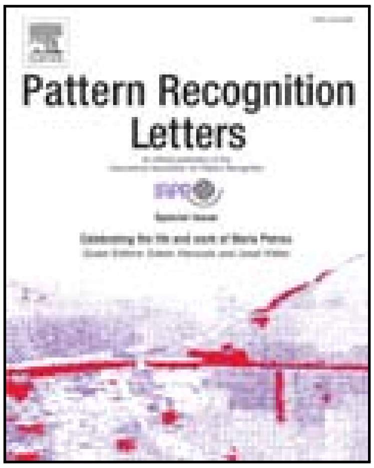


Epileptic Seizure Detection and Prediction using Stacked Bidirectional Long Short Term Memory

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Highlights

- Seizure detection and prediction using EEG is carried out.
- Bi directional long short term memory is used for detection and prediction.
- Precision, recall & ROC AUC are used to evaluate the performance of the model.
- Achieved results with AUC: 0.9 for seizure detection.
- Sensitivity 89.21 % for seizure prediction.

# Epileptic Seizure Detection and Prediction using Stacked Bidirectional Long Short Term Memory

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## ABSTRACT

Epilepsy is a not a disease but a neurological disorder. But people with epilepsy cannot lead a social life like others. Proper diagnosis and advance prediction of epileptic seizures definitely improves the life of epilepsy patients. In this paper an effort is made to develop a seizure detection and prediction method using stacked bidirectional long short term memory technique. This is the most suitable technique for the analysis of time series datasets as it overcomes the vanishing gradient problem identified in recurrent neural network. The dataset for detection and prediction experiments was taken from Bonn University. Our model could perform the seizure detection with the highest accuracy of 99.08% with 98% precision, 99.5% recall and ROC AUC: 0.984346. A binary classification method with AUC more than 0.9 is considered to be outstanding. Seizure prediction was conducted using the same dataset by classifying preictal states of EEG from interictal and ictal states. For the case of prediction our model could identify preictal states with the overall sensitivity: 89.21% and false prediction rate: 0.06. In future the model could be used to program the wearable devices like wrist watch which can be used by epileptic patients for seizure prediction. The device could be programmed to fire alarm during the detection of the preictal EEG signal before the onset of the seizure.

Keywords: Epilepsy, Seizure, LSTM, detection, prediction, deep learning.

## 1 Introduction

People suffering from epilepsy are the only one who really knows the pain they go through in their life because of recurrent seizures. They cannot lead social life like other common people. The mental toll of anticipation they undergo and the uncertainty in the occurrence of seizures are more stressful than the embarrassment and injury they suffer during seizures [1][2]. The uncontrolled seizures may also sometimes lead to sudden unexpected death. Diagnosing epilepsy is a big challenge. Even today neurologists are depending on manual analysis of EEG signals along with video monitoring of the patient to diagnose epilepsy. For accurate diagnosis, the recording must be done for 2 days three days or even for a week. Analyzing such huge recordings manually is a laborious process. Therefore auto detection methods are very much required to help neurologists in proper diagnosis. Development of auto detection methods is going on from many decades. Many researchers have come out with various approaches in this regard. Year by year more accurate methods are being identified for diagnosing epilepsy. So far researchers have used many statistical approaches with EEG feature extraction techniques like wavelet transform[3], Fourier Transform [4], principle component analysis[5] etc. and many machine leaning approaches like, support vector machine, decision tree, naive Bayes, Random forest etc for classification. Nowadays deep learning methods are gaining more attention and giving impressive results in all fields. In this paper an effort to come out with a good seizure detection and prediction method using deep learning [6][7] has been made.

As seizure is a dangerous activity, it is very important for the epileptic patients to get a small hint about the occurrence of seizure by some means before actually it occurs. This helps them to take some precautions before seizure occurs. Seizure detection and forecasting is one of the most challenging subjects in research. Seizure prediction has become the goal for many researchers. Most commonly used tool for predicting seizures is electroencephalogram (EEG) [8][9][10]. Both Seizure detection and forecasting can be performed using EEG data. This is the most widely used tool and the one which can help in clearly distinguishing the different states of the brain.

The amplitude levels of the EEG signals [11] indicate the voltage level released at each time step. Four states are identified in the EEG signal. They are Interictal, Preictal, Ictal and Postictal state [12][13]. The voltage level of the signals at all the four states is different. Ictal state is the one which occurs during seizure occurrence. Preictal state is the one which occurs few minutes before the ictal state. Interictal is the state between two successive seizures. Postictal is the state after the occurrence of the seizure. According to this knowledge it can be understood that, for seizure detection we need to classify ictal states from all the remaining states of the EEG signals and for seizure prediction we need to classify preictal state from interictal and ictal states. Seizure detection methods have to identify presence or absence of an ongoing seizure. The method can be binary classification; classifying seizure or non-seizure or it can be more refined classification; classifying interictal, preictal, ictal, or postictal. But in case of multiclass classification the performance of the model reduces because of ‘curse of dimensionality’. Therefore in this experiment a binary classification method has been developed.

Epileptic patient will be in the preictal state before the seizure occurs. Therefore, It is required to identify the preictal state of the patient so that it is possible to provide some hint to the patients about the symptom of seizure occurrence by some means, say for example in the form of a wearable device [8] like wrist watch shown in figure 1 which can give alarm when ever a preictal state is identified. By this, seizure occurrence can be avoided by drug and also patient can avoid dangerous activities like driving, swimming, walking on the road side etc [14][15][16].

Seizure detection and prediction is one of the challenging and ongoing researches even today [17]. Though lot of research has been conducted on this subject, even today many of the neurologists are depending on manual diagnosis because of not having confidence on the computerized methods identified. There can be no such thing as a perfect method or perfect model for detection or prediction. But there can only be the best model that was able to discover. In this paper an attempt to develop a method that can guarantee the seizure detection and prediction with good accuracy using bidirectional long short term memory (LSTM) technique is made.

LSTM is derived from recurrent neural network. Recurrent neural network is a type of neural network which is used for analyzing sequential data. In case of traditional neural networks, each instance of input data is assumed to be independent of each other. Whereas, in case of sequential data, the output of one time step depends on the output of the previous time step. Therefore, in RNN, the output of each time step is provided as input along with the new input at the next time step. These recurrent neural networks are trained using back propagation through time (BPTT). BPTT suffers from vanishing gradient and exploding gradient. LSTM is the architecture specially designed to solve vanishing and exploding gradient problem of RNN. In this work a method is developed for seizure detection and prediction using stacked bidirectional LSTM.

In future the seizure prediction model developed could be programmed to a wearable device [8] like the wrist watch shown in the figure 1. The device could be programmed to give the alarm for the patient when the preictal state is recognized. The device must fire the alarm at least few minutes before the seizure is onset. For this; a prediction time zone should be defined. If warning alarm occurs within that prediction time zone before the seizure is onset then it is considered to be true alarm. If the alarm occurs before the prediction time zone then it is treated as false alarm. If the alarm doesn’t occur neither before nor during the prediction time zone and before the seizure onset then it is treated as false negative alarm. The figure 2 given below illustrates more about seizure prediction alarms. Figure 2a shows the case of true positive alarm firing few minutes before the seizure is onset. Figure 2b shows the case of false positive alarm firing before prediction time zone. Figure 2c shows no alarm firing which is the case of false negative alarm.

Figure 1: Wrist watch. Wearable device for epileptic patients which gives alarm during preictal state [8]

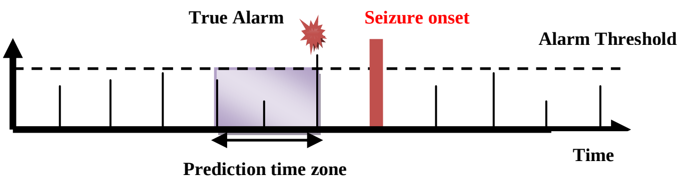


Figure 2a: True positive alarm

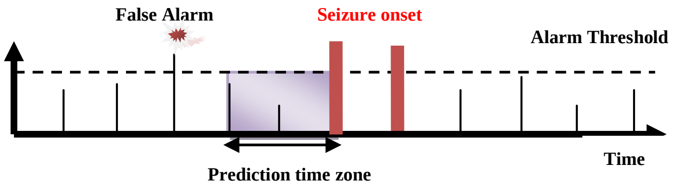


Figure 2b: False positive alarm

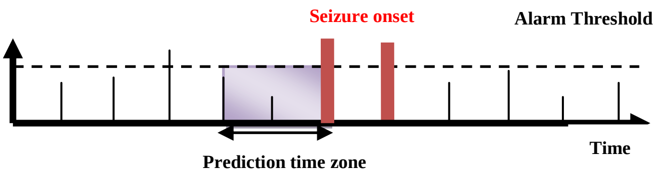


Figure 2c: False negative alarm

Figure 2: Epilepsy seizure prediction alarms

### 1.1. Motivation

Papers from PRL are the great inspiration for the upcoming researchers like us. One of the PRL papers that have motivated us is “A Fuzzy Neural Network Approach for Automatic K-Complex Detection in Sleep EEG Signal” by Rakesh Ranjan, et al [20]. The team has contributed an outstanding research work in developing a k-complex auto detector. They have performed a detailed sleep analysis based on EEG signals. They used Fuzzy neural network approach; fuzzy c-means algorithm and back propagation algorithm for rapid k-complex detection in their experiment. For classification purpose they have used 3 types of linear models like 1-layer feed forward neural network, Logistic regression and SVM. And 2 types of non linear models like, multi layered feed forward neural network and SVM. They used EEG signals recorded for 2 hrs in sleep state. The recorded signals included artifacts from power line interference. They removed artifacts by applying digital notch filters. The second stage EEG signals are extracted using bandpass filter. The third stage EEG signals are smoothened using Savitzky-Golay filter. The smoothened EEG signals are then provided as input to fuzzy c-means algorithm. They used features like, maximum/ minimum amplitude and time period to perform classification of EEG signals into k-complex and non k-complex. Further the k-complex signals are passed as input to neural network for performance assessment using back propagation algorithm. Evaluation is done by calculating accuracy, sensitivity and specificity. The work shows amazing results in k-complex detection. Thanks to the team for giving such a remarkable contribution in the field of biomedical signal processing. The paper consists of 7 sections; very neatly organized. It is written very systematically and easy to understand. The authors in [20] provided me the source code of their paper. I have used their implementation and validated it on my test cases. Their approach gives excellent results in all of my test cases. The paper provides step by step description of the complete flow of the experiments.

### 1.2. Related work

Seizure detection and prediction is an ongoing research. So far many different approaches using machine learning and deep learning [19][21] have been tried by several researchers on seizure prediction [22][23]. Some of them are, Xuelin Ma et al [24] used a framework based on long short term memory with multi task learning for seizure prediction. They used LSTM for sequential data processing and multi task learning for performing prediction. They obtained prediction accuracy: 89.36%. The dataset they used consist of 2 patient’s data with 263 and 210 samples respectively. They used Keras framework for implementing the neural network. They use optimizer function Adam with learning rate of 0.5, dense layer consisting of 128 nodes and total of 32 lstm cells in the hidden layer.

MINGRUI SUN et al [25] have worked on seizure prediction using deep learning algorithms. They used Fourier transform method for the conversion of time domain signals to frequency domain signals. Both time domain and frequency domain signals were extracted using two layer convolutional neural networks using four different methods (2 methods on linear model and 2 methods on deep learning) for seizure prediction. The intracranial EEG data included data of 2 canines and 2 humans. The canine’s data was sampled at 400 Hz and 2 human’s data was sampled at 5000 Hz. Two methods under linear model are: 1. linear discriminant analysis and 2: linear regression. For deep learning case they used 1. Convolutional neural network and 2. Recurrent neural network. Finally they gave the comparison of both types of models and concluded that Convolutional neural network outperformed all the remaining methods by giving best AUC performance metrics.

Ahmed M. Abdelhameed et al [26] tried early detection of seizures using deep learning method. A convolutional autoencoder was used to extract spatial features of raw unlabeled EEG data and recurrent neural network with lstm was used for classification. They initialized weights using transfer learning method. Having 1 hour prediction window their model was successful in giving prediction accuracy of 94%.

The reason for not having good progress in this field is not having datasets with well defined train set, test set. A 26 hours intracranial EEG data from 8 dogs is made available publicly by American Epilepsy Society on kaggle.com. The dataset consists of predefined train set, validation sets and test sets with the view of helping researchers to evaluate the results of various algorithms directly. Iryna Korshunova et al [rel 8] have used this dataset provided for seizure prediction challenge. They worked on three different approaches, SVM, LDA and CNN. Among these CNN performed best with highest AUC scores.

Carlos Emiliano Sol´orzano-Esp´ındola et al [11] have made an attempt for pediatric seizure prediction using Gaussian mixture model hidden markov models. They performed pre-processing of the data using band-pass filter selecting band-pass butter worth filter for removing biological noise in the data and Butterworth notch filter for removing noise from the power line. They performed dimensionality reduction using principal component analysis technique. They extracted features like Entropy, Teager-Kaiser energy and Kurtosis from EEG data. At last for classification they used GMM-HMM models. The results showed about 95% of sensitivity and 86% of specificity.

Keider Hoyos-Osorio et al [18] have tried an experiment on seizure prediction using both EEG and ECG signals. They used EEG and ECG signals collected from 7 patients suffering from focal epilepsy. They collected features using discrete wavelet transform from EEG signals and heart rate variations from ECG signals. They used sequential forward selection along with linear-Bayes and k-nearest neighbor classifiers to identify the features that can provide more accurate information about the occurrence of preictal signals. All features are computed over a window size of few seconds. They obtained a total average accuracy of about 94% for seizure prediction.

### 1.3. Dataset

The dataset used for the experiment consists of 5 different folders each having 100 files. Each files representing the data of one person or subject. In total the dataset consists of EEG data of 500 subjects. Each file consists of recording done for the duration of 23.5 seconds with 4097 data points. We divided and shuffled 4097 data points of all the files into 23 chunks. The shuffled data in each chunk is organized into a matrix consisting of 178 columns for 1 second. $179^{th}$ column represents the class label. The matrix consists of 5 class labels (1, 2, 3, 4, and 5). Class labels 2, 3, 4 and 5 are the one which do not experience seizure. Class label 1 is the one with seizure activity.

## 2. Proposed method

### 2.1. Long Short Term Memory

Long short term memory is a derivation of recurrent neural network most widely used for sequence prediction problems. It is used to overcome the vanishing gradient problem observed in recurrent neural network. In case of RNN because of vanishing gradient problem, gradient goes smaller as it goes back to the early layers. Because of this, learning does not happen properly in the early layers. In turn the performance of the neural network goes down. Therefore to overcome this problem, the architecture of the LSTM is designed to have input gate, forget gate and output gate which help in remembering the results of the input sequences computed long ago. These three gates are the three vectors composed of sigmoid activation function and dot product operation. The important thing in the LSTM is its cell state. The LSTM cell memory gets updated for every time step. For example, at time step t the cell state is moved from $C_{t-1}$ to $C_t$ as can be seen in figure 3.

The figure 3 shows the single LSTM cell with input gate ($\mathrm{i_t}$), forget gate ($\mathrm{f_t}$) and output gate ($\mathrm{O_t}$). LSTM can be used with different architectures. For example it can be used as,

- Vanilla LSTM: the neural network consists of single LSTM layer
- Stacked LSTM: in this a deep neural network constructed by placing lstm layers one on top of the other.
- CNN LSTM: in this Convolutional neural network is used for images feature learning purpose. On top of that, LSTM is used to process the images in sequential order.
- Encoder-Decoder LSTM: in this one lstm network is used for encoding the input sequences and the other is used for decoding the encoded sequence.
- Bidirectional LSTM: in this the sequential input provided is processed and learnt in both forward and backward direction.
- Generative LSTM: in this LSTM network learns the input sequences and also synthesizes the new sequences of similar kind.

In our experiment a hybrid model used; the combination of stacked and bidirectional architectures.

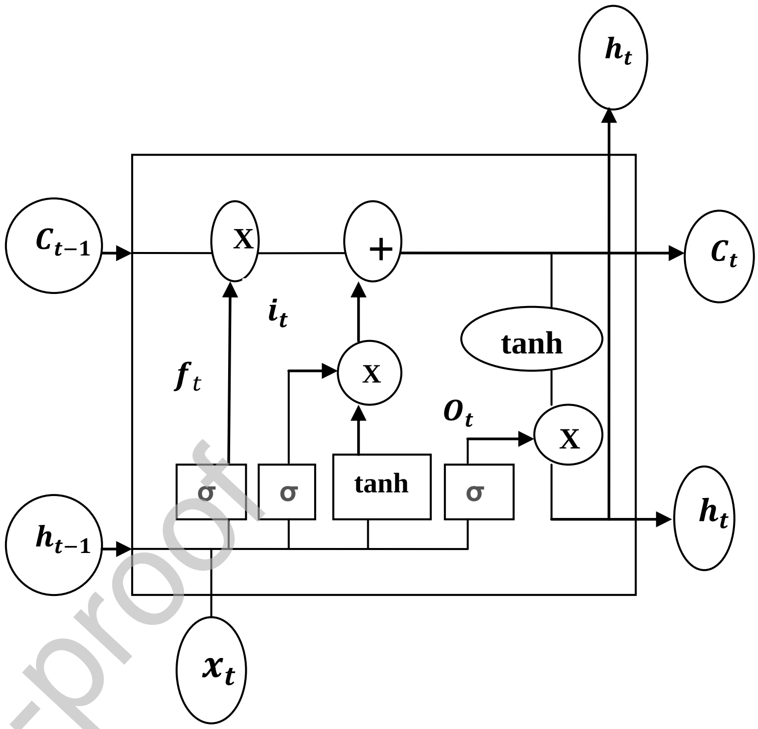


Figure 3: Single LSTM cell/block

The equations of the three gates of LSTM architecture are given below:

$i_t = \sigma(\mathrm{x_t\,U^i + h_{t-1}W^i})$ - - - - (1)

$f_t = \sigma(\mathrm{x_t\,U^f + h_{t-1}W^f})$ - - - - -(2)

$O_t = \sigma(\mathrm{x_t\,U^o + h_{t-1}W^o})$ - - - - (3)

$C_t^1 = tanh(\mathrm{x_t\,U^g + h_{t-1}W^g})$ - - - - (4)

$C_t = \sigma(\mathrm{f_t * C_{t-1} + i_t * C^1})$ - - - - (5)

$h_t = tanh(\mathrm{C_t}) * \mathrm{O_t}$ - - - - (6)

Where, $\mathrm{x_t}$ is the input vector (input EEG dataset), $i_t$ is the input gate vector, $f_t$ is the forget gate vector, $O_t$ is the output gate vector; all three gates activated using sigmoid activation function, $h_t$ is the output of the LSTM cell at the time step t, $C_t$ is the current cell state, $\mathrm{U^i}$, $\mathrm{W^i}$,$\mathrm{U^f}$, $\mathrm{W^f}$, $\mathrm{U^o}$ and $\mathrm{W^o}$ are the weights used during learning. LSTM cells are good in remembering information computed long ago. But storing all the past information computed may affect the performance of the network. So, to overcome this problem, each cell is designed to have three gates.The gates will take the current time step input $x_t$ and the output of the previous time step $h_{t-1}$. It can be observed that, equations (1), (2) & (3) of input vector, forget vector and output vector respectively follow same structure but with different weights.

Forget gate keeps track about how much information should be removed from the memory of the LSTM cell during each time step. It removes all the information that is less important for the prediction task from the cell memory. This is done by performing dot product operation between $f_t$ and $C_{t-1}$. Input gate keeps track of the amount of input data entering the network at each time step. It is responsible for adding the information into the cell state. It adds only the information required for the prediction and stops all redundant and unwanted data entering into the cell memory. This is obtained by performing dot product operation between input gate vector $i_t$ and tanh layer vector $C_t^1$. Finally, output gate is  Output gate will keep track about how much content of the memory is useful for the task and will output only that part of the information as output ($h_t$) of the current cell state. It uses activation function tanh to transform the values of the current cell state vector to fall between the range -1 to +1. These transformed values undergo dot product operation with output gate sigmoid activation vector. The resulting vector is considered as the final output ($h_t$) of the cell at time step t. Algorithm used for the experiment is shown in figure 4 below.

- *Importing dependencies*
- *Data preprocessing*
- *Partition the dataset into training set and test set.*
- *Perform feature scaling of the dataset using suitable feature scaling technique.*
- *Reshape X*
- *Create the model; define the number of units in the input layer, hidden layer and the output layer.*
- *Compile the model*
- *Choose the training window size and organize dataset accordingly.*
- *For no_of_epochs and batchsize do*
    - *Train the network using training set*
    - *End for*
- *Evaluate the network using validation set.*
- *Calculate accuracy and loss functions for both training set and validation set.*
- Plot visualizations

Figure 4: Algorithm for the proposed LSTM model

The EEG signals recorded from the brain are sequential in nature. And LSTMs are good in analyzing sequential dataset, for this reason LSTM is the best technique suitable for seizure detection and seizure prediction using EEG signals. In our experiment stacked bidirectional LSTM is used and the same is shown in figure 5.

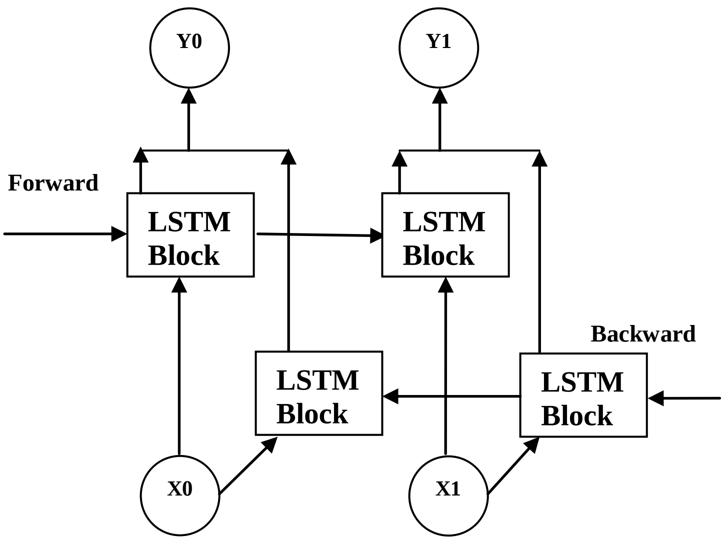


Figure 5: Two layered stacked bidirectional LSTM

### 2.2. Proposed model

The experiment is conducted using Keras, Numpy, Tensorflow, Sklearn and Matplotlib. As a first step visualization of the dataset consisting of 178 data points for 500 individuals is done. Figure 6 below shows the intuition of seizure events in the dataset with time on the X-axis and amplitude in micro volts on y-axis. Lines 5 and 4 represent the healthy signals, lines 3 and 2 represent the interictal signals and line 1 indicates the seizure events.

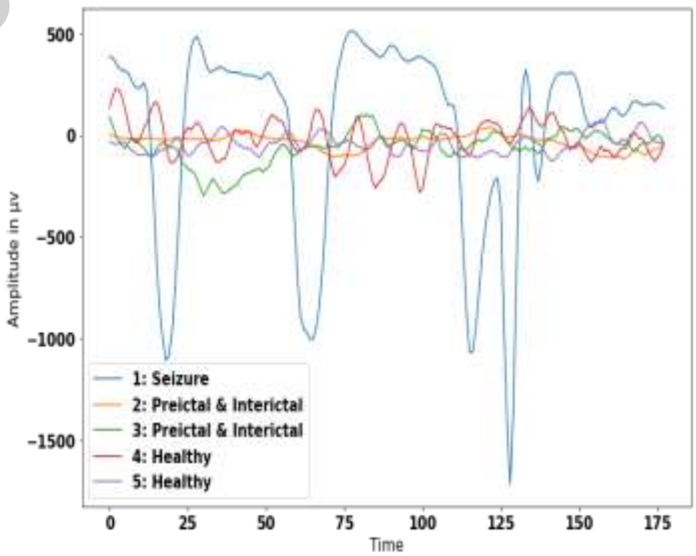


Figure 6: Intuition of the seizure events in the dataset

The architecture of the proposed model is shown in figure 7. The model consists of stacked (2 layers) bidirectional LSTM layer, dropout and dense layers. Activation function 'tanh' is used on the hidden layers and 'softmax' on the output layer. The optimizer function 'adam' is used for optimization. The summary of the complete model is shown in table 1 below. The model processed 39,549 parameters in total. Number of parameters evaluated on the first lstm layer is 12992, parameters on the second layer 25312 and on the output layer 105. The model is compiled using the loss function 'binarycrossentropy', optimizer 'adam'. The performance of the model is evaluated using accuracy. The model is trained on 9200 samples and tested on 2300 samples using 50 epochs and batch size 15.

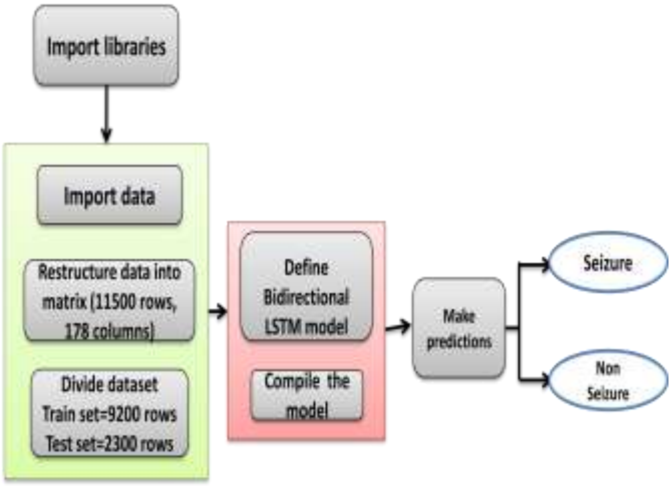


Figure 7: Architecture of the proposed work

Table 1: Summary of the model

| Layer (type) | Output Shape | Param # |
|---|---|---|
| lstm_49 (LSTM) | (None, 45, 56) | 12992 |
| dropout_44 (Dropout) | (None, 45, 56) | 0 |
| lstm_50 (LSTM) | (None, 56) | 25312 |
| dropout_45 (Dropout) | (None, 56) | 0 |
| dense_29 (Dense) | (None, 20) | 1140 |
| activation_29 (Activation) | (None, 20) | 0 |
| dense_30 (Dense) | (None, 5) | 105 |
| activation_30 (Activation) | (None, 5) | 0 |

Total params: 39,549
Trainable params: 39,549
Non-trainable params: 0

## 3. Results & Discussion

This section presents the results of the model. The Bidirectional LSTM model was executed to perform seizure detection. This is a binary classification problem. The input samples are classified into either seizure event or non-seizure event. Figure 8 shows classification accuracy of the training and test set respectively. Figure 9 shows the loss of training set and test set respectively of the proposed LSTM model. An accuracy of 99.89% on the train set and 99.08% on the test set is achieved.

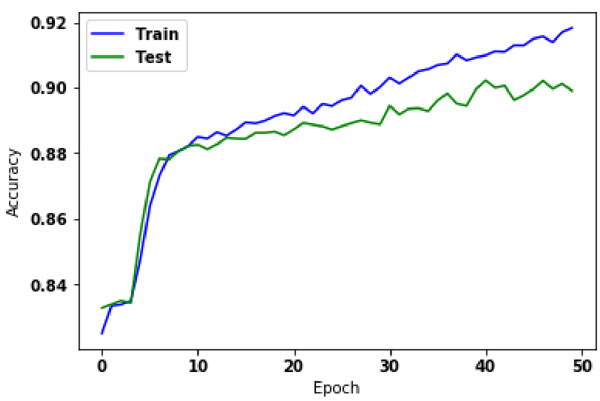


Figure 8: Accuracy Graph of the model between Train set and Test set

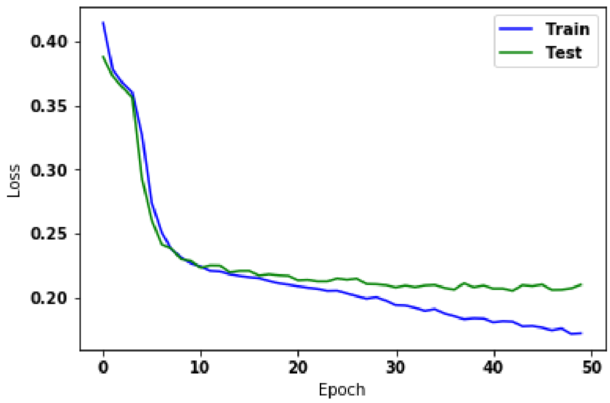


Figure 9: Loss Graph of the model between Train set and Test set

Table 2 gives the accuracy, precision, recall and F1 Score of the proposed LSTM model for both training set and test set. Table 3 gives the comparison of the proposed work with the latest published work.

Table 2: Performance metrics of test and train set

| Parameter | | Score |
|---|---|---|
| Accuracy | Test set | 0.91 |
| | Train set | 0.93 |
| Precision | Test set | 0.95 |
| | Train set | 0.96 |
| Recall | Test set | 0.96 |
| | Train set | 0.96 |
| F1_Score | Test set | 0.91 |
| | Train set | 0.92 |

The performance matrices Precision, Recall, and F1_Score are calculated using the following formulas.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

$$\text{Sensitivity (or Recall)} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

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

Table 3: Comparison of accuracy of proposed work with the latest published work.

| | Method | Accuracy |
|---|---|---|
| Xuelin Ma et al [24] | LSTM | 89.36% |
| Our experiment | Stacked Bidirectional LSTM | 91% |

The receiver operating characteristics shown in figure 10 above gives the tradeoff between sensitivity and specificity. It shows the ability of the model in classifying True positive elements of the EEG data from false positive elements. The area under curve (AUC) of ROC is 0.984346. It gives the average measure of performance of the model across all possible thresholds. A binary classification model with AUC 0.5 is considered to be nominal to diagnose the presence or absence of the seizure. In our experiment our model is giving outstanding performance with AUC 0.984346.

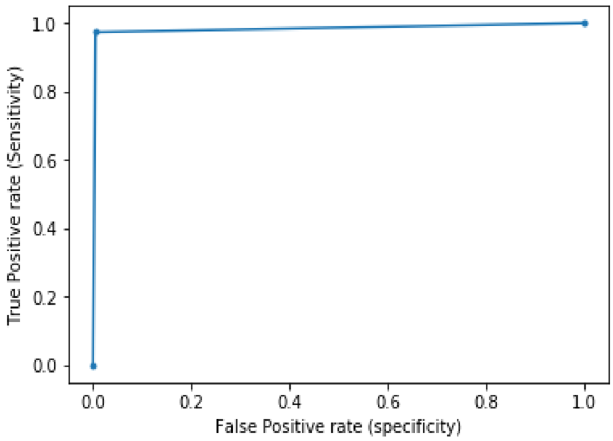


Figure 10: Receiver operating characteristics of validation set. With AUC: 0.984346

The dataset used in the experiment consists of 5 folders in which folders 3 and 2 consists of data collected during preictal and interictal period and folder 1 consists of data collected during ictal period. For the case of seizure prediction it is required to classify preictal periods of EEG data from interictal and ictal periods. To achieve this, model is executed once again by considering only three folders (3, 2 and 1) of the whole dataset. These three folders consist of EEG data of 300 individuals. Classification task is performed using the same model for classifying preictal state of EEG from interictal and ictal states. Sensitivity and specificity of few subjects obtained are shown in the table 4 below. The table shows our model could achieve on an average of 89.21% of sensitivity and an average false prediction rate of 0.06.

Table 4: Sensitivity and specificity of seizure prediction of the model

| Patient | No of seizures | Sensitivity | Specificity |
|---|---|---|---|
| P01 | 6 | 100% | 0 |
| P02 | 5 | 84.5% | 0 |
| P03 | 3 | 60% | 0.2 |
| P04 | 4 | 80% | 0.1 |
| P05 | 5 | 100% | 0.08 |
| P06 | 3 | 100% | 0 |
| P07 | 7 | 100% | 0.04 |
| Total | 32 | 89.21 | 0.06 |

The experiment was run on the computer system with 4GB RAM, 1.7 GHz of processor speed with core i5 processor. It took 22 minutes to complete the execution for 11500 samples with 50 epochs and batch size 15. The time needed may vary depending on the configuration of the computer system.

## Conclusion

In this experiment we proposed a seizure detection and prediction methods using two layered bidirectional long short term memory using EEG dataset from Bonn University Germany. Our experiment was able to detect seizures with good accuracy of about 99%. If the person is detected with epilepsy then it is very important to help such patients to forecast the seizure so that they can take suitable precautions before the seizure occurs. Therefore, in this experiment an effort is made to conduct seizure prediction as well. We were able to succeed in the experiment by obtaining around 89.21% of sensitivity in predicting the preictal states of the patients. Thus, in future we like to work more on seizure prediction to help epilepsy patients to live normal life like others.

Conflict of Interest

None


## Acknowledgement:

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