of 80:20 for balanced dataset is used in all the models of this paper. A balanced dataset of CHB-MIT dataset is extracted from ieee-dataport dataset for cross validation. It can be observed that the results hold good for all possible combinations of testing and training on the proposed deep learning model.

Table 4 : Summary of cross validation results using CHB-MIT dataset and Category 2 dataset from SNMC, Bagalkot

| Algorithm | Training Dataset | Testing Dataset | Accuracy | Precision | Sensitivity | Specificity | F1 Score |
|---|---|---|---|---|---|---|---|
| **Deep BiLSTM + SVM** | SNMC, Bagalkot | SNMC, Bagalkot | 94.41% | 94.06% | 94.04% | 94.04% | 94.28 % |
| **Deep BiLSTM + SVM** | SNMC, Bagalkot | CHB-MIT | 92.85% | 92.96% | 93.04% | 93.04% | 92.60 % |
| **Deep BiLSTM + SVM** | CHB-MIT | SNMC, Bagalkot | 93.62% | 95.01% | 95.16% | 95.16% | 93.33 % |
| **Deep BiLSTM + SVM** | CHB-MIT | CHB-MIT | 95.49% | 95.41% | 95.37% | 95.37% | 95.39 % |

**Comparision :** The proposed model is compared with results from earlier researchers who have worked with CHB-MIT dataset. The proposed model is trained and tested with 100% of the available patients' data. Table 5 summarizes the results. The results from the proposed model, Deep BiLSTM + SVM are marginally better compared to BiLSTM using Autoencoders model.

Table 5: Comprision of results with Deep BiLSTM + SVM model on SNMC Dataset and other research works on CHB-MIT Dataset

| Algorithm | Accuracy | Percentage of Patients considered |
|---|---|---|
| **Short Time Fourier Transform (STFT) [4]** | 98.26 % | 37.50% |
| **Long Short Term Memory (LSTM) network [5]** | 97.40% | 20.83% |
| **Convolutional Neural Networks (CNN) [6]** | 94.33% | 20.83% |
| **Bidirectional LSTM (BiLSTM) [7]** | 99.60% | 33.33% |
| **Random Forest [8]** | 98.81% | 70.83% |
| **Support Vector Machine [9]** | 86.50% | 45.83% |
| **Deep BiLSTM + SVM (Proposed Model)** | 94.41% | 100% |

## 6. Conclusion and Future Scope

The major work carried out in this research work are introducing a new epileptic seizure dataset for Indian patients and proposing a model with Deep BiLSTM + SVM through MinMaxScaler normalization. The dataset introduced is small compared to CHB-MIT dataset. But the need of easily accessible and readable dataset is huge in the present research era[18]. Preprocessing on complete dataset using normalization helps training a deep learning model successfully. The detection of epileptic seizures can be marginally improved compared to other models by the proposed methodology. Deep learning models that have undergone cross-validation will be efficient in detecting epileptic seizures in people of all ages and locales. This should help medical professionals and patients in understanding and acting on the epileptic seizure conditions in . Future research work can be carried to reach an efficiency of 100% by training and testing deep learning models using combination of datasets which are being made publicly available recently.

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