Epilepsy seizure detection in EEG signal using Deep Learning

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by

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Date: 7 May 2021

CERTIFICATE

This is to certify that the project entitled **"Epilepsy seizure detection in EEG signal using Deep Learning"** submitted by **Harsh Yadav** (19MT0153) for the award of **Master of Technology** in Computer Science and Engineering is based upon his own work under the supervision of **Dr. Haider Banka** in the Department of Computer Science and Engineering, IIT (Indian School of Mines), Dhanbad and that neither the project report nor any part of it has been submitted for any degree/diploma or any other academic award anywhere before.

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I hereby declare that this thesis is an authenticated record of the research work carried out by me. To the best of my knowledge, it contains no material previously published or written by another person or material which has been accepted for the award of any degree or diploma of the university or other institutes of higher learning, where due acknowledgment has been made in the text.

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ACKNOWLEDGEMENT

I, **Harsh Yadav**, student of MTech Second Year of Dept. of Computer Science and Engineering, Indian Institute of Technology (Indian School of Mines), Dhanbad am glad to present a project entitled **“Epilepsy seizure detection in EEG signal using Deep Learning”**

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ABSTRACT

Epilepsy is a life-threatening and common chronic neurological disorder which affects almost .6 to .8 % of the world population (40 to 50 million people) all over the world. Electroencephalography (EEG) is a test used to evaluate the electrical activity in the brain and one of its application is used to detect epilepsy seizure. Manual inspection of EEG is done by trained neurologist, but it is a extensive and burdensome process, thus affecting the performance of neurologist. In this proposed work, we have compared various models like LSTM & GRU (and their other variants like Stacked, Bidirectional, etc.) based on accuracy, sensitivity, and specificity. And find out that Bidirectional LSTM works best for detecting epilepsy seizure in normal vs. ictal with 100 % accuracy, ternary epilepsy case e.g., ictal vs. normal vs. inter-ictal with 98% accuracy and at last multi-class detection e.g. normal(1) vs. normal(2) vs inter-ictal(1) vs interictal(2) vs ictal with 82% accuracy. After that, we tested our model on smaller EEG signals (having time-duration 3sec, 6sec, and 12sec, etc). It gave good results on smaller EEG signals; hence, it can alert patients about their incoming epileptic seizure.

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<u>List of Abbrevations</u>

RNN	**Recurrent Neural Network**
CNN	Convolutional Neural Network
GRU	Gated Recurrent Unit
LSTM	Long Short-Term Memory
FC	Fully Connected
BRNN	Bidirectional recurrent neural networks

Chapter 1 Introduction

Epilepsy is a common neurological disorder of the brain characterized by two or more unprovoked seizures that affect people at any age. Approximately .6 to .7% (50 to 60 million) of the world population is suffering from epilepsy,it can be considered as the second most neuro disease after migrane. The characterizing feature of epilepsy is two or more unprovoked repetitive seizures that occur abruptly. Symptoms of seizure can be a short suspension of awareness to violent convulsions and maybe loss of consciousness.

Electroencephalography (EEG) is a test used to evaluate the electrical activity in the brain and one of its application is used to detect epilepsy seizure. Manual inspection of EEG is done by trained neurologist, but it is a extensive and burdensome process, thus affecting the performance of neurologist.

A lot of research has been done for automatic detection of epilepsy seizure in EEG signal but most of these approach depend on handwritten features which are extracted in time domain, frequency domain (fourier transformatioin) or combination of time and frequency (wavelet transformation). And they all suffer from some problems like “trained on small dataset” ,”unable to perform good when artifacts and white noise are present in signal” and at last they don’t work very well with non-stationary signals (EEG belong to non-stationary signals). All these reason lead to decrease in performance of model.

1.1 Recurrent Neural Network (RNN)

In a multilayer perceptron (MLP), input data is a vector; in Convolutional Neural Network (CNN), input is an image. What if our input data is a sequence of words or in the time-series form? When data contains some type of series, we go with Recurrent Neural Network (RNN).

RNN is a special type of neural network in which the output of the previous state becomes the input for the next state. The most important feature of RNN is their internal state or hidden state, which acts as a memory for RNN, thus helping them remember past information thus making them best for data containing any form of series.

In a neural network, previous input and current input are independent of each other, but in the case of RNN, previous and current input have a dependency that’s why RNN are recurrent or looping in nature i.e. the same function is performed for each input of data, and the output of the current input depends on the previous computation output. After computing the output, it is duplicated and sent back as input of the RNN.

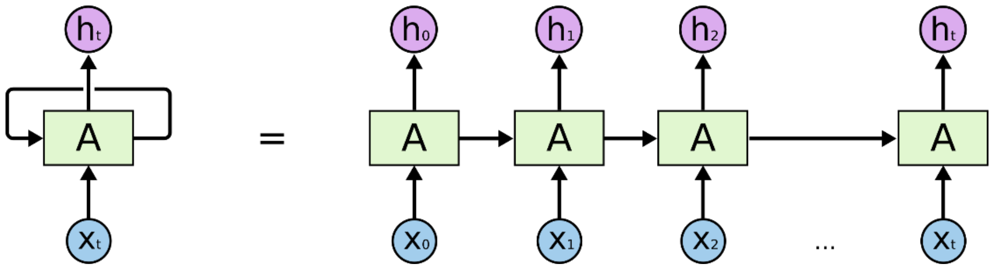


Fig 1.1 Simple RNN Structure

At t=0, the first input i.e. X_0, from the input sequence (X_0 , X_1 , X_2 ,…… X_t), is passed to the RNN, which gives output h_0 . At t=1, the previous output h_0 and current input i.e. X_1, are passed to RNN again. This process continues till the last input X_t is processed. This way, RNN keeps remembering the information while training.

Calculating current state:

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

Applying tanh activation function after summation:

$$h_t = \tanh (W_{hh}h_{t-1} + W_{xh}x_t)$$

$\mathbf{W_{hy}}$ = weight (connect last input to the softmax classifier), **h =** single hidden vector, $\mathbf{W_{hh}}$ = weight at previous hidden state (connect previous input to the neural network), $\mathbf{W_{hx}}$ = weight at current input state (connect the input to the neural network), **tanh** = Activation function, that implements a Non-linearity that squashes the activations to the range[-1,1]

Output: Yt is the *output state*.

$$y_t = W_{hy}.h_t$$

In summary, we can say input that has a sequence of data is suited best by RNN as well they can be used with CNN for better pixel neighborhood. But at the same time, RNN faces problems like Gradient vanishing and exploding problems, plus it cant process a very long sequence if we use activation function like tanh or relu.

1.2 Long short-term memory (LSTM)

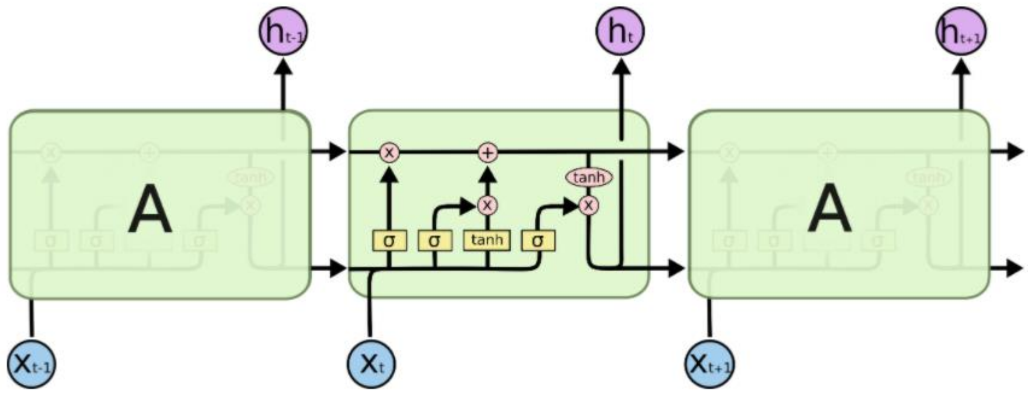


Fig 1.2 Repeating module of LSTM

To remove the vanishing gradient and exploding gradient problem, we use Long Short-Term Memory (LSTM) networks; they can be considered the modified version of RNN, making it easier to remember past data in memory plus remembering extended information. The most important part of LSTM is the Cell state; it controls how much information is passing from the previous state to the current state and how much info will be added. LSTM trains the model by using back-propagation. In an LSTM network, there are mainly three gates, which are known as:

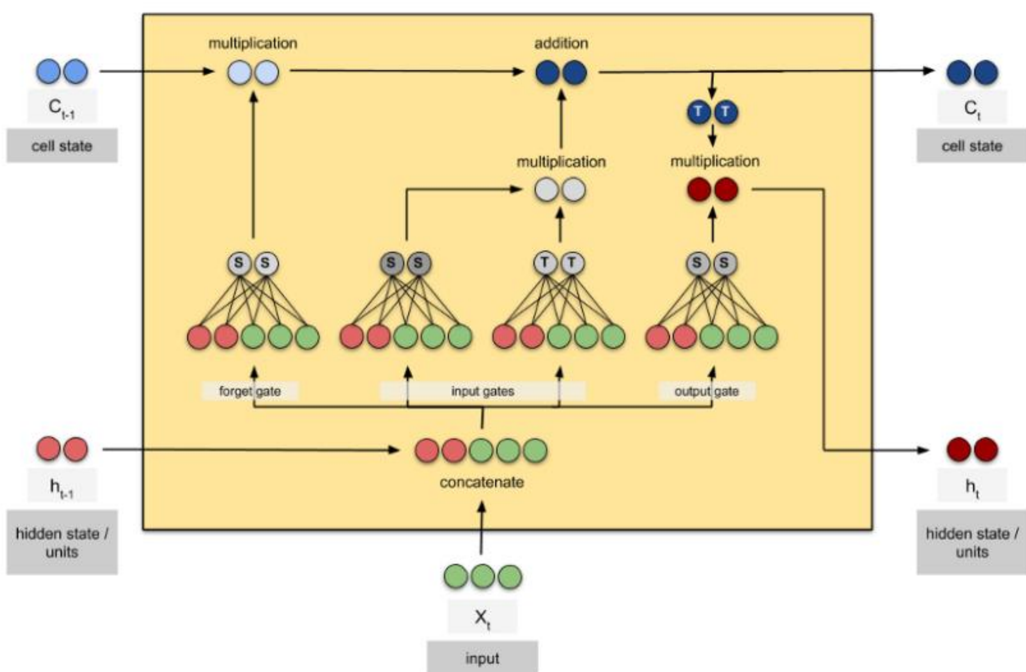


Fig.1.3 Internal Structure of LSTM

1. Input gate: the main task of the input gate is to determine how much we have to add to our previous cell state (previous input). It contains the Sigmoid function and tanh function. The work of the sigmoid layer is to decide which value to update, and the other function i.e. tanh, gives weightage to the values between -1 to 1 depending upon the importance of the state.

$$i_t = \sigma\,(W_i\,.\,[h_{t-1}\,, x_t] + b_i)$$

$$C_t^{\sim} = tanh\ tanh\ (W_c\,.\,[h_{t-1}\,, x_t] + b_c)$$

2. Forget gate: The Main task of forget gate is to decide what information to reject from the cell state. It takes previous output h_{t-1} and current input X_t together as input and passes it to the sigmoid layer, which output number between 0 to 1. 1 means keep complete information 0 means reject all information.

$$f_t = \sigma\left(W_f\,.\,[h_{t-1}\,, x_t] + b_f\right)$$

3. Output gate: the current input and the memory (cell state) of the block is used to decide the output. The previous output h_{t-1} and current input X_t are passed through the sigmoid layer and multiplied with the tanh of cell state to get the output.

$$O_t = \sigma\,(W_o\,.\,[h_{t-1}\,, x_t] + b_o)$$

$$h_t = O_t * tanh\,(C_t\,)$$

1.3 Stacked LSTM

It is a common notion in Deep Learning that the deeper the network better is the result, and the same applied to LSTM i.e. if we can make our LSTM deeper i.e. more layers of LSTM, it will provide better results. Thus Stacked LSTM is a variant of LSTM in which there are multiple (more than one) LSTM layers.

Usually, LSTM provides a single output, but in the Stacked LSTM, every layer of LSTM provides a sequence of output, which further acts like input for the above LSTM layer. It can be considered as one output per timestep rather than only one output for the entire input sequence.

Multiple hidden LSTM layers are stacked one over another LSTM, referred to as a Stacked LSTM model. Also, by default, LSTM output is in 2Dim, but this output can't be input for another LSTM as they need 3Dim input, so during its implementation in python, we keep return_sequences=True for getting 3Dim output from LSTM.

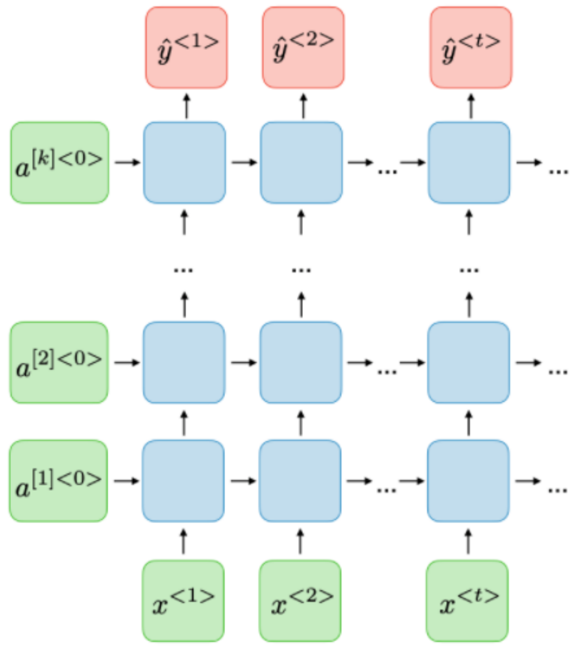


Fig1.4: Deep RNN or Stacked LSTM

1.4 Bi-Directional LSTM

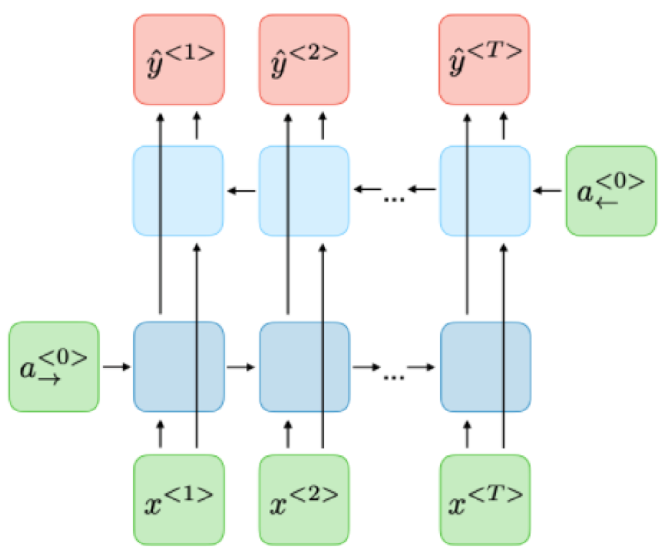


Fig1.5: Bidirectional RNN or Bidirectional LSTM

Bidirectional long short-term memory (Bi-LSTM) are another variant of LSTM, it is similar to Stacked LSTM but with changes like it has only 2 LSTM layer and those two layers work in opposite direction and output of these layers can be either concatenated or multiplied or added into one output at each timestep. The first layer gets the input sequence as it is, but the other layer gets the reversed copy of the input sequence i.e. last input X_t is fed at t=0 to it and X_0 in the very last. This enables Bi-LSTM to receive information from the past and from the future, i.e. any time they have information of backward information and forward information.

Bi-LSTM is trained with similar algorithms as LSTM since the two-directional layer does not interact with one another. For training Bi-LSTM, we have to apply forward propagation two times, one time for the forward cells and the backward cells & the same thing for the backpropagation algorithm. After complete forward and backward passes, then only weights of the Bi-LSTM are updated.

1.5 Gated Recurrent Unit (GRU)

GRU is another type of RNN or, more precisely, generalized form of LSTM. The main advantage of GRU over LSTM is that they have a lesser number of trainable parameters as compared to LSTM, and hence training time for GRU is less as compared to LSTM with the same efficiency of LSTM. They were first introduced in 2014; therefore, they are new as compared to LSTM.

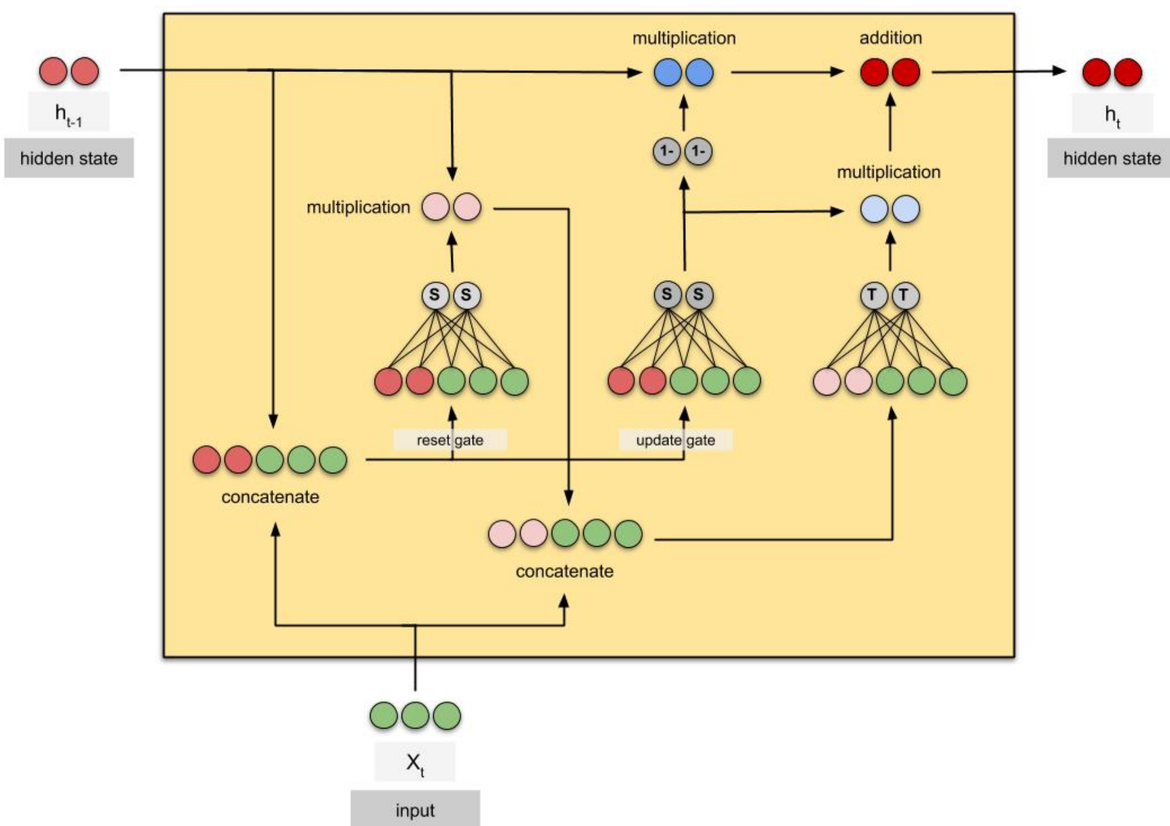


Fig 1.6 Internal Structure of GRU

The GRU has two gating units i.e. Update and the reset gate, that allow the flow of information inside each hidden unit. At any time t in each hidden state, computation is done using the following equations [8]:

Update gate:

$$z_t = \sigma\,(W_z \,.\, [h_{t-1}\,, x_t])$$

Reset gate:

$$r_t = \sigma\,(W_r \,.\, [h_{t-1}\,, x_t])$$

New memory:

$$h_t = tanh\,(W \,.\, [r_t * h_{t-1}\,, x_t])$$

Final memory:

$$h_t = (1 - z_t) * h_{t-1} + z_t * h_t])$$

This report is composed as follows: Section 2 is a literature survey of related works done in the field of epilepsy seizure detection. Section 3 covers information related to the dataset used in the paper. Section 4 explains the process of the proposed work i.e., how work has been done., alongside the results acquired and the observations that can be taken from it. Section 5 includes results and their analysis. Section 6 explains the summary of the work done and Section7 the improvements that can be made in the future.

Chapter 2 <u>Literature Survey</u>

In the recent past, a lot of work has been done in epilepsy detection, and different types of datasets are used for the same. This section discusses a few of the works which helped in building the insight into the problem.

Ihsan Ullah et al., 2018 proposed system is an ensemble of **P-1D-CNN i.e. (pyramidal one-dimensional convolutional neural network)** models. In this paper author has focused on ternary classification of epilepsy detection i.e. normal vs interictal vs ictal (AB vs. CD vs. E & A vs. C vs. E). Also author has focused on less memory required by the model i.e. design of model is such that it take only 39% of the total parameter as compared to traditional approach. They have also discussed two augmentation technique so that model can be trained in less dataset size.the Pyramidal 1D CNN is a ensemble different type of **P-1D-CNN.** It gives an accuracy of 99% approximately on Bonn university dataset within very short time interval.

Subhrajit Roy et al., 2018 proposed a new architecture and coined it by the name of Chrononet. In this architectute there are multiple 1dimension convolution layer (stacked over each other with varying filter length) and stacked GRU in feed forward manner. To remove problem of vanishing gradient author has used densely connected GRU hence no isuue for training accuracy degradation. Presence of many filter of different length give chrononet power of combine features from many timescale.

Ramy Hussein et al., 2018 proposed a robust architecture for the detection of epilepsy seizure using Long Short-Term Memory (LSTM) network. The main feature of this architecture is that they can work even if input EEG signal has artifacts (muscle activities, eye movement) or background noise and white noise. Initially dataset is segmented into two parts, after that it is fed to LSTM & and output of lstm is sent to fully connected layer and output of FC layer is sent to average pooling layer and in the end it is passed to softmax layer for its classification

U Rajendra Acharya et al., 2017 in this journal author has used only Convolution Neural Network (CNN) for the classification of normal, preictal (inter-ictal) and ictal EEG signal. First dat is preprocessd by Z-score normalization i.e. standard deviation = 1and mean = 0. After the preprocessing data is fed to 1Dimension deep CNN. The architecture of the model contain total 13 layers such that after every CNN layer one max pooling layer is used, this structure is repeated five times and in the end three Fully connected layer has been used (size of convolution filter is different for each layer).

Thara D.K. et al., 2019 proposed a architecture of 3 layers of 1Dim CNN layer. In this paper author used Binary classification to classify seizure vs. non seizure eeg signal. In this paper main focus was on different type of feature scaling technique like MinMaxScaler, StandardScalerNormalizer and RobustScaler plus type of error function used like meansquare error, mean absolute error, logcosh and Binary cross Entropy. Activation fuction used was relu and for binary classification sigmoid was used in this paper.

Thara D.K. et al., 2019 proposed a model for seizure detection as well as seizure prediction. Author has used two variants of LSTM i.e. stacked lstm (two layers stacked over each other) and bidirectional lstm and named as two layered stcked bidirectional lstm. Accuracu of the model is 99% on Bonn university dataset

M. Golmohammadi, et al., in this paper author has compared LSTM and GRU model along with many initialization techniques like L1, L2, Orthogonal, lecun uniform, glorot uniform, glorot normal, He normal and etc. Architecture of model contain 1Dim CNN, 2Dim CNN and either LSTM or GRU. Data is preprocessed by linear frequency cepstral coefficient (LFCCs), this long architecture leads to learn long term dependency.

Yang Li et al., 2020 in this paper author has used NLSTM i.e. Nested Long Short Term Memory approach. This architecture contains 1Dim CNN along with nested LSTM. Input data is first passed to the three layer of 1D CNN, output of this is passed to the NLSTM which is further passed to the Fully connected layer and at last Softmax function for the classification task. CHB-MIT , Bonn university and may other dataset was used for training the model. Convolutional block helps in learning the seizure characteristics and for NLSTM helps in learning temporal dependencies.

Chapter 3 **Dataset**

For training our model we have selected widely used and publicly availaible EEG database produced by Bonn University. This database conatain five classes from A to E and each class contain EEG signal from 5 participants, each EEG signal is 23.6 sec long plus for each class we have 100 EEG signals.

Table 1. University of Bonn epilepsy dataset details.

A	B	C	D	E
Nonepileptic Eyes opened	Nonepileptic Eyes closed	Epileptic Interictal	Epileptic Interictal	Epileptic Ictal

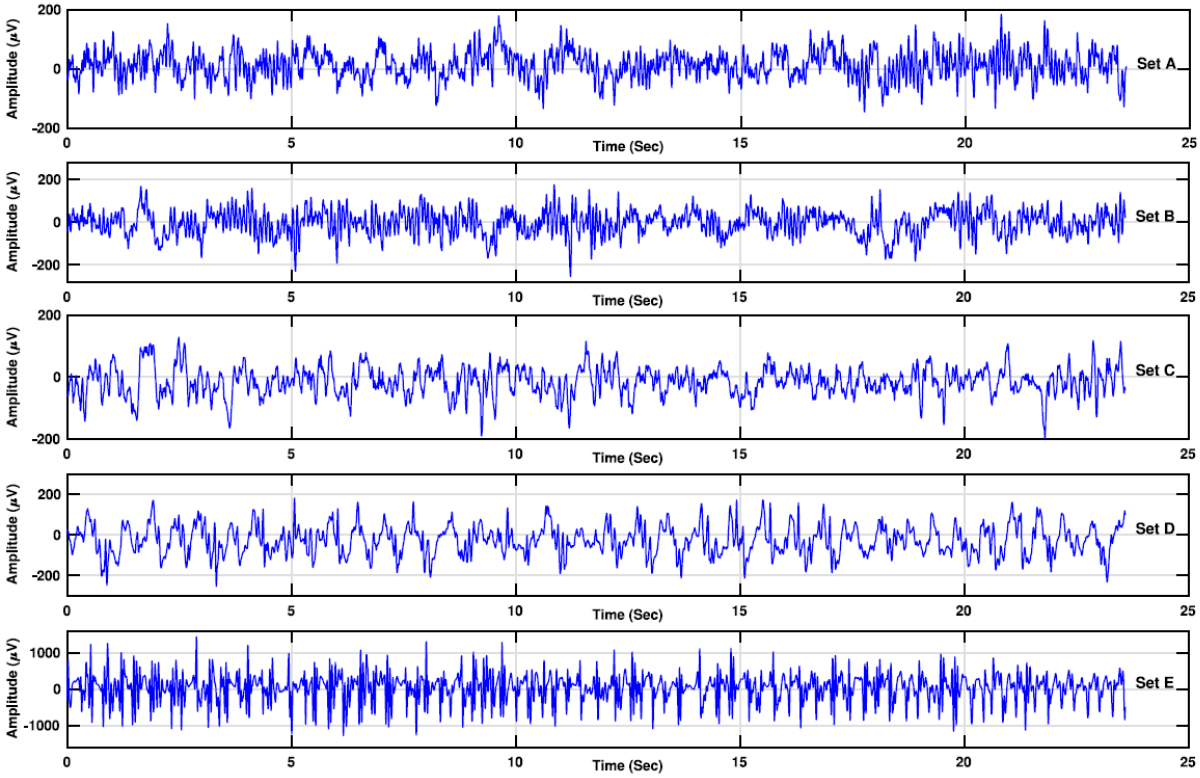
- All EEG signals are collected through the standardized 10–20 system for scalp EEG electrode placement.

- Folders A and B include surface EEG signals collected from five healthy participants. The only difference between EEG signals from A and B is that participants from B have eyes closed during capturing of EEG signals. In contrast, in the case of A, participants were awake i.e. eyes open.

- Folder C, D contain inter-ictal EEG signal i.e. EEG signal was recorded between seizures. Participants of the C folder were having electrodes install within the brain epileptogenic zone. For the participants of D, it was the hippocampal formation of the obverse cerebral hemisphere.

- Folder E contain ictal EEG signal i.e. EEG signal during active seizures period

Fig 3.1 Dataset Representation



Chapter 4 Methodology

For the classification of EEG signals, we will design a system that is modeled by different models like LSTM, GRU, Stacked LSTM, Bi-Directional LSTM. All these models are checked one at a time. After that, we compare all these models' results and find out the best model among them.

After getting the best model, we test our model on shorter EEG signals of time duration 3sec, 6 sec & 12sec.

Simply, we first pre-processed the available dataset and then divide the dataset into training data and testing data. Thus, we then train the model using our training data. The model is then used to predict the class of the testing data. We compare the predicted values to actual values in the testing data to determine the accuracy, sensitivity & specificity.

In this section, we have discussed more about our dataset like data preparation step, data preprocessing step and other important things like architecture etc.

4.1 Description of the dataset:

As discussed in chapter 3 our original Dataset was divided into five Folders (each folder represents one class) and each folder contains 100 notepad files denoting 100 records of EEG signals. Each Text file consists of 4,096 samples of one EEG time series.

Class Name	Folder Name	Notepad Files
SET A	Z.zip	Z000.txt - Z100.txt
SET B	O.zip	O000.txt - O100.txt
SET C	N.zip	N000.txt - N100.txt
SET D	F.zip	F000.txt - F100.txt
SET E	S.zip	S000.txt - S100.txt

Table 4.1: Description of Dataset with folder name

To generate a CSV file from the respective folder a python script file was written which reads 100 notepad files in one run and creates a new csv file of size 100 x 4096. A Similar process was applied to generate the other 4 CSV files and finally, all five CSV files were merged into single files with their respective classes to generate a new dataset of size 500 x 4096.

4.2. High-level picture

Firstly, EEG data undergoes EEG segmentation, after this step data is passed to LSTM (80 cells). The output of LSTM layer is passed to Fully connected layer (50 units) so that information learnt from lstm can be transformed into meaningful seizure realred features. Then output of fully connected layer is passed to the average pooling layer (the logic behind this step is some seizures may occur in initial and other may occurred at last, to give equal weightage we have used average pooling).And in the last step softmax layer is used for the classification.

4.3. Methodology

4.3.1. Data reshape (EEG segmentation)

EEG signals have non-stationary nature i.e. their characteristics changes over time duration, hence we applied EEG segmentation as a pre-processing step to convert EEG non-stationary nature into stationary nature (segmentation is a common preprocessing step to get stationary signal in EEG signal, this lead to common temporal and spectral features throughout signal).

Our dataset contains 500 EEG signal, each of which is 23.6 seconds long. We sampled it with a 173.6 Hertz sampling frequency, thus 23.6*173.6=4096 i.e. we have total of 4096 data points after sampling. And after segmentation each signal is break into 2 parts thus size of Dataset become 500*2048*2.

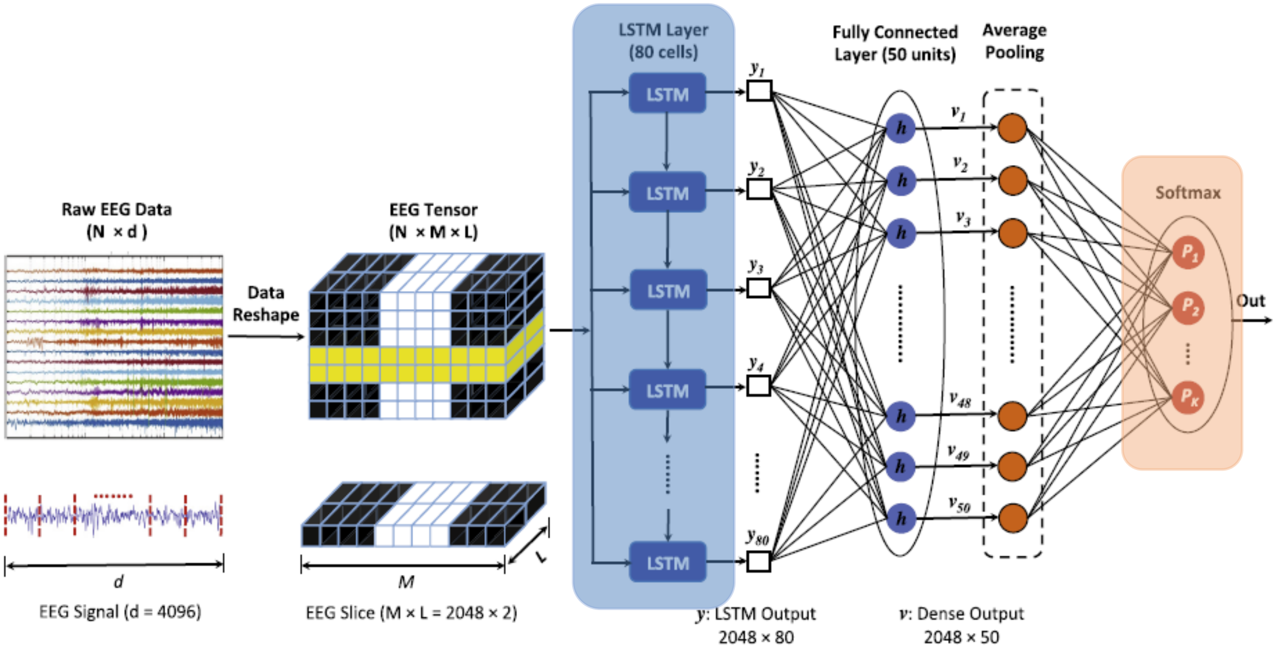


Fig 4.1: Schematic diagram of the base seizure detection approach (Orange box [LSTM &GRU variants] & Blue box changes respectively for 2class, 3class & 5 class classification problem)

4.3.2. EEG deep feature learning

To know best features for identifying epilepsy seizure for EEG data, data was firstly passed through the LSTM/GRU layer (having 80 cells). It will help our network to learn long-term and short-term dependency between different EEG signals.

The output of the LSTM/GRU layer was passed to the fully connected (dense layer having 50 units or cell) layer so that model can learn seizure related features. And also we have used time-distributed fully connected layer not the default FC layer. Hence the cost function was calculated for each time interval instead of last timestep only.

And finally output of FC layer was passed to the 1Dim avg. pooling layer so that all segments of EEG should contribute equally and at last it was passed to softmax layer for predicting its tag or label.

4.3.3. EEG feature classification

For the prediction of class or labels of the EEG signal we have used SoftMax layer in the end of model. Softmax function also known as multi-class logistic regression is used to calculate probability distribution for K class such that summing all probability will give us one.For 2 class classification number of neurons in the Orange box of softmax layer will be two, similarly for three class problem it will be three and for five class problem it will be five.

4.3.4. Network configuration

Our LSTM/GRU network used categorical cross entropy for calculating Loss, and Adam optimizer was used. Learning rate for the model was selected 1x10^(-3). 80 cells were used in LSTM/GRU and 50 cells were used in FC layer. Batch size was selected as 64 and droput rate was set to .1 and in most cases epoch was 100.

4.4 Model for different Classification

4.4.1 Two-Class Classification [A vs E]

For the two-class classification, Dataset was reduced to only two class i.e. class A and E. And size of dataset reduced to only 200*4096. In the fig 4.1, we have replaced orange box with softmax 2 neurons as we are having two-class classification problem.

RNN Type Architecture (Blue Box)	Accuracy	Specificity	Sensitivity	Epoch	Batch size	Dropout
LSTM (Single Layer)	100%	100%	100%	100	64	.1
Bidirectional LSTM	100%	100%	100%	100	64	.1
GRU (Single Layer)	100%	100%	100%	100	64	.1

Table 4.2 Two-Class Classification [A vs E]

4.4.2 Three-Class Classification [AB vs CD vs E]

For the three-class classification, Dataset was reduced to only three class i.e. class A and B merged into single class (say AB), class C and D merged into single class (say CD) and last class E. Size of dataset remained same i.e. 500*4096 as no class records were removed. In the fig 4.1, we have replaced orange box with softmax 3 neurons as we are having three-class classification problem.

RNN Type Architecture (Blue Box)	Accuracy	Specificity	Sensitivity	Epoch	Batch size	Dropout
LSTM (single Layer)	98.00%	99.06%	98.12%	100	64	.1
LSTM (Stacked)	98.00%	99.06%	98.12%	100	64	.1

LSTM (Bi-Directional)	96.67%	98.30%	96.59%	100	64	.1
GRU (single Layer)	97.33%	98.61%	97.22%	100	64	.1
GRU (Stacked)	96.00%	97.98%	95.97%	100	64	.1
GRU(Bi-Directional)	98.00%	98.92%	97.84%	100	64	.1

Table 4.3 Three-Class Classification [AB vs CD vs E]

4.4.3 Five-Class Classification [A vs B vs C vs D vs E]

For the five-class classification, Dataset remained same as original dataset five classes i.e. class A ,B ,C ,D and E. Size of dataset remained same i.e. 500*4096 as no class were removed. In the fig 4.1, we have replaced orange box with softmax 5 neurons as we are having five-class classification problem.

RNN Type Architecture (Blue Box)	Accuracy	Specificity	Sensitivity	Epoch	Batch size	Dropout
LSTM (single Layer)	78.67%	94.50%	78.01	120	16	.1
LSTM (Stacked)	82.00%	95.50%	81.99%	200	64	.5
LSTM (Bi-Directional)	82.67%	95.44%	81.76%	200	64	.3
GRU (single Layer)	76.33%	94.19 %	77.14 %	120	64	.1

Table 4.4 Five-Class Classification [A vs B vs C vs D vs E]

4.5 Checking model on shorter EEG signal

From the previous discussion, it is clear that Bi-Directional LSTM is working best among other models with an accuracy of 100% in both the Two-class Classification [A vs. E **&** ABCD vs. E], 98.67% & 97.78% in Three-class classification [AB vs. CD vs. E **&** A vs. C vs. E respectively] and 84% for Five-class classification [A vs. B vs. C vs. D vs. E].

Till now, we have trained and tested our model on Dataset of time-segment 23.6 seconds (23.6 seconds *173.6 Hz = 4096 points). Now we will test our model on shorter time-segment to know whether they are efficient for smaller (short duration) EEG signals seizure prediction.

4.5.1 Two-class classification

Dataset	***Time-Duration***	***Accuracy***	***Sensitivity***	***Specificity***	***Loss***
A vs. E	23.6/2 = 11.8 sec	100 %	100 %	100 %	.0022
A vs. E	23.6/4 = 5.9 sec	100 %	100 %	100 %	.0012
A vs. E	23.6/8 = 2.95 sec	100 %	100 %	100 %	.0147
ABCD vs. E	23.6/2 = 11.8 sec	100 %	100 %	100 %	.0029
ABCD vs. E	23.6/4 = 5.9 sec	100 %	100 %	100 %	.0018
ABCD vs. E	23.6/8 = 2.95 sec	100 %	100 %	100 %	.0132

Table 4.5 Two-Class Classification on shorter EEG signal

4.5.2 Three-class classification

Dataset	***Time-Duration***	***Accuracy***	***Sensitivity***	***Specificity***	***Loss***
AB vs.CD vs. E	23.6/2 = 11.8 sec	96.51 %	98.05 %	96.25 %	.0225
AB vs.CD vs. E	23.6/4 = 5.9 sec	96.28 %	98.12%	96.37 %	.0315
AB vs.CD vs. E	23.6/8 = 2.95 sec	96.35 %	97.68%	97.29 %	.0587
A vs. C vs. E	23.6/2 = 11.8 sec	96.37 %	96.35 %	98.17 %	.0852
A vs. C vs. E	23.6/4 = 5.9 sec	99.21 %	99.23 %	99.61 %	.0588
A vs. C vs. E	23.6/8 = 2.95 sec	97.91 %	97.16 %	98.97 %	.0486

Table 4.6 Three-Class Classification on shorter EEG signal

Chapter 5 Results and Analysis

After trying all models (LSTM, Stacked LSTM, Bi-Directional LSTM, GRU), we came to the point that Bi-Directional LSTM performs best and also it gave good results on shorter EEG signals.

We have selected metrics like Accuracy(acc), Sensitivity (Sen) and Specificity (Spec) for testing the performance of our model.

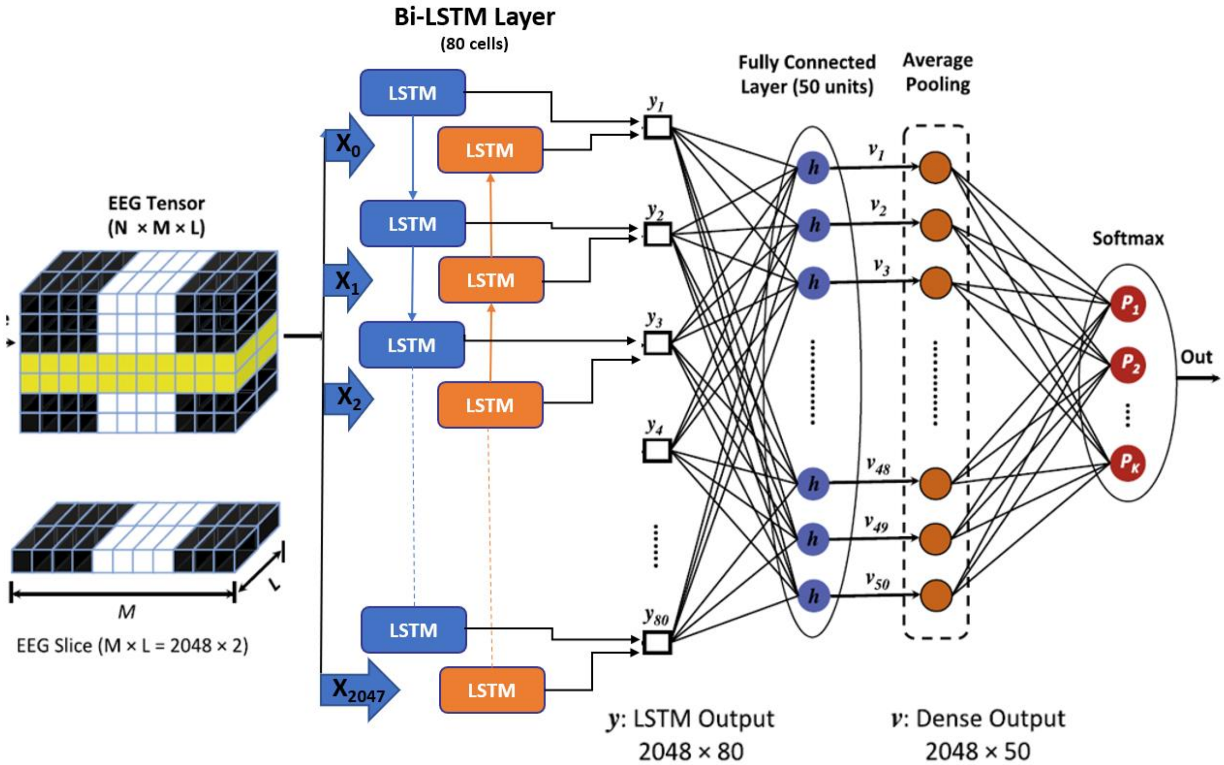


Fig 5.1: Schematic diagram of seizure detection approach (Bi-Directional LSTM)

5.1. Two-class classification results

5.1.1 A vs. E

The 'A' class represent healthy participants and 'E' class represent epileptic patients experiencing active seizures. The size of dataset is 200*4096 (as we are taking only two class).

Model	*Accuracy*	*Specificity*	*Sensitivity*
LSTM (Bi-Directional)	100%	100%	100%

Table 5.1 Two-class classification results (A vs E)

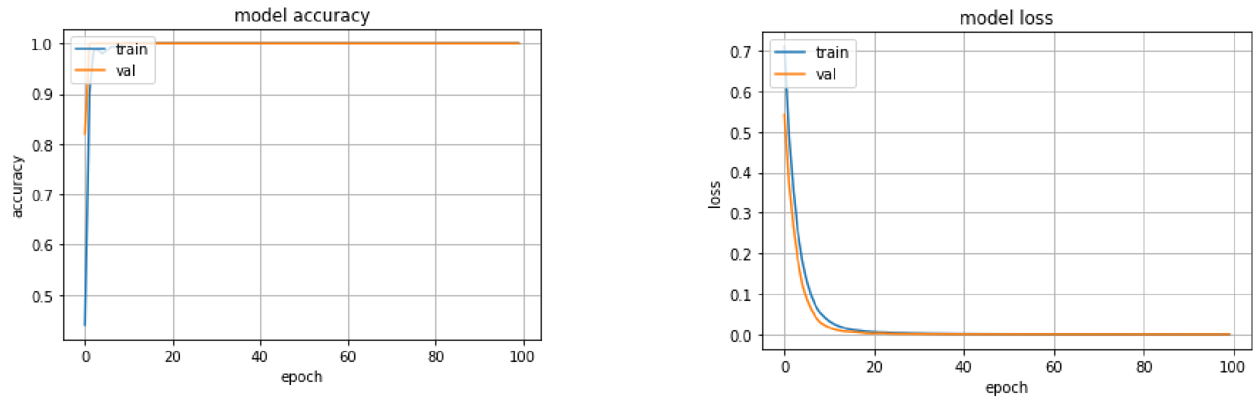


Fig 5.2 Two-class classification results (A vs. E)

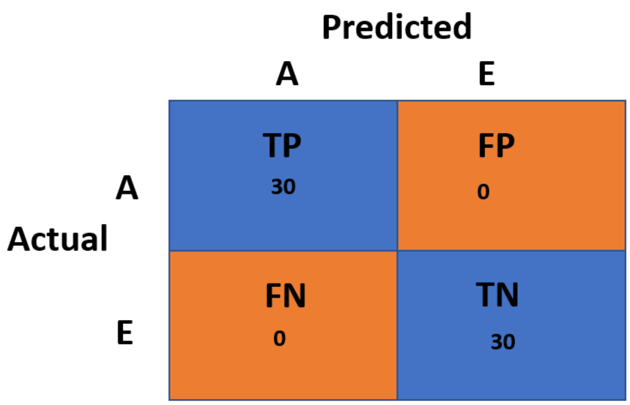


Fig 5.3 Confusion Matrix (A vs. E)

5.1.2 ABCD vs. E

The second category of the two-class classification include ABCD (all these 4 classes are considered as one class) vs 'E' class.

Model	*Accuracy*	*Specificity*	*Sensitivity*
LSTM (Bi-Directional)	100%	100%	100%

Table 5.2 Two-class classification results (ABCD vs. E)

		Predicted	
		ABCD	E
Actual	ABCD	TP 120	FP 0
	E	FN 0	TN 30

Table 5.4 Confusion Matrix (ABCD vs. E)

5.2 Three-class classification results

For three-class classification we have to test on two type of dataset. First is AB vs CD vs E (here A and B are considered as same class and same for 'C' and 'D'), second A vs C vs E.

5.2.1 AB vs CD vs E

Model	Accuracy	Specificity	Sensitivity
LSTM (Bi-Directional)	98.67%	99.67%	98.75%

Table 5.3 Three-class classification results [AB vs CD vs E]

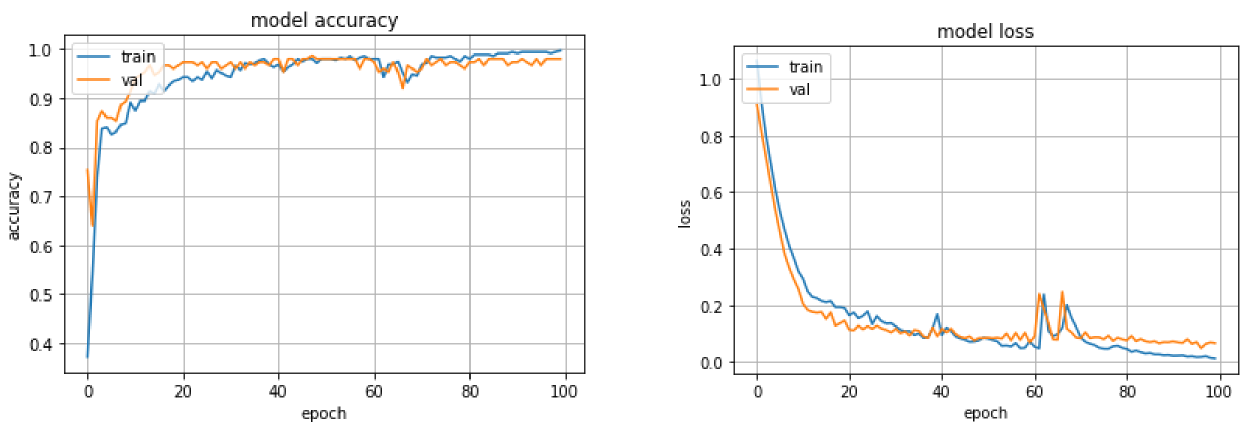


Fig 5.5 Three-class classification results[AB vs CD vs E]

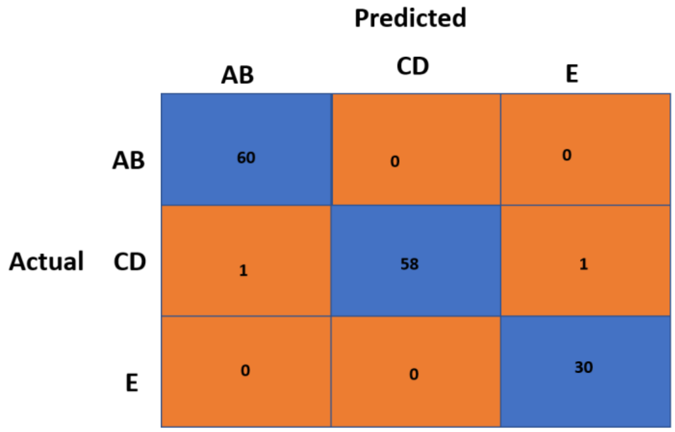


Fig 5.6 Confusion Matrix [**AB vs CD vs E**]

5.2.1 A vs C vs E

Model	***Accuracy***	***Specificity***	***Sensitivity***
LSTM (Bi-Directional)	97.78%	98.72%	97.44%

Table 5.4 Three-class classification results [A vs C vs E]

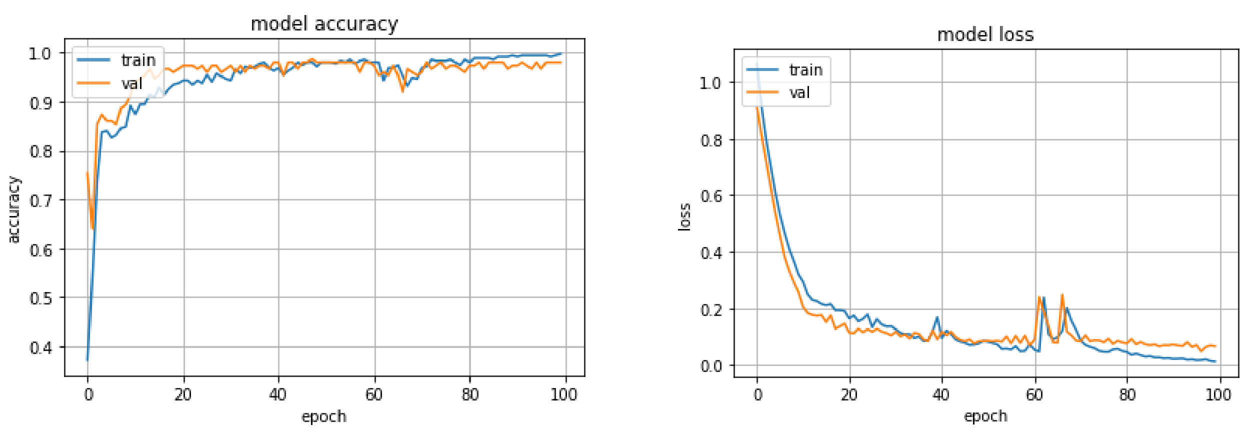


Fig 5.7 Three-class classification results [A vs C vs E]

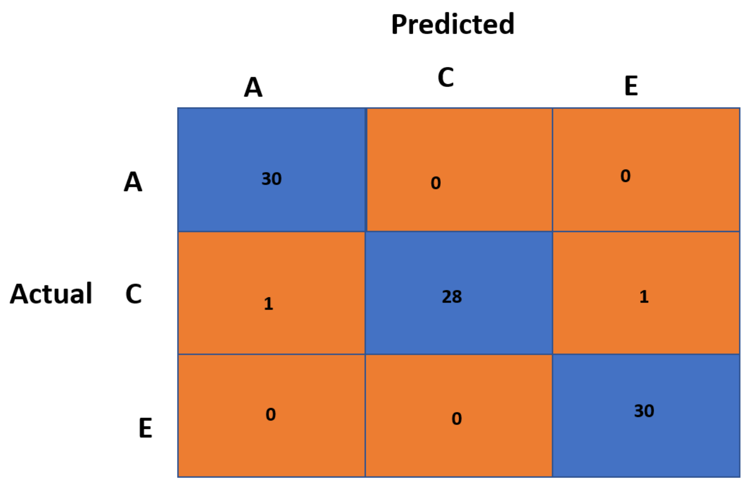


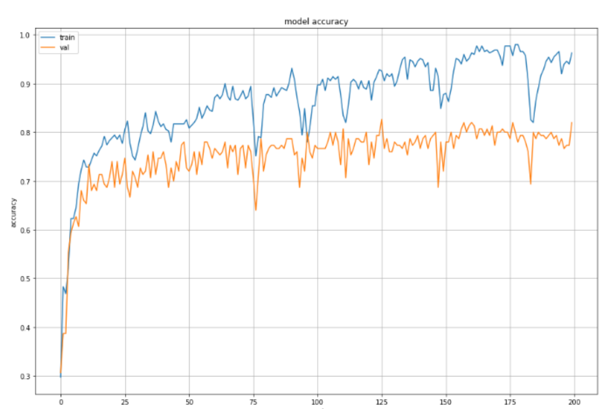
Fig 5.8 Confusion Matrix [**A vs C vs E**]

5.3 Five-class classification results

For five class classification, we used the dataset as it is. Total size of dataset 500* 4096 and total 5 class i.e. A vs B vs C vs D vs E .

Model	*Accuracy*	*Specificity*	*Sensitivity*
LSTM (Bi-Directional)	82.67%	95.44%	81.76%

Table 5.5 Five-class classification results



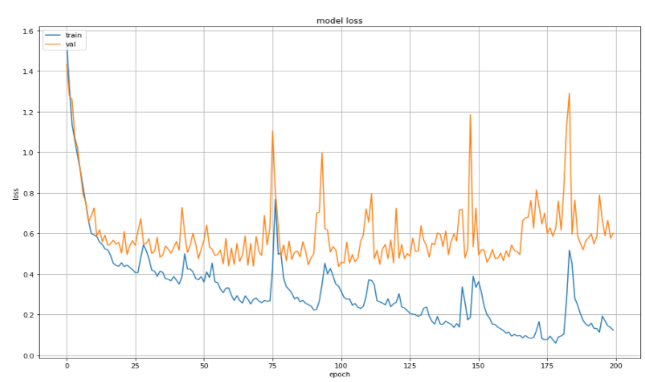


Fig 5.9 Five -class classification results

Actual \ Predicted	A	B	C	D	E
A	21	6	0	3	0
B	4	25	0	1	0
C	0	3	18	9	0
D	0	0	8	21	1
E	0	0	0	0	30

Fig 5.10 Confusion Matrix [A vs B vs C vs D vs E]

Chapter 6 **Conclusion**

This report introduces approach for Epilepsy seizure detection in EEG signal using Deep Learning. In this approach we have checked various variants of LSTM and GRU and find out that Bidirecrional LSTM works best in all cases like 2 class, 3class and 5 class classification. Also we have discussed real-time predicting Epilepsy seizure with smaller eindow size, which can be useful in detecting real-time seizure.

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The proposed approach has been examined on the Bonn EEG . Our dataset was minimally processed still model gave good result, indicating our model robust nature toward artifacts and white noise.

As the Deep learning technique requires a large amount of data for training, hence if a bigger dataset is provided then our model will perform much better for five-class classification.

Chapter 8 References

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