Summer Project Report
(2020-2021)

"To Develop a pre-trained model for EEG signal classification "

UNDER THE GUIDANCE OF
Prof. Anupam Agrawal
Department of Information and Technology
(IIIT Allahabad)

Submitted by
UJJWAL KUMAR
IIT(BHU) Varanasi

PROJECT REPORT

ANALYSIS OF EEG SIGNALS
DIAGNOSIS OF EPILEPTIC SEIZURES

SUBMITTED TO:
DR. ANUPAM AGRAWAL

ACKNOWLEDGEMENT

I would like to express my special appreciation and thanks to my Professor **Dr. Anupam Agrawal**, you have been a tremendous mentor for me. I would like to thank you for encouraging my research and for allowing me to grow as a person . Your advice on research have been priceless.

I would also like to thank **Gopal sir** for giving me this opportunity to work on this project on signal processing using python to “develop a pre-trained model for signal classification” for suggesting various feature extraction techniques, algorithms and providing me with some of good research papers based on seizure net and EEG net and other research works.

ABSTRACT

This neurological disorder is caused by improper functioning of brain cells. EEG is a monitoring device which can be used to diagnose. It records brain electrical activity using multi channels.

My objective in this report is to classify the signals as seizure or non-seizure with high accuracy. The dataset used for this CHB- MIT. All 24 subjects are taken into consideration. The data was trained with the CNN model containing dense and transition blocks . The highest accuracy this model obtained was 92 % using sigmoid classifier.

INTRODUCTION

ELECTROENCEPHALOGRAM (EEG) is a set of electric potential differences that contain the information about the human brain activity. It is a common neurological disorder which affects people of all ages and almost 1% of the whole world population .

EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time, usually 20-40 minutes, as recorded from multiple electrodes placed on the scalp. The following report presents a method diagnosis of epileptic seizure in patients with brain related disorders. This is done through collection of large samples of EEG data of patients showing seizures and non-seizures and using certain feature extraction techniques to help uniquely classify the seizure-signals.

The data of patients with seizures was extracted from ictal region of the brain. The signal sample space used consists of CHB MIT data of 24 patients. This report focuses on the implementation of this base paper **identification of epileptic EEG Signals using CNN by Murat Arsalan** [12].

In literature, **Fan and Chou** (2018) proposed spectral graphs to extract the spatial-temporal patterns for seizure detection [1].The work of **Zandi**(2018) proposed the wavelet-transform based features to differentiate seizure and non-seizure [2].**Vidyaratne** (2016) proposed bidirectional-recurrent neural network to extract features[3]. **Golmohammadi** (2017) proposed LSTM approach on university of Bonn dataset[4]. Recently, deep learnings method were used by **Thodoreff** (2016) [5].**Ullah** (2018) divided the data set into four parts of 1024 each. these were 50% overlapped. Classification was done based on 1D CNN model.it detected the seizure with 99.1% accuracy[6].

Hussein (2018) first transformed EEG data into non-overlapping segments. Then LSTM model was applied with soft-max classifier to get accuracy in range of 90 to 100[7].**Yuan** (2018) transformed EEG into scalogram using the wavelet transformation . in this PCA technique was applied globally. SVM classifier was used and was found 100% accuracy.[8]

In summary, the main contributions for this paper are as follows:

1. I presented a deep learning framework, which uses convolutional layers with deep densely connected layers and learns features from the EEG data.
2. Experiments has shown that this proposed model learns some highly robust features for cross-patient seizure type classification without suffering much from over-fitting from limited amount of training data.

Materials and Methodology

CHB-MIT Dataset -

Dataset used in our thesis is CHB-MIT Dataset. It comprises the record of 24 cases which are taken for 23 patients since two dataset was of same female patient . The recording of each patient varies from almost 9 - 42 hours. Most of the cases are recorded using 23 channels while some are 28 channels. All files were having a sampling frequency of 256 Hz with 16-bit resolution. Each patient case contains 20-50 continuous EDF files. most recordings are of one hour while some recordings are even 2-4 hrs long. Positions of electrode and nomenclature was done on existing 10-20 system. All main 23 channels were taken in order to provide better accuracy for this model. These channels provide useful information about predicting seizures. the channels that has been used are –

[FP1-F7, F7-T7, T7-P7, P7-O1,FP1-F3,F3-C3,C3-P3,P3-O1, FP2-F4, F4-C4, C4-P4, P4-O2, FP2-F8, F8-T8 ,T8-P8 ,P8-O2, FZ-CZ, CZ-PZ, P7-T7, T7-FT9, FT9-FT10, FT10-T8,T8-P8]

The data represented through these channels for window size of 60 sec are shown in the figures below-

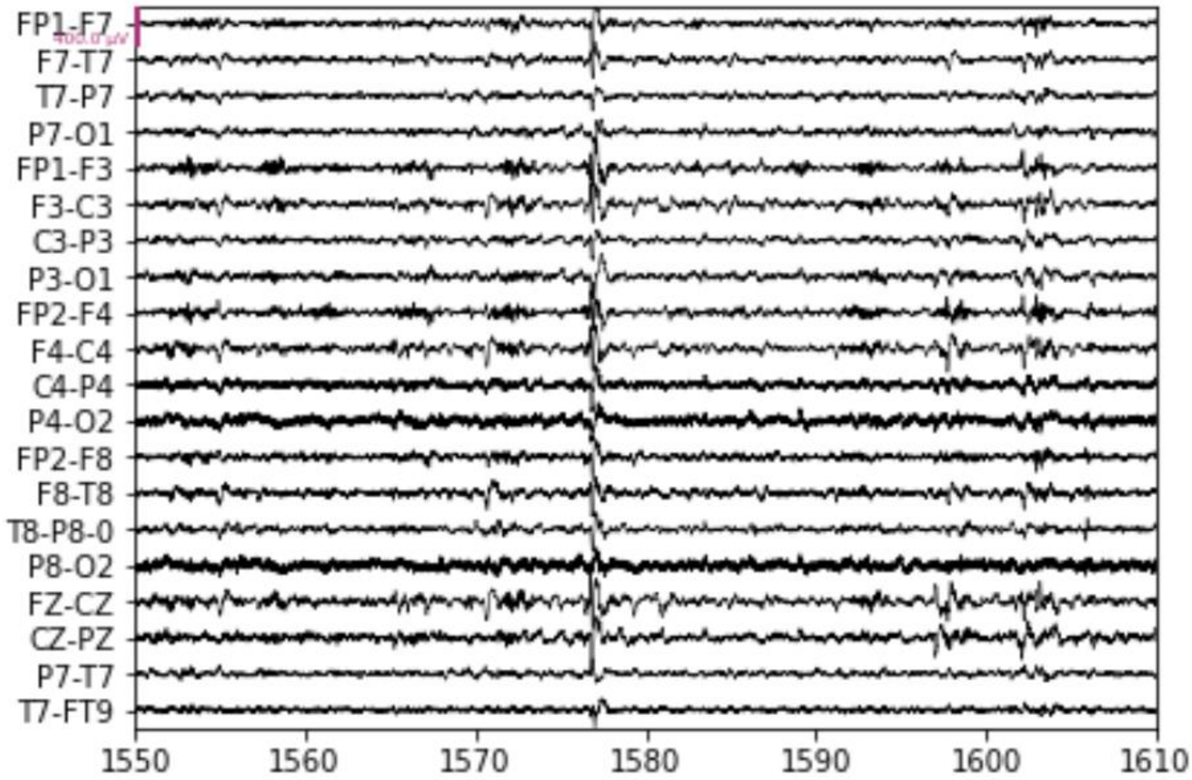


Fig.1. 23 channels without onset of seizure (60sec) Patient 1(chbmit01/18)

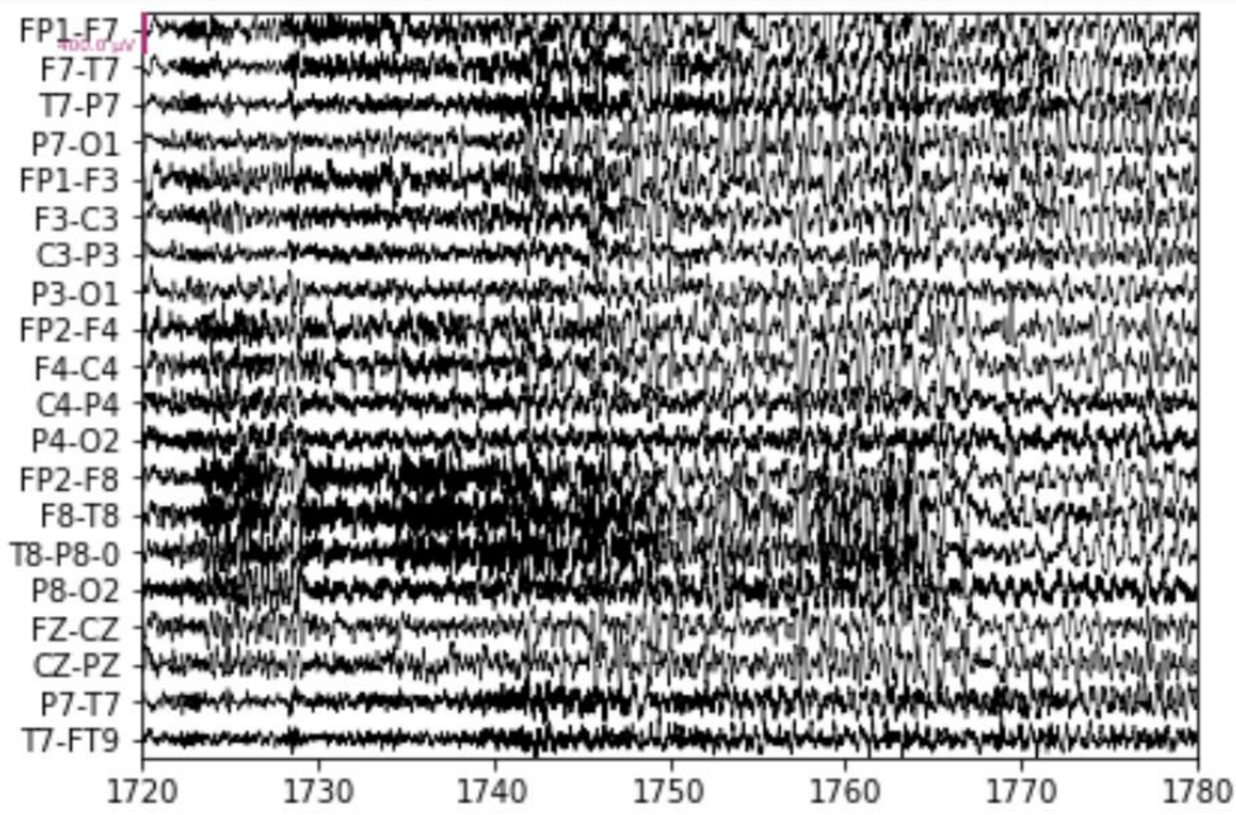


Fig.2. 23 channels with onset of seizure(60 sec)
Patient 1 (chbmit01/18)

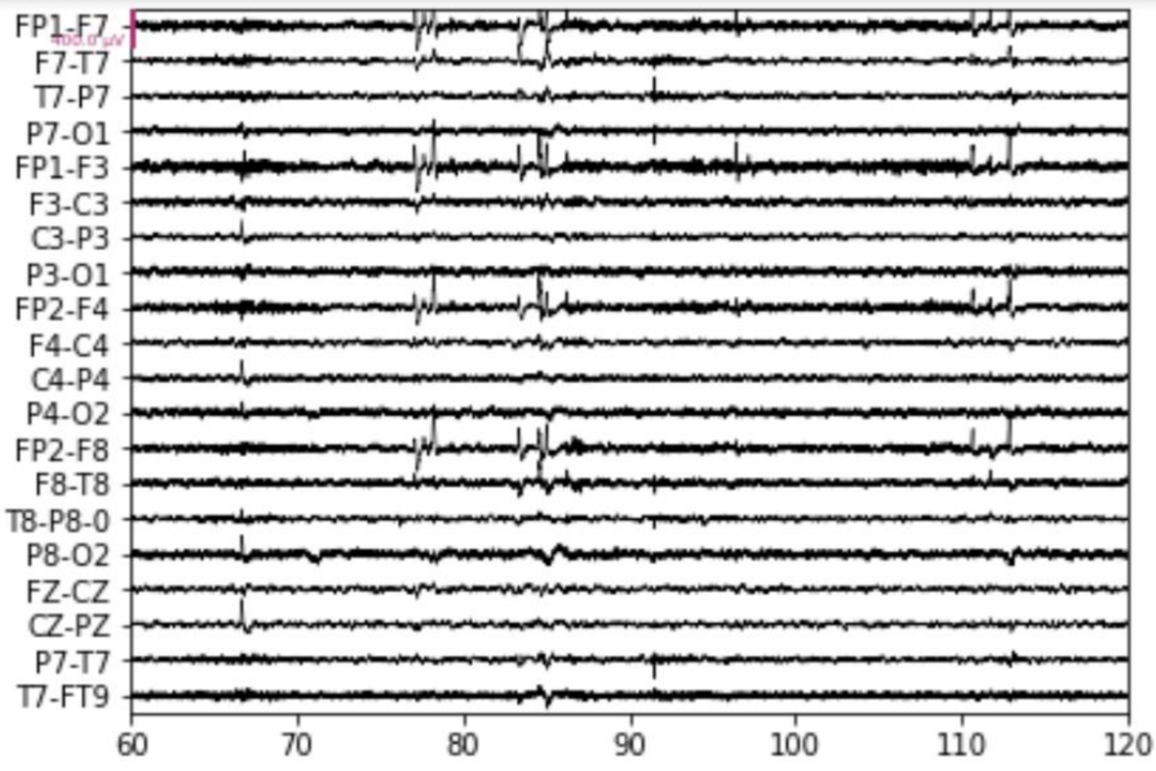


Fig.3. 23 channels with non-seizure(60 sec)
Patient 1(chbmit01/01)

preparation of data

Part info dictionary contains details of each file including the details of no. of channels present, start time , end time and the seizure window present. seizure window contains the details of starting and end time if each seizure file. So for non-seizure this is empty list. it is prepared by the help of regex module. Further seizure files were created which is a list where seizure files are appended with the help of seizure window containing starting and ending time for all files including multi-seizure. Then non-seizure files were appended when the seizure window was empty. After this a 3d array is prepared called seizure array where each seizure file is added by converting into 2d array with the help of EDF reader . Time taken was 60 sec starting from onset of seizure that contains almost 15360 rows for training of data. Further, unwanted files i.e. those files which don't contains all 23 channels were removed from this. similarly, non-seizure array was prepared which is also a 3d array which contains non-seizure array. Unwanted files were removed .it is done with the help of random and shuffle module. concatenation of seizure and non-seizure array was done and further reshaping to create training of x data.so 0 was marked for non-seizure label while seizure was marked with label 1 .For preparation of the test samples, same process was repeated as it was done earlier to prepare the train x and train y. so non seizure test and seizure test array was prepared.

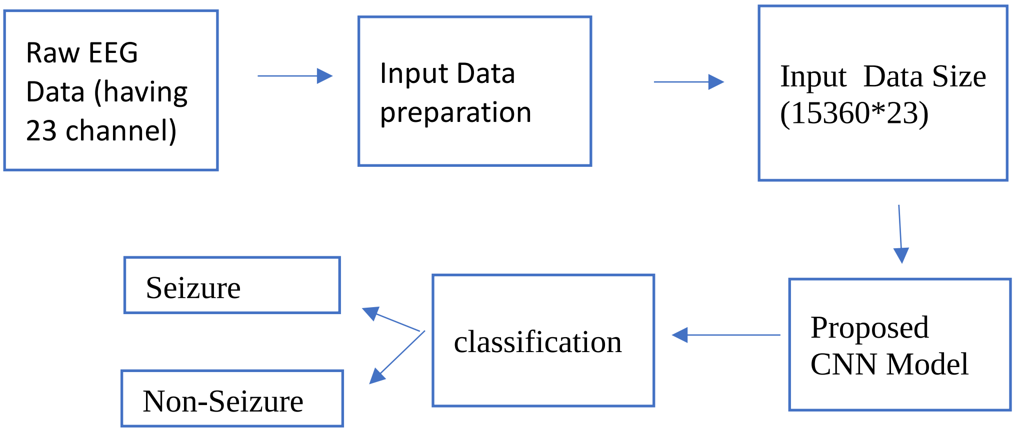
So, since all patients were taken into consideration. So, total there was almost 500 non-seizure while 180 seizures files present. Out of 500 ,120 non-seizure files were taken in which Training was performed on 90 file and testing was performed on 30 file. These all non-seizure files were selected randomly.

Also, out of 180 seizure files training was done on first 90 files and testing was performed on 20 seizure files. So, the data size was 15380*23 for each seizure as well non-seizure file. Total Training data was split into 80% and 20% validation data.

THE PROPOSED CNN MODEL

Proposed Method

The block diagram of the proposed methodology on CHB-MIT dataset is described in the figure.



Basic building block of our model architecture is made up of multiple bottleneck convolution and finally interconnected by dense unit.it starts with 7x7 convolution and further adding of max-pool of 3x3 , BN and RELU layer. Further dense block is implemented which consists of 9 dense layers with varying filter size starting from filter size 64 to 512.this is done to pass relevant information from preceding layer to next layer. each dense layer includes 1x1 convolution followed by 3x3 and then adding of BN, RELU and average pool of 2.Further transition layer is implemented in this model with the 3x3 convolution layer having filter size 512 and then adding of BN, RELU layer.

So after concatenation of all the features extracted by these layers, it produces the feature maps which are squeezed to flattening the layers. finally a fully densely connected layers are implemented with 1024 units and 512 units and dropouts layer. Then these are finally passed through sigmoid function for label output for seizure and non-seizure detection.

Mathematically, the output of fully connected layer (Yfc) and the sigmoid layer can be written as:

$$Y_{fc} = Y_{dense} * W_{fc} + B_{fc} \qquad \ldots(1)$$

$$Y_{Sigmoid} = \text{Sigmoid}(Y_{fc}) \qquad \ldots(2)$$

Where W_{fc} represents the weights of the layers while B_{fc} represents the biases used.

Binary cross-entropy loss function was used in this model . mathematically this equation can be written as:

Cross Entropy

Binary Cross-Entropy is defined mathematically as —

$$BCE\ (t, p) = -(t * \log(p) + (1 - t) * \log\ (1 - p))$$

Fig.4.

The block diagram for this model-

So dense block contains 9 dense layers . the input data given was 15360*23 with 180 training samples .

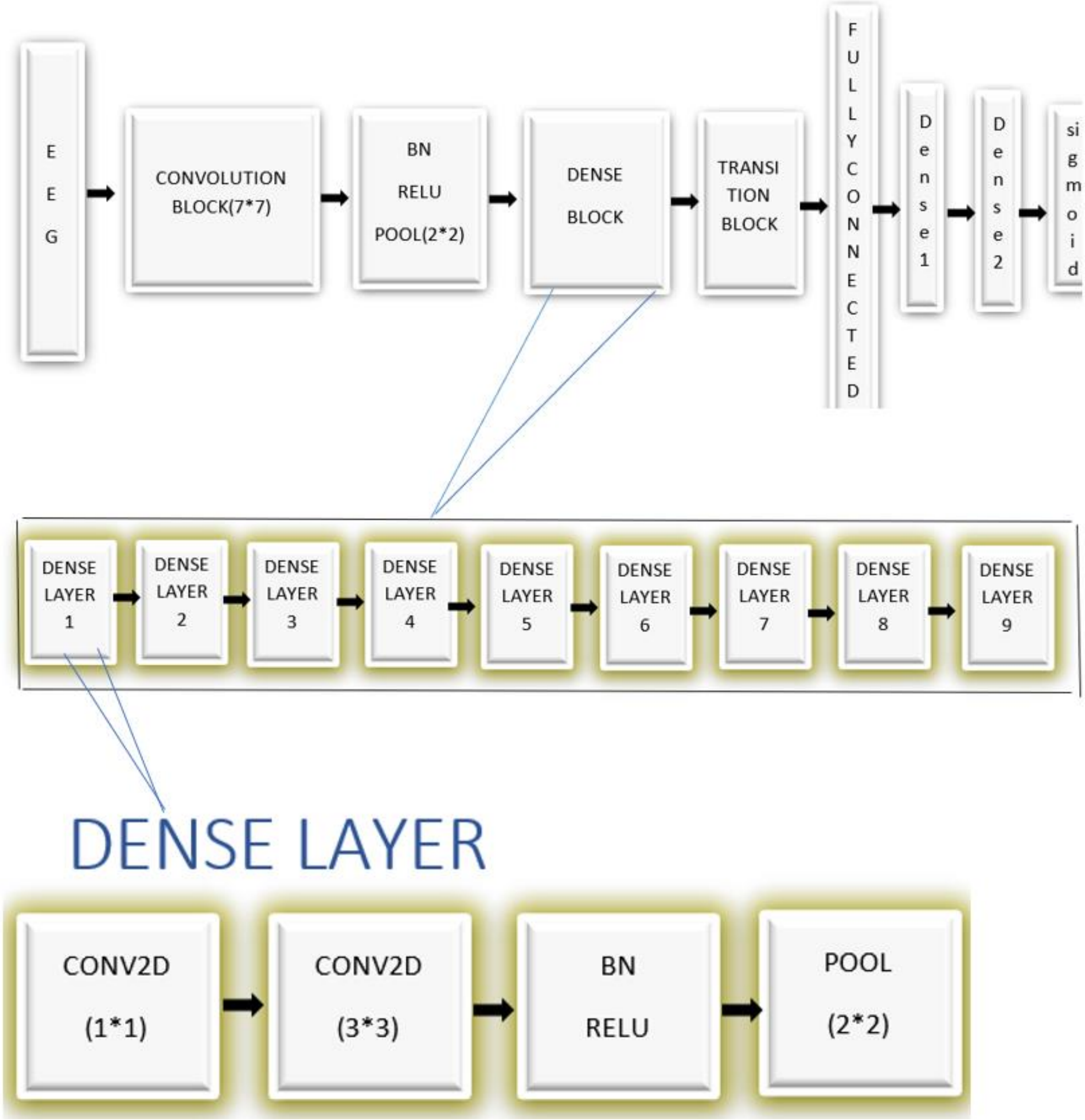


Fig. 5

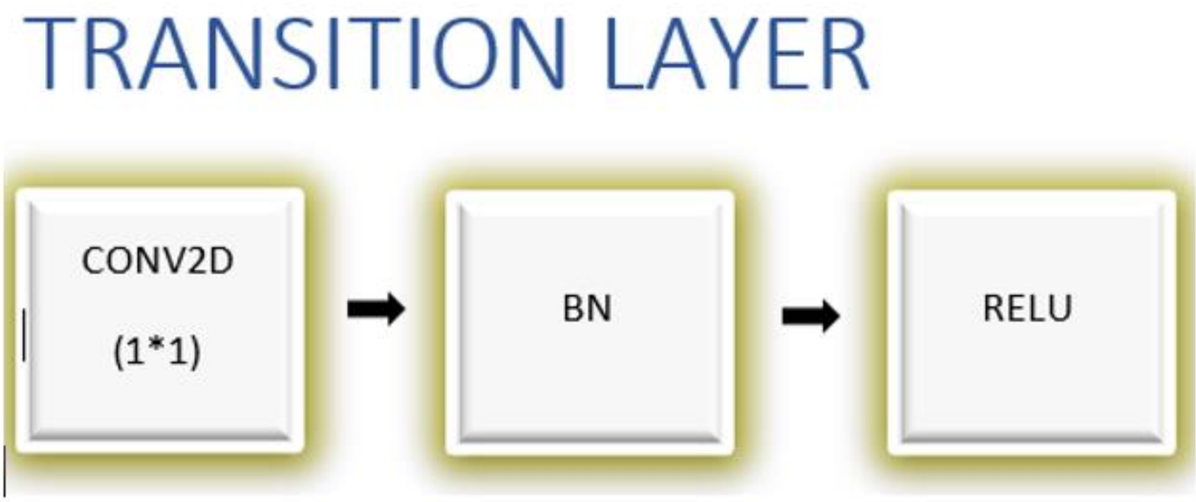


Fig.6

4.2 Hyperparameter Tuning

Proposed model is compiled with Adam optimizer and binary-cross-entropy loss function . learning rate was kept 0.001 to get better result.

Validation set was prepared with test size of 0.25 .Model fitting was done with having a batch size of 16. It will run till 40 epochs.

RESULT

After tuning the parameters , experiments were performed 2 times for same 40 epochs and hyper tuned parameters to cross-check all the accuracies score and check the variation in this model.so it was tested on 50 files i.e. 30 non-seizure and 20 seizure files.

Experiment 1:

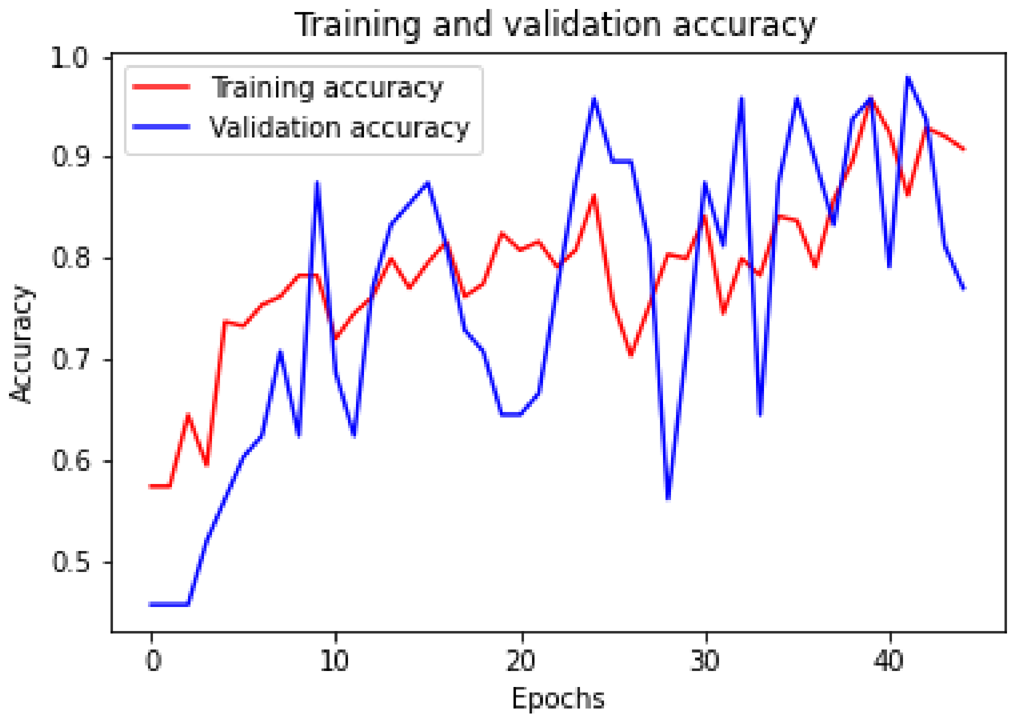


Fig.7 Accuracy vs Epochs

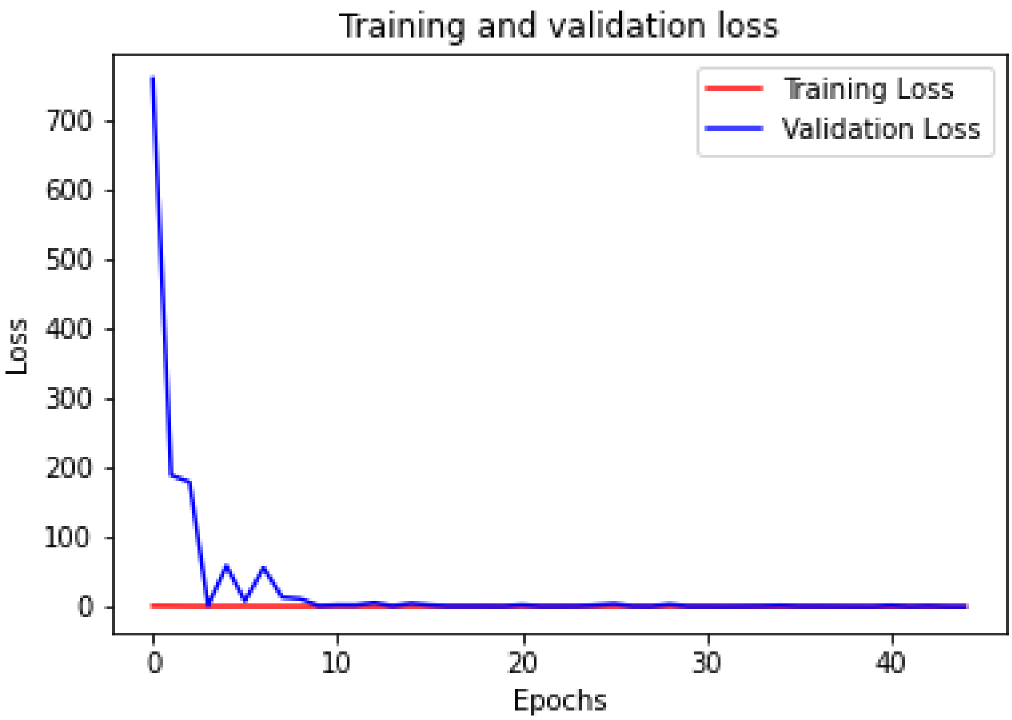


Fig.8 Loss vs Epochs

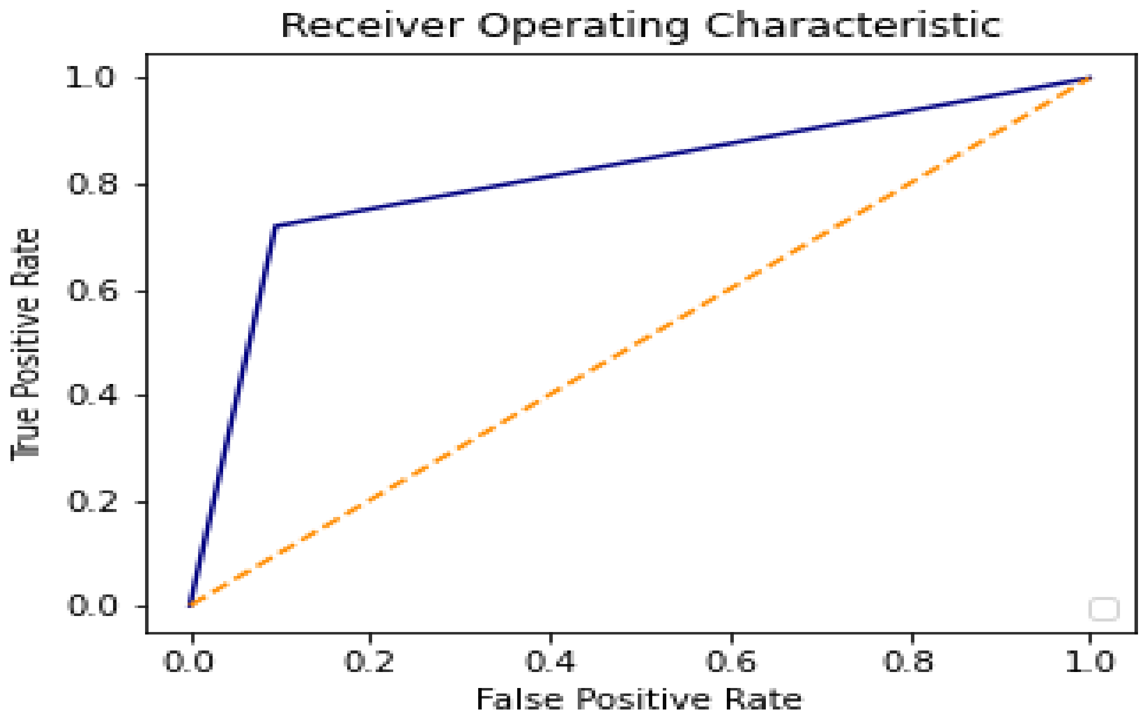


Fig.9 Roc-Auc Curve

It gave me roc-auc value 0.87 .

Confusion-Matrix-

```
[[25   5]
[2  18]]
```

So, Out of total 50 test file, Inference can be drawn from above experiment that out of total 30 non-seizure it predicted 25 correctly while out of 20 seizure 18 are predicted correctly.

Experiment 2:

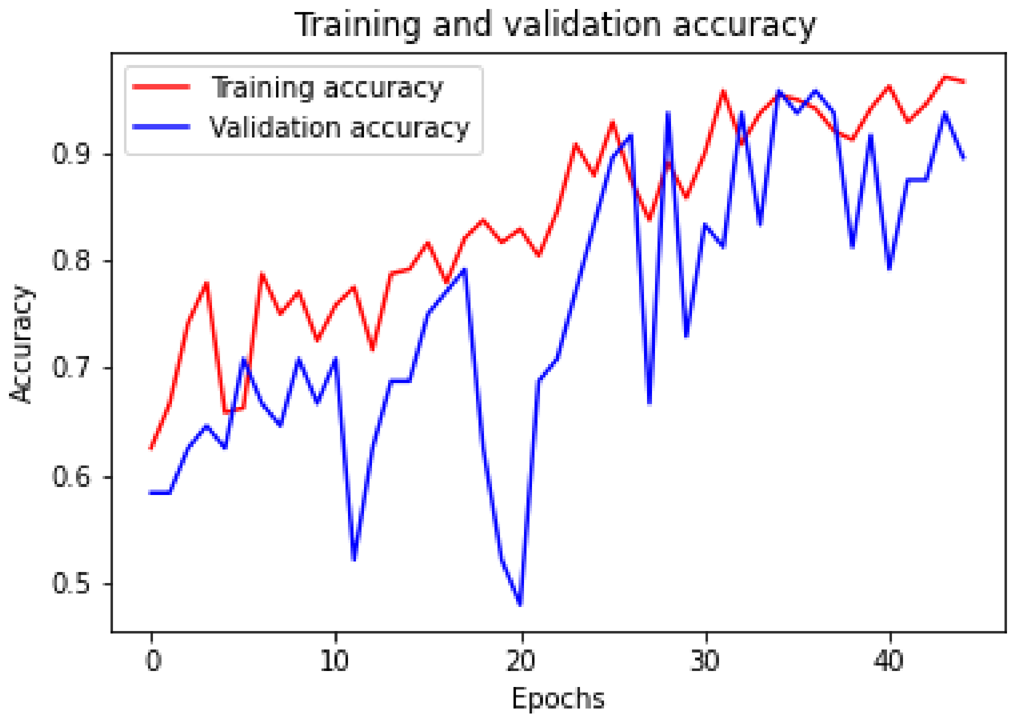


Fig.10 Accuracy vs Epochs

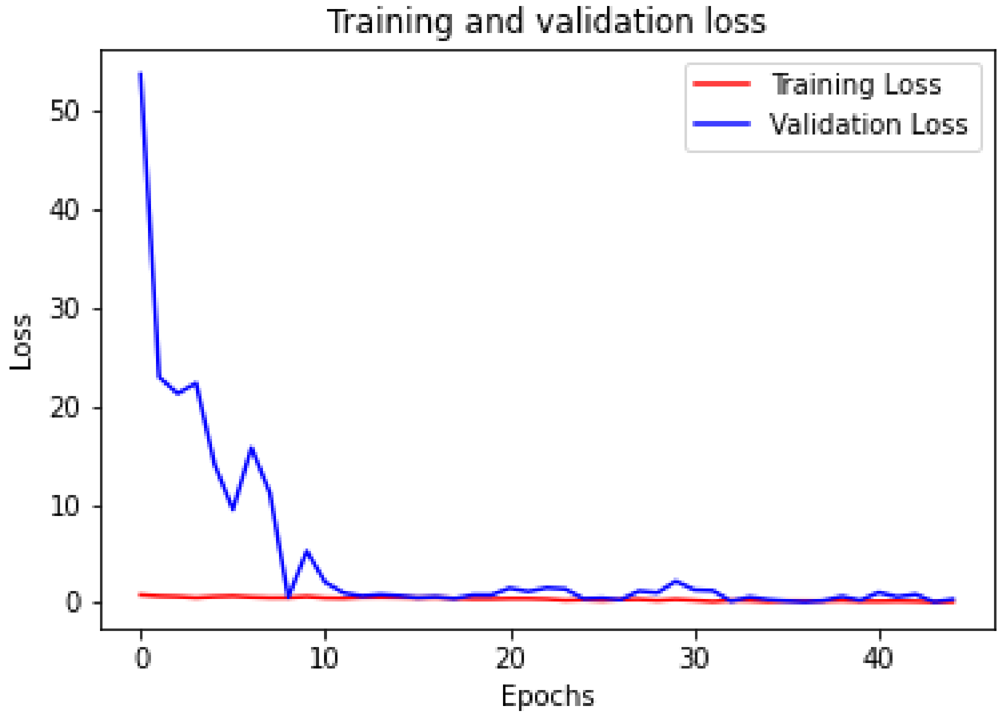


Fig.11 Loss vs Epochs

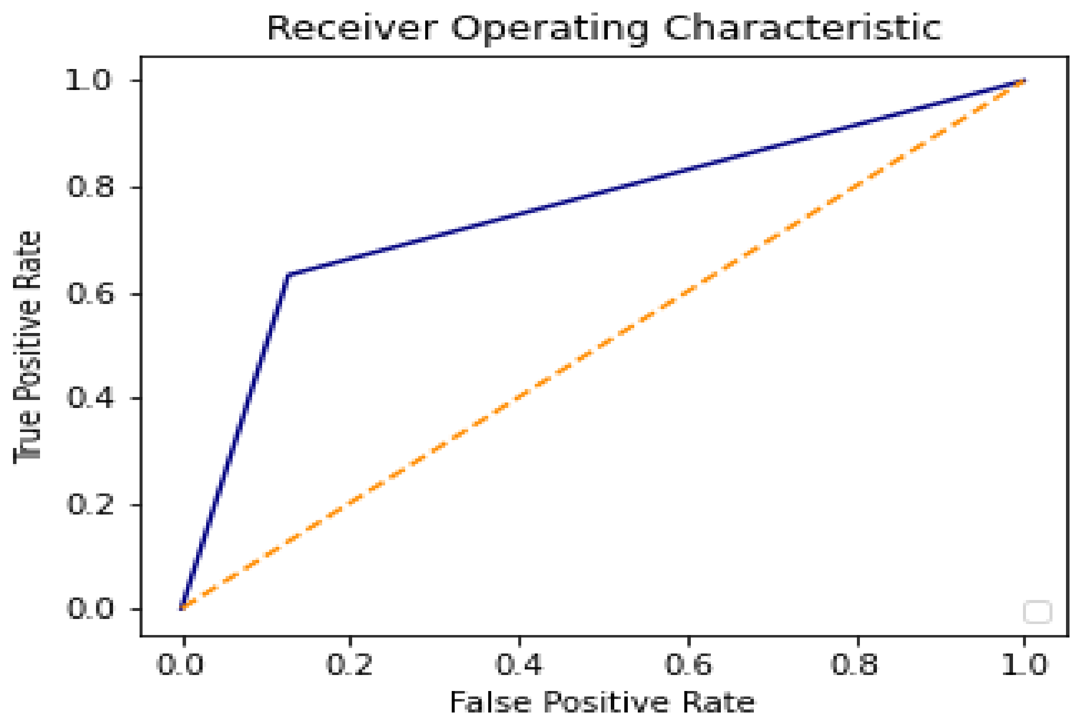


Fig.12 Roc-Auc Curve

It gave roc-auc value 0.77

Confusion-Matrix-

```
[[24   6]
[5  15]]
```

So, Out of total 50 test file, Inference can be drawn from above experiment that out of total 30 non-seizure it predicted 24 correctly while out of 20 seizure 15 are predicted correctly.

Results For both experiments:

EXP.	EPOCHS	Accuracy	Precision	Recall	F1	Roc-Auc
1.	40	86	76	95	84	0.87
2.	40	78	71	75	73	0.77

Table 1

<u>Comparison</u>

	CNN(Murat Aslan) [12]	**MY MODEL**
DATA	CHB-MIT	CHB-MIT
Author	Murat Aslan, Ahmet illhan	Ujjwal
Optimiser	Rms Prop	Adam
Loss function	Binary-cross entropy	Binary-cross entropy
Channels used	22	23
Epochs	150	40

Learning Rate	0.001	0.001
Train-Test split (for validation)	0.3	0.2
Activation Layer(last)	Soft-max	Sigmoid
ACCURACY	91%	84%

Table 2

Conclusion

So, The average accuracy that my model that predicted was around 80 to 85% while The best accuracy this model got was 92%.

Future Scope

One of greatest challenge that one is facing is to learn robust features from limited patients data.in order to achieve this I used deep CNN model with densely connected layers. From above experiments , inferences can be drawn that this don't suffers overfitting and extracted features actually be used for seizure detection with pretty good accuracy. In future , more efficient can be used to diagnose patient and will be used in real-world applications. Future research is focusing on using a combination of CNNs and LSTMs and other feature extraction techniques to develop an identification system for the CHB-MIT dataset.

REFERENCES

[1] [fan and chou 2018] Detection abnormal pattern of epileptic seizures by temporal synchronization of EEG signals.

[2] [VidyaRatne 2016] Deep recurrent neural network for seizure detection .in 2016 international joint conference (IJCNN) ,pages 1202-1207 ,2016

[3] [golmohhammadi 2017] Gated Recurrent neural network for seizure detection (SPMB) pages 1-5 iEEE,2017

[4] [Huang 2017] Densely connected convolutional networks . CVPR ,2017

[5] [Thodoroff] Learning robust features using deep learning for automatic seizure detection.pages 178-190 ,2016

[6] Ullah, I.; Hussain, M.; Aboalsamh, H. An automated system for epilepsy detection using EEG brain signals based on deep learning approach. *Expert Syst. Appl.* **2018**, *107*, 61–71. [**Google Scholar**] [**CrossRef**]

[7] Hussein, R.; Elgendi, M.; Wang, Z.J.; Ward, R.K. Robust detection of epileptic seizures based on L1-penalized robust regression of EEG signals. *Expert Syst. Appl.* **2018**, *104*, 153–167. [**Google Scholar**] [**CrossRef**]

[8] Yuan, Y.; Xun, G.; Jia, K.; Zhang, A. A novel wavelet-based model for eeg epileptic seizure detection using multi-context learning. In Proceedings of the 2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Kansas City, MO, USA, 13–16 November 2017; IEEE: Piscataway, NJ, USA; pp. 694–699. [**Google Scholar**] [**CrossRef**]

[9] research gate - https://www.mdpi.com/2076-3425/9/5/115/htm#:~:text=In%20order%20to%20compare%20the,C%2C%20D%2C%20and%20E.

[10] https://www.mdpi.com/2076-3425/9/5/115/htm#:~:text=In%20order%20to%20compare%20the,C%2C%20D%2C%20and%20E.

[11] medium article

[12] Identification of Epileptic EEG Signals Using Convolutional Neural Networks
https://www.mdpi.com/2076-3417/10/12/4089/htm