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PERFORMANCE ANALYSIS OF LSTM AND RNN FOR THE PREDICTION OF EPILEPSY USING INTRACRANIAL EEG

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Abstract.

Epilepsy is the one of the most common neurological disorders in the world second only to migraine which makes it one of the important neurological problems to be combated in the modern world and the most sensitive of all nervous system related disorders. Automatic detection of these Epileptic seizures can improve the patient's quality of life. Current Electroencephalogram (EEG)-based seizure detection systems meet a variety of challenges in real-life situations, The EEG signals are non-stationery and seizure patterns vary across patients and recording sessions [4] . Moreover, EEG data are prone to many types of noise that negatively affect the detection accuracy of epileptic seizures. We propose a new framework that learns directly from the data, without extracting a feature set which automatically learns the discriminative EEG features of epileptic seizures. Specifically, to reveal the correlation between successive data samples, the time-series EEG data are first segmented into a sequence of nonoverlapping epochs. [2] Long Short-Term Memory (LSTM) network and Recurrent Neural Networks are developed as independent models to learn the high-level representations of the normal and the seizure EEG pattern, these two Deep learning models are trained and tested respectively and contrasted on various metrics for their performance analysis. The astounding results obtained from our LSTM model on the well-known benchmark clinical dataset from CHB-MIT University [4] repository demonstrate the superiority of our proposed approach over the existing ultramodern methods and models. Compared to current methods that are quite sensitive to noise, the proposed [4] LSTM Deep Learning model maintains its high detection performance in the presence of common EEG artifacts (muscle activities and eye-blinking) as well as white noise.

Keywords: Epilepsy, Electroencephalogram (EEG), Deep Learning, Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN), Performance Analysis

1. Introduction

The proposed model named Detection of Epilepsy using Deep Learning involves development of end-to-end application. Epilepsy is a central nervous system (neurological) disorder caused by the sudden abnormal discharge of the brain neurons [3]. According to the World Health Organization 50 million of the world population is enduring from epilepsy. Estimated 2.4 million people are diagnosed with epilepsy every year [1]. A group of neurons synchronously discharge or misfire from several focal points and spread out to other hemispheres (or the whole brain) at the start or onset of a seizure [5], is followed by electrophysiological anomalies and its diagnosis is mostly performed using electroencephalography (EEG) . Notably, the process of manual detection is very time-consuming and inefficient, especially during cases of long-term EEG recording. Moreover overlapping symptomatology of epilepsy with other neurological disorders and contamination of EEG signals [2] (especially the extracranial or scalp recordings) by artifacts makes the visual scrutinization procedure incredibly challenging even for an experienced neurophysiologist [1]. The repercussions of slowed up or inaccurate diagnosis could lead to permanent neurobiological, cognitive, social, and psychological impairments. Portable EEG devices are capable of continuous monitoring and streaming the [3] EEG signals wirelessly onto devices capable of storing, visualizing, and processing such data . Lack of movement and continuous application of conducting gel of wet electrodes are being resolved by the development of dry electrodes that can provide a clean signal with a high signal to noise ratio. In these cases, the duration of continuous monitoring is more . So, there is a need to automate the process of detecting epileptic form patterns more efficiently, and this has been the basis for the development of various Deep Learning based models . Hence an end-to-end application is devised based on Deep Learning Process [6], where a Neural Network is created which employs a Long short-term Memory (LSTM) and Recurrent Neural Network (RNN) Model that is primarily known for processing sequential data. A following multiclass dataset consisting of [1] 11500 pieces of information(row), each information contains 178 data points for 1s (column), this data is pre-processed to get an effective reshaped, normalized, and split data that help us in boosting accuracy when trained on the model. A LSTM, RNN Model is built on compiled on this dataset and finally save the model onto our disk. Performance Analysis of the selected deep learning models is done by using confusion matrix of the vi predicted results of each model. Various metrics such as [9] Accuracy, Precision, Recall, AUC (Area Under Curve) scores etc... will provide us with the means to compare the performance of two networks. Compared to current methods that are quite sensitive to noise, the proposed LSTM Deep Learning model maintains its high detection performance in the presence of common EEG artifacts (muscle activities and eye-blinking) as well as white noise.

1.1 Overview

Deep learning is based on the branch of machine learning, which is a subset of artificial intelligence. Since neural networks imitate the human brain and so deep learning will do [7]. In deep learning, nothing is programmed explicitly. It is a machine learning class that makes use of many nonlinear processing units to perform feature extraction as well as transformation. The output from each preceding layer is taken as input by each one of the successive layers.

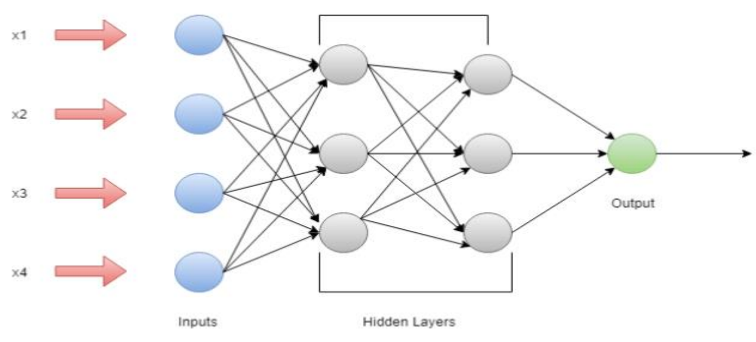


Figure 1. Deep Learning Structure

Deep learning models are capable enough to focus on the exact features themselves by requiring a little guidance from the programmer and are extremely helpful in solving out the problem of dimensionality. Deep Learning Algorithms are used, especially when we have a huge no of inputs and outputs. Since deep learning has been evolved by the machine Learning, which itself is a subset of artificial intelligence and as the idea behind the intelligence is to mimic the human behaviour, so same is "the idea of deep learning to build such algorithm that can mimic the brain" [4]. Deep learning is implemented with the help of Neural Networks, and the idea behind the motivation of Neural Networks is the biological neurons, which is nothing but a brain cell.

Deep learning is a collection of statistical techniques of machine learning for learning feature hierarchies that are based on artificial neural networks So basically, deep learning is implemented by the help of deep networks, which are nothing but neural networks with multiple hidden layers [6]. Networks in Deep Learning Are Artificial Neural Networks, Convolutional Neural Networks and Recurrent Neural Networks.

1.2 Significance and Motivation

Electroencephalogram (EEG) is one amongst the foremost effective techniques to trace and record brain wave patterns. Neurologists read and analyse these EEG records to detect and categorize the sort of epilepsy diseases. The EEG examination is a visual process that needs too many hours to look at 1-day of recording. it is very time consuming, ends up in fatigue and tiredness also requires the services of an expert, this ends up to put a heavy load on the neurologist and reduces their efficiency. By interpreting the recorded EEG signals visually, neurologists can distinguish between epileptic brain activities during a seizure (ictal) state and normal brain activity between seizures (interictal) state. Over the last twenty years, however, an abundance of automated EEG-based epilepsy diagnostic studies has been established [5]. This was motivated by the exhausting and time-consuming nature of the human visual evaluation process that depends solely on the doctors' ability. Besides that, the necessity for aim, rapid, and effective systems for the processing of vast amounts of EEG recordings has become unavoidable to be ready to diminish the chance of misinterpretations. the provision of such systems would enhance the standard of lifetime of epileptic patients. The above-mentioned challenges are what motivates us to develop an automatic convulsion detection system with machine learning methods, using epileptic multi-channel EEG signals including EEG signal acquisition, pre-processing, features extraction, and classification. Most of the proposed systems depend on feature extraction techniques to discriminate abnormal signals from the background. Selection of discriminative features could be a matter of the performance of such systems. Deep neural networks enable learning directly on the information without the domain knowledge needed to construct a feature set. Seizures type in EEG signals may have different important across patients and even overtime for the identical patient, which imply difficulty to develop automatic cross-patient detector. We offer an automatic seizure detection system to handle the challenges mentioned above for classifying EEG signals into normal and abnormal using LSTM algorithm and is contrasted against RNN algorithm.

1.3 Data set Collection

The dataset plays an especially vital role in deciding the efficiency and accuracy of the model implemented on a holistic level hence a rightfully apt dataset must be chosen. The dataset must include data of EEG recordings of people from different and diverse age groups and it should be recorded for a significant period to make a significant inference to make a near perfect prediction.

Reviewing through three different datasets which include The Department of Epileptology Bonn University dataset , Barcelona University of Medical sciences, and Children's Hospital Boston- Massachusetts Institute of Technology (CHB-MIT) Scalp EEG dataset, we concluded that [4] CHB-MIT dataset is more inclusive and larger enough for best training and testing our Deep Learning Network also meeting the necessary conditions mentioned above in flying colours.

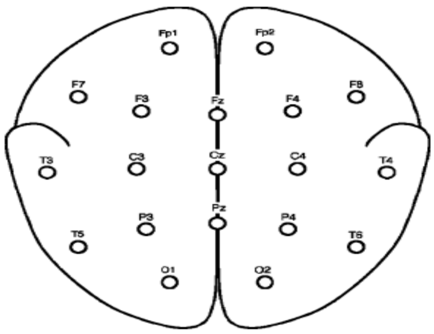


Figure 2. Scheme of the locations of surface electrodes according to the international 10-20 system. Names of the electrode positions are derived from their anatomical locations. Segments of sets A and B were taken from all depicted electrodes.

All EEG signals were recorded with the same 128- channel amplifier system, using an average common reference [omitting electrodes having pathological activity 3, 4, and 5 or strong eye movement artifacts 1 and 2]. After 12 bit analog-to-digital conversion, the data were written continuously onto the disk of a data acquisition computer system at a sampling rate of 173.61 Hz. Band-pass filter settings were 0.53–40 Hz (12 dB/oct) [1].

CHB-MIT Scalp EEG dataset is the dataset which we have used to Train and Test our LSTM and conventional RNN layer. [4] The dataset is 42.06 GB in size with the data ranging across different age groups and the datapoints are in .csv file format.

1.3.1 Insight into the dataset

The chosen dataset "CHB-MIT Scalp EEG dataset "consists of a total of 5 different folders, each folder contains 100 files, each file represents a single subject or a person. Every file in the folder is a recording of brain activity for 23.6 seconds [4]. The corresponding time-series data is further sampled into 4097 data points. Each data point sampled is the value of the EEG recording at a different point in time. So, we have a total of 500 individuals with each having 4097 data points recorded for 23.6 seconds [1].
We have divided and shuffled every 4097 data points into a total of 23 chunks, each chunk has 178 data points for recorded for 1 second, and each data point in the file is the value of the EEG recording at a different point in time. So now we have 23 x 500 = 11500 total pieces of information(row), each information has 178 data points recorded for 1 second(column), the last column in the dataset stands for the label y {1,2,3,4,5}. The response variable is y which is in column 179, the Explanatory variables are X1, X2, X3, X4, X5 ..., X176, X177, X178. y holds the category of the 178-dimensional order of the input vector. Specifically, y in {1, 2, 3, 4, 5} :

1 - Recording during seizure activity

2 - Recording the EEG signal from the area where the tumour was found.

3 - Find where the region of the tumour was in the brain and recording the EEG activity from the healthy brain area.

4 - Eyes closed, means the EEG signal was recorded when the patient had their eyes closed

5 - Eyes open, means the EEG signal was recorded when the patient had their eyes open

View of the Dataset:

	A	X1	X2	X3	X4	X5	X6	X7	X8	X9	...	X170	X171	X172	X173	X174	X175	X176	X177	X178	y
0	X21.V1.791	135	190	229	223	192	125	55	-9	-33	...	-17	-15	-31	-77	-103	-127	-116	-83	-51	4
1	X15.V1.924	386	382	356	331	320	315	307	272	244	...	164	150	146	152	157	156	154	143	129	1
2	X8.V1.1	-32	-39	-47	-37	-32	-36	-57	-73	-85	...	57	64	48	19	-12	-30	-35	-35	-36	5
3	X16.V1.60	-105	-101	-96	-92	-89	-95	-102	-100	-87	...	-82	-81	-80	-77	-85	-77	-72	-69	-65	5
4	X20.V1.54	-9	-65	-98	-102	-78	-48	-16	0	-21	...	4	2	-12	-32	-41	-65	-83	-89	-73	5

5 rows × 180 columns

Figure 3. Overview of the CHB-MIT Dataset from Jupyter Notebook

2.Preamble

Epileptic seizure detection as mentioned in the previous sections needs an implementation of a reliable and a robust deep learning model for the automatic detection of the seizure.

All of the prevailing models have not dwelled in to Long Short-Term Memory (LSTM) architecture for seizure detection at a multi layered level although it has several architectural upper hands over the conventional Recurrent Neural Network (RNN) and Convolutional Neural Network (CNN).

2.1 Introduction:

Block Diagram of the proposed model.

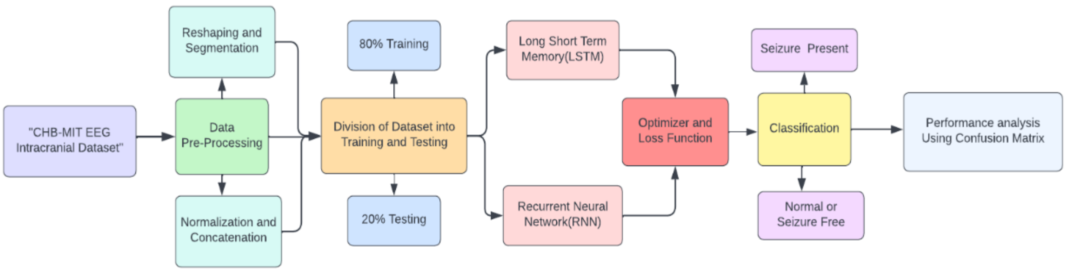


Figure 4: Block Diagram of the Proposed Model

A brief explanation of the proposed model.

Children's Hospital of Boston- Massachusetts Institute of Technology (CHB-MIT) EEG scalp dataset is obtained the CHB-MIT repository of the size 42.06 GB and the data set is fed into the Deep Learning model after Data pre-processing.

The dataset is pre-processed to get it apt and ready to be fed into the neural network, data pre-processing prepares the data in the most meaningful of ways for the further detailed analysis.

Our CHB-MIT dataset it is first reshaped in order to make sure that all the input arguments are of the same dimension and then the dataset is normalized to remove redundant data and for a better and a faster execution.

After the data pre-processing the entire dataset is divided into 80"% for training the network and 20% of the entire dataset is reserved for testing and validating the models employed.

The dataset is divided into 80:20 ratio for training and testing in order to build a reliable machine learning model as we are dealing with a relatively Big Data Ecosystem which requires appropriate division of the dataset into Training, Testing and Validation in order to get accurate results by avoiding biased results and preventing under and over fitting.

Then the data is fed into the Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) independently and then the output of the Neural network is fed in to an appropriate Optimizer followed by an appropriate Loss function.

Then the model is fitted against the data points modelled through the neural network and Classification and Prediction is performed after the model fitting.

Classification Accuracy is plotted against epochs and it is tested by plotting Validation accuracy against epochs for RNN and LSTM network respectively.

After Classification and Prediction both the RNN and the LSTM Deep Learning Models are analysed for their performances using the Confusion Matrix.

Metrics such as Classification accuracy, Precision, Recall or Sensitivity, Specificity, F1- score are used for a detailed analysis of the models, all these metrics are plotted against the epochs for comparing RNN and LSTM network.

Finally, the RNN and LSTM networks are compared using every metrics mentioned above and the best out of the two models is obtained.

2.1 Methods

The Levels of classification :

The below is the block diagram showing the different levels of classification implemented in our model starting from the acquired CHB-MIT dataset.

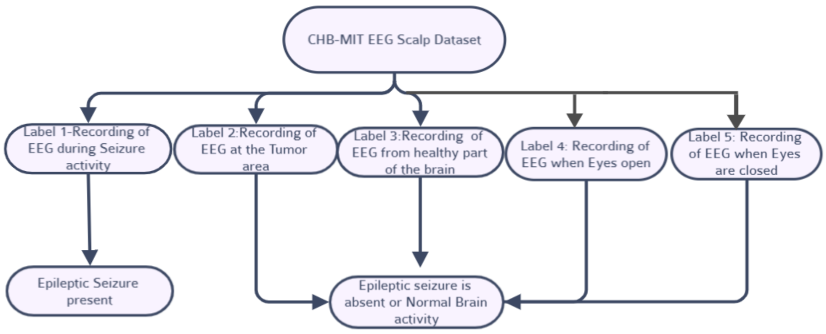


Figure 5: Different Classification Levels

2.1.1 Intuition on the Dataset:

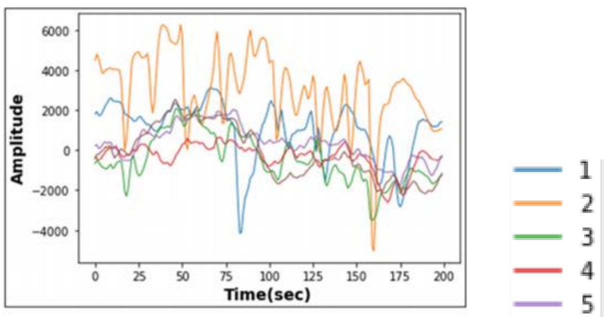


Figure 6: Plot of EEG recording of the brain activity without seizure

Understanding of the EEG recording of brain activity with and without seizure

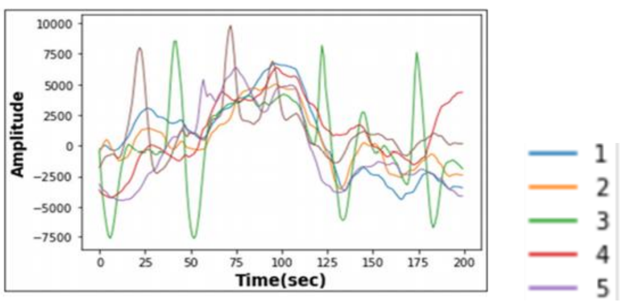


Figure 7: Plot of EEG recording of the brain activity which has a seizure

2.1.2 Data Pre-processing:

Data pre-processing is one of the most important steps in developing a Deep Learning Model because it prepares the data in the most meaningful of ways for the further detailed analysis.

Data "pre-processing turns the raw data gathered from a variety of diverse sources into cleaner and viable information that's more suitable for work. It's a very significant preliminary step that takes all of the available data reshapes it, organizes it, sorts it, and finally merges it for consequent feeding into the neural network.

For our CHB-MIT dataset it is first reshaped in order to make sure that all the input arguments are of the same dimension and then the dataset is normalized to remove redundant data and for a better and a faster execution.

To prepare the CHB-MIT EEG scalp dataset before it is fed to the training phase, all the segments in the dataset combined are pre-processed by applying z-score normalization for all channels unified into one to ensure that all values are standardized by having a zero mean (μ) and unit standard deviation ($\boldsymbol{\delta}$).

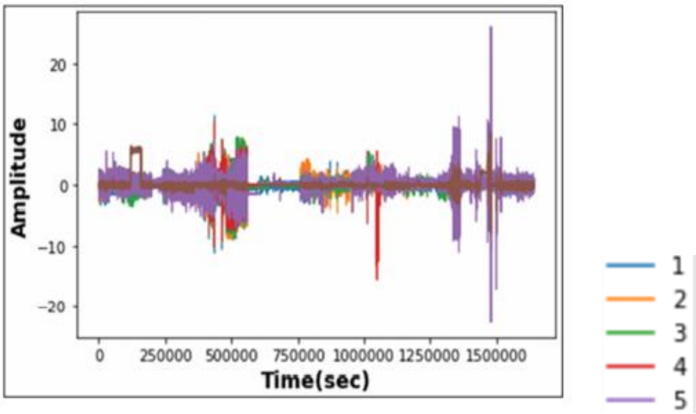


Figure 8: Plot of Normalized normal or seizure free EEG recording of the Brain Activity

Understanding of the Normalized EEG recording of the brain activity with and without

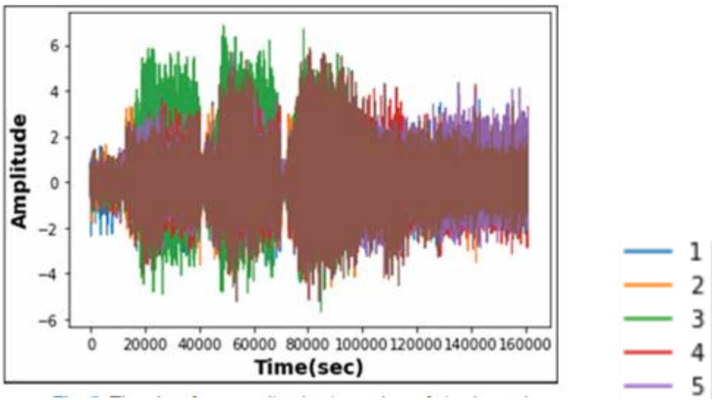


Figure 9: Plot of Normalized seizure infested EEG recording of the Brain Activity

After the above operation, as a batch, the whole dataset values are scaled to the range between [-20, 20] using Min–Max normalization technique to ensure that the original and the reconstructed segments have the same range of values and the same dimensions for clear division of the data into Training and Testing in the following steps.

The final operations of pre-processing include shuffling, segmenting, and reshaping the data from the dataset. Each time a series of EEG single channel in seizure and normal file are both shuffled and divided into smaller non-overlapping segments. The purpose of this operation is to provide the same probability for each sample to be selected for training or testing of the neural network.

On the top of it, each non-stationary EEG signal is divided into sub stationary signals.

Each EEG raw signal from the data is reshaped into T x L matrix, where L is the length of each segment in the, and T is the number of time-steps.

Hence, the input data in both the models of Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) will take shape (D, T, and L).

The input vector is of the order D×T×L which for our dataset is 2300×178×1.

2.1.3 Working of the Recurrent Neural Network for Epileptic Seizure Detection:

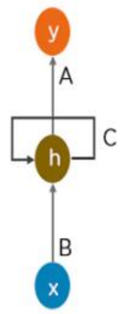


Figure 10: A single RNN Unit

After Pre-processing the dataset is divided in the ratio of 80:20 where 80% of the dataset is segmented for Training the RNN network and the remaining 20% is segmented for Testing and validation of the RNN network.

After the complete data pre-processing the data is fed into the RNN network.

Recurrent neural network is a sequential model that is the present input depends upon the previous output from the network. RNN architecture consists of feedforward neural networks with cyclic connections. It maps the entire history of input in the neural network in order to predict each output by establishing the temporal relationships between the data at each point in time.

In the above magnified view of the Recurrent Neural Network (RNN), The nodes present in the different layers of the neural network are totally compressed to form a single layer of recurrent neural networks.

From the RNN architecture in the above diagram A, B, and C are the parameters of the RNN network which are present at three different nodes in the network their importance is explained in detail in the following sections.

In the architecture of the RNN "x" is the input layer, "h" is the hidden layer, and "y" is the output layer. A, B, and C are the network parameters which are used to improve the overall output of the model. At any given instant of time t, the current input is a combination of input at the instant x(t) and x(t-1). The output at any given time is fetched back to the next input of the network to improve on the output this is done for three different layers as our implemented RNN layer is 3-layered.

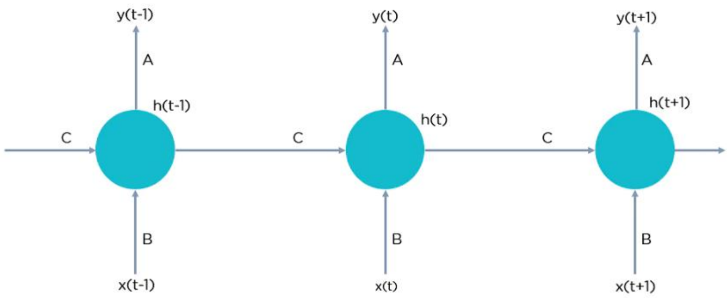


Figure 11. Detailed Working of the RNN network

Dense layer is used at all the three layers in the RNN architecture in order to establish a deep and a fully connected connection with the preceding layer to carry on the previous output on to the next state as input.

Drop out layer of magnitude 0.2 is used after all successive layers in the network in order to prevent overfitting and they are placed on top of the fully connected network.

Network Parameters:

Table 1: Network Parameters used in RNN Network

Network Parameter	Type
Activation Function Layer-1	Tanh
Activation Function Layer-2	ReLU
Activation Function Layer-3	SoftMax
Optimizer	Adam
Loss Function	Binary Cross Entropy

The above network parameters are used for optimal functioning of the algorithm and finally the model is fully built the total number of parameters from the model summary are 46,821 and after passing the model through Adam optimizer and Binary cross entropy Loss function the model is ready to be fitted with the trained datapoints the fitting is run for 100 epochs.

The model is then tested and validated at 5 cross folds and finally Classification is done along with Prediction.

2.1.4 Working of the Long Short-Term Memory for Epileptic Seizure Detection :

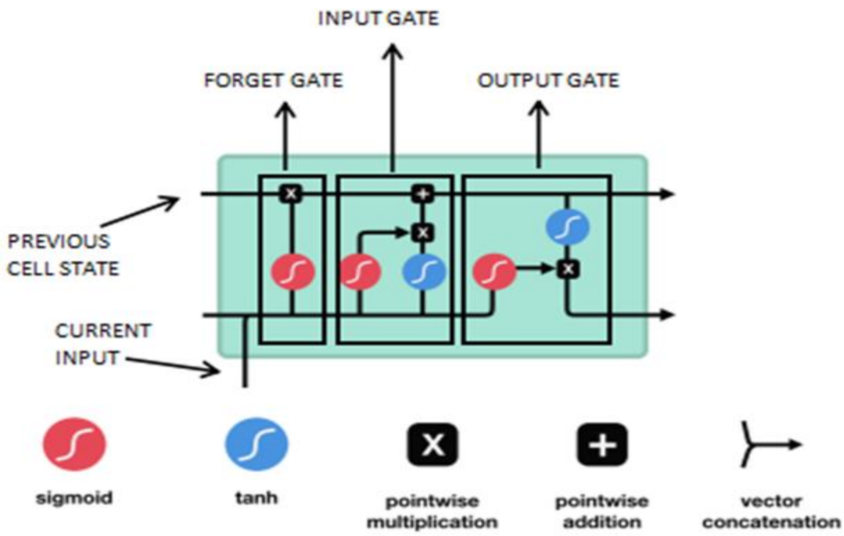


Figure 12: A single LSTM Unit

After the complete data pre-processing the data is fed into the LSTM network.

LSTM network works best on time-series with short- and long-term dependencies.

After the pre-processing stage the pre-processed EEG segments of the data are fed into the LSTM cells to learn about deeper-level characterizations of the EEG scalp signals at each and every segment. The outputs of the LSTM cells are used as an input to the time-distributed layer (dense layer) respectively.

Working of the gating units present in each layer of the LSTM network.

Forget Gate: Forget gate determines to what extent to the previous data has to be forgotten before it is been sent to the next gating unit in the network.

Input Gate: Input gate determines the total extent of information that has to be written onto the Internal Cell State.

Output Gate: Output gate determines what output (next Hidden State) has to be generated from the current Internal Cell State which is sent as the input for the next state.

Our deep neural network design consists of six layers and, with using (SoftMax activation function) on the top of the system. At the beginning, the segment of data entered to the LSTM layer, is passed through 100 cells this takes place for all the six layers present in the network. The short- and long-term memory the LSTM Network learns from the overlapping between each segment in the same EEG signal and dissimilar EEG signal of the same class.

The best characteristic of the LSTM network is the retaining of information for an extended period of time and makes the LSTM the strongest nominee for handling long-term EEG signal recordings. Then, the output of the LSTM layer is entered as an input into the time distributed layer (dense) as a feedback in the sequential LSTM network. Finally, the dense layer output is used as an input to the SoftMax layer to classify the incoming data at the output of the Network.

Network Parameters:

Table 2. Network Parameters used in LSTM

Network parameter	Type
Activation Function Layer-1	ReLU
Activation Function Layer-2	ReLU
Activation Function Layer-3	ReLU and tanh
Activation Function Layer-4	ReLU and sigmoid
Activation Function Layer-5	ReLU
Activation Function Layer-6	Softmax
Optimizer	Adam
Loss Function	Categorical Cross Entropy

Complete Block Diagram of the LSTM network Working:

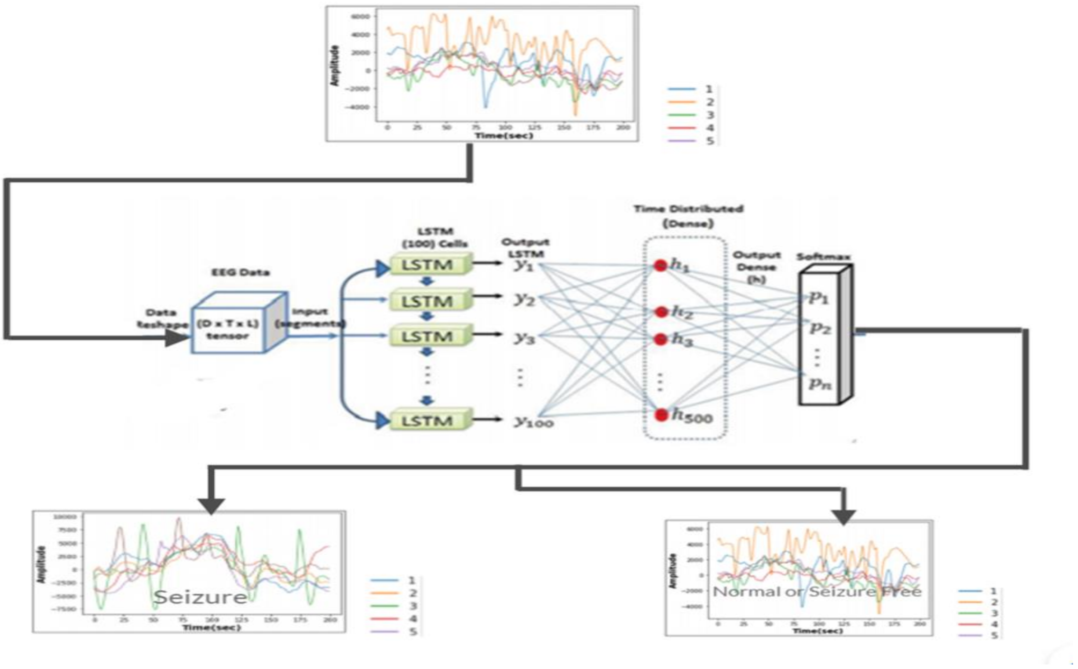


Figure 13: The working of LSTM Network

Drop out layer of magnitude 0.2 is used after all successive layers in the network in order to prevent overfitting and they are placed on top of the fully connected network.

The above network parameters are used for optimal functioning of the algorithm and finally the model is fully built the total number of parameters from the model summary are 74,613 and after passing the model through Adam optimizer and Binary cross entropy Loss function the model is ready to be fitted with the trained datapoints the fitting is run for 100 epochs."

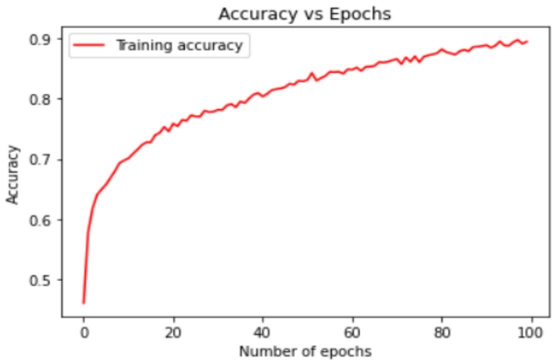
The model is then tested and validated at 5 cross folds and finally Classification is done along with Prediction.

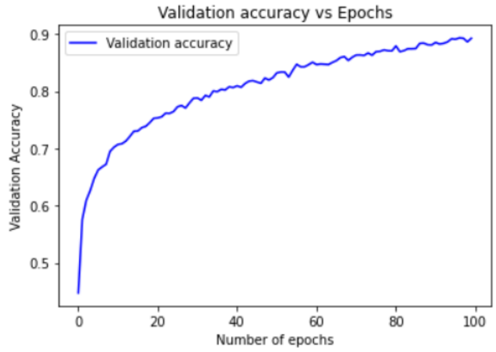
2.3 Results

2.3.1 Recurrent Neural Network (RNN) for Epileptic Seizure Detection:

The Classification Accuracy obtained is: 90.85 %

The Classification Accuracy obtained on the Validation data is: 89.12 %





Confusion Matrix

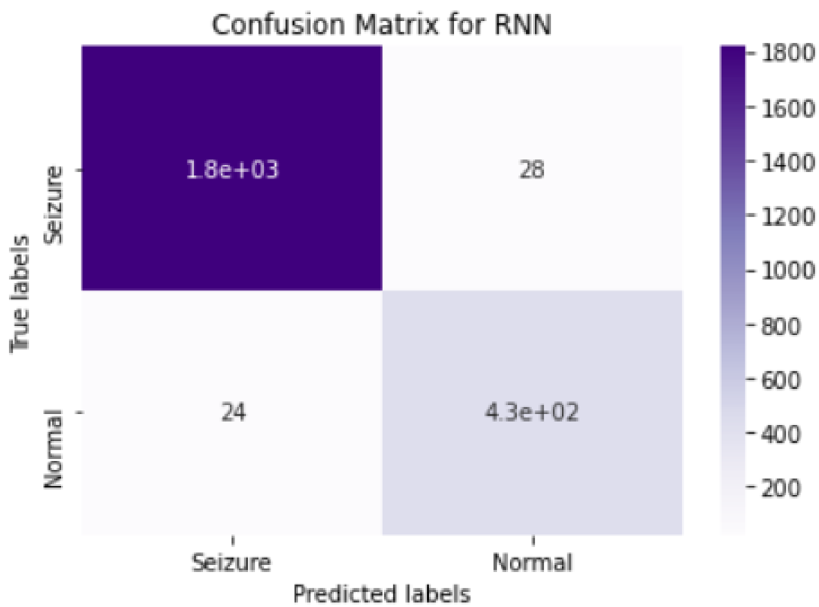


Figure 14 : Confusion Matrix for RNN

Performance Metrics:

Precision:

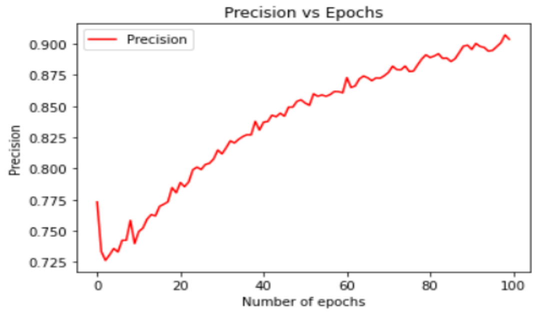


Figure 15: Plot of Precision vs Number of Epochs

Recall or Sensitivity:

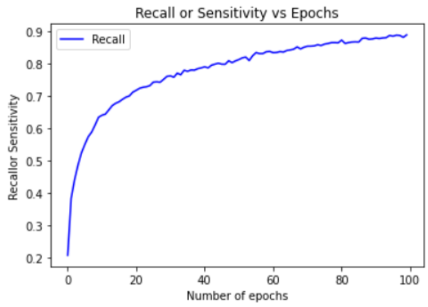


Figure 16:Plot of Precision vs Number of Epochs

Specificity:

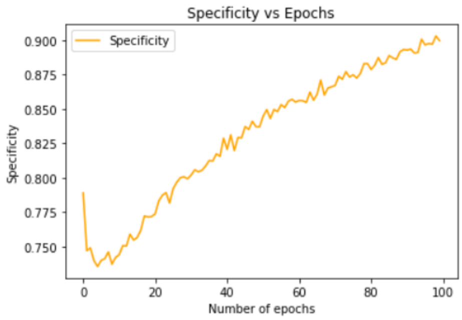
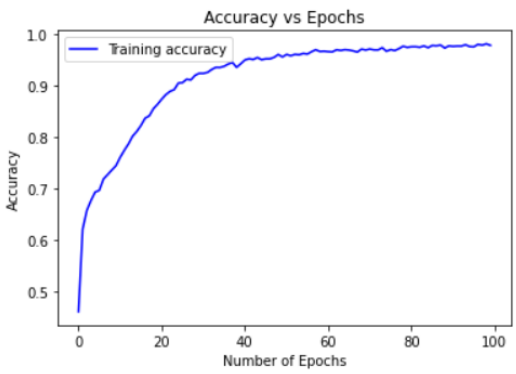


Figure 17: Plot of Specificity vs Number of Epochs

2.3.2 Long Short-Term Memory (LSTM) for Epileptic Seizure Detection:

The Classification Accuracy obtained is: 98.84 %

The Classification Accuracy obtained on the Validation data is: 97.12 %



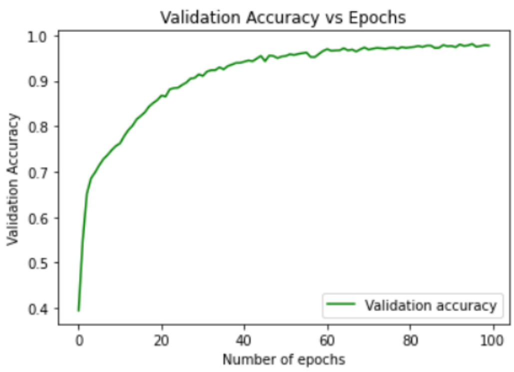


Figure 18 : Plot of Accuracy vs Number of Epochs *Figure 19 : Plot of Accuracy vs Number of Epochs*

Confusion Matrix:

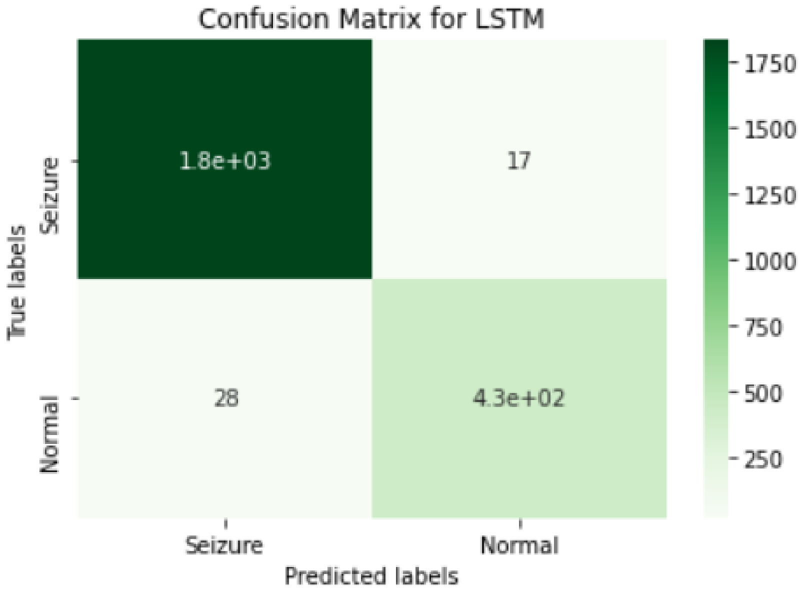
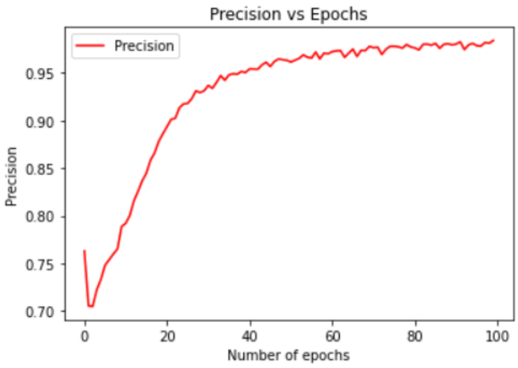


Figure 20: Confusion Matrix for LSTM

Performance Metrics:

Precision:



Recall or Sensitivity:

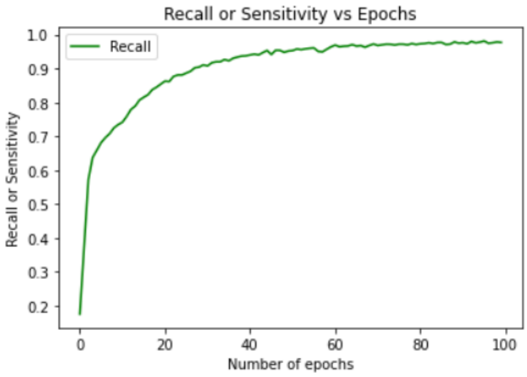


Figure 21: Plot of Precision vs Number of Epochs

Figure 22: Plot of Precision vs Number of Epochs

Specificity:

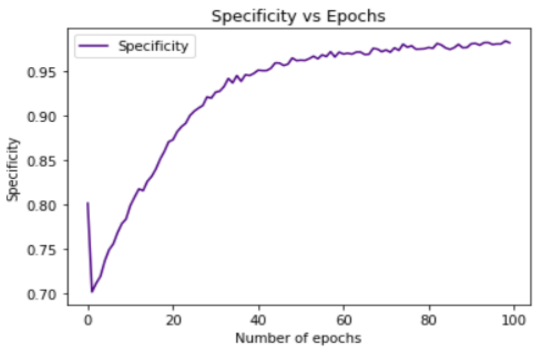


Figure 23: Plot of Specificity vs Number of Epochs

2.4 Discussion

Comparison of the above Implemented RNN and LSTM models across different metrics.

Performance Metrics	RNN Network (Value in %)	LSTM Network (Value in %)
Accuracy	90.85%	98.84%
Precision	91.85%	96.16%
Recall or Sensitivity	88.83%	93.83%
Specificity	90.81%	97.25%
Area Under Curve (AUC)	95.61%	95.96%
F1-scrore	93.25%	94.01%

Figure 24: Performance analysis of RNN and LSTM

Graphical Analysis of the Above Table:

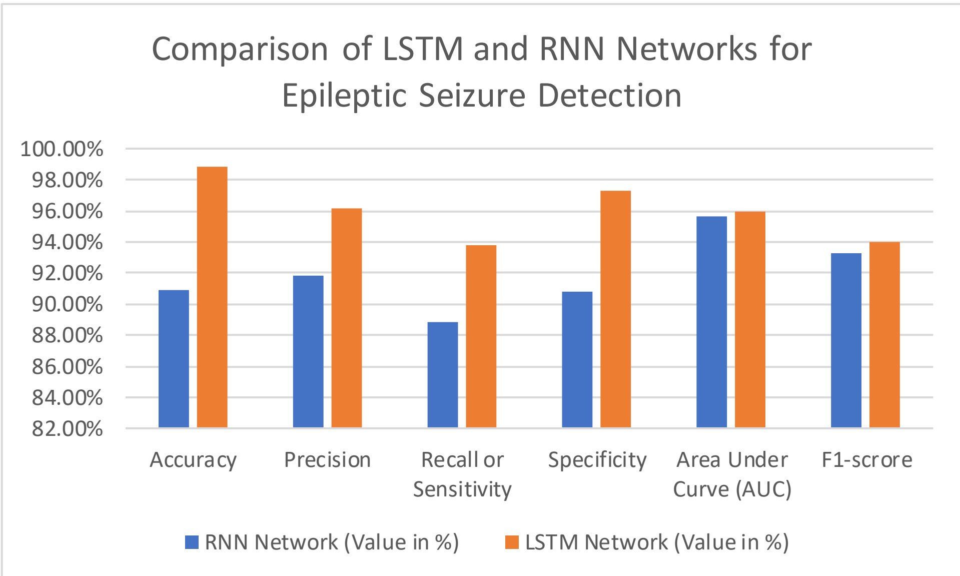


Figure 22 : Clustered graph comparison of LSTM and RNN Network for Epileptic Seizure Detection

From the above Table and graphical analysis, it is very clear that LSTM model performs exceptionally well against the corresponding RNN network.

LSTM outperforms RNN across all the performance metrics as it overcomes the problem of exploding and vanishing gradient which is prevalent in RNN, CNN and many other models or architecture used for Classification.

3. Conclusion

From all of the above analysis and modelling the two different neural networks of RNN and LSTM it is an established fact that LSTM network's performance is excellent as it has the additional time to store the previous output for a longer period of time in the memory which helps the neural network to predict accurately as this previous output which is stored in the memory can be effectively fed as the input to the next cell state thereby improving the sequential model resulting in a whooping Classification accuracy of 98.84%. The experimental results obtained, shows the effectiveness and superiority of the proposed method in detecting epileptic seizures for a more diverse dataset. The model achieves the superior detection accuracies under ideal as well as noisy imperfect conditions present in the dataset acquired.

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