MINOR PROJECT PRESENTATION

Epilepsy Seizure Classification Through EEG Signals Using 1D CNN

Under the Guidance of

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CSE - 3

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What is Epilepsy Seizure?

Seizure:
Disturbance in the electrical activity of brain.

Fig-1: Brain Signals

Epilepsy:
Repeated Seizures

Classification :
- Focal
- Generalized

CAUSES OF EPILEPSY

- Missing medication doses
- Heavy alcohol use
- Cocaine, ecstasy, or other illegal drugs
- Lack of sleep
- Other medicines that interfere with seizure medications
- Flashing lights, images, and repetitive patterns may cause seizures in persons with photosensitive seizure disorder.
- Trauma

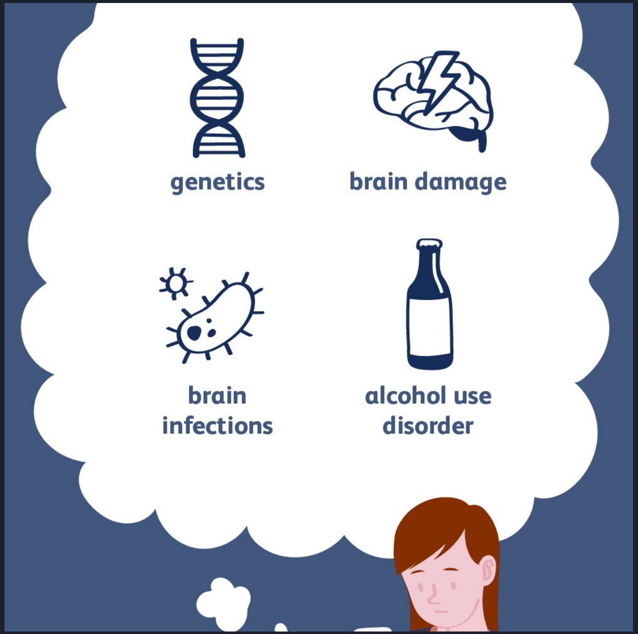


Fig-2: Causes Of Epilepsy

SYMPTOMS OF EPILEPSY

- Loss of consciousness
- Confusion
- Jerking moments
- Strange sensations
- Sudden falls
- Staring

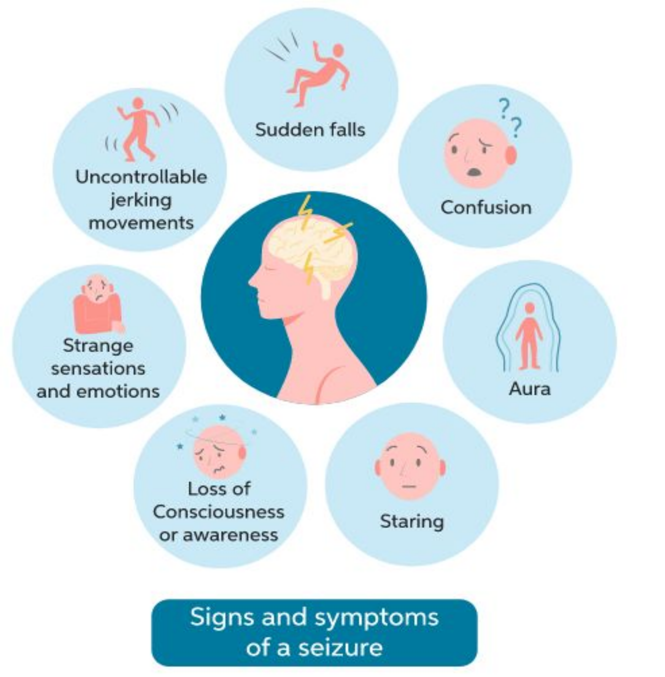


Fig-3: Symptoms of Epilepsy

ELECTROENCEPHALOGRAPHY (EEG)

Electroencephalogram is a type of brain monitoring. It is a recording of the electrical activity of the brain by placing a small number of electrodes on your head and then measuring the electrical activity. This can be used to examine the brain and diagnose certain brain diseases, including epilepsy and seizures.

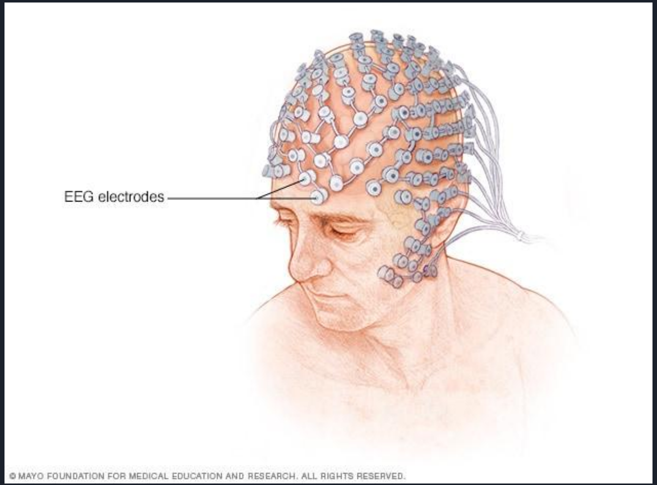


Fig-4: EEG Electrodes [7]

NORMAL EEG VS EEG WITH EPILEPTIC SEIZURE

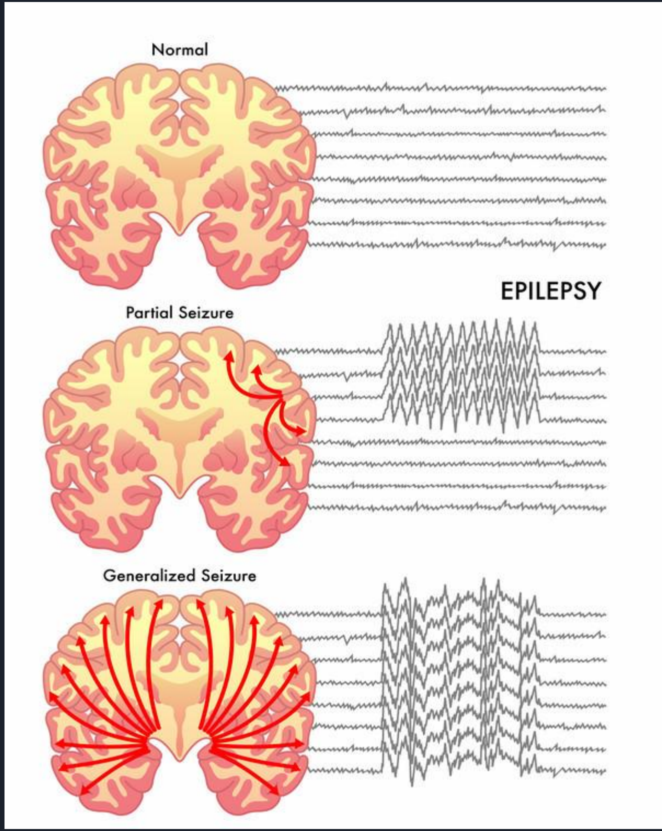


Fig-5: Comparison of Normal and Abnormal EEG Signals [8]

DATASET

- Dataset contains EEG recordings of 500 subjects.
- 4097 data points were measured for each subject during the interval of 23.6 seconds.
- These 4097 data points are divided into 23 chunks.
- Each chunk contains 178 data points.
- Sampling Frequency = 173.61 Hz

- There are 5 Classes - 1,2,3,4,5
- 5 - Recording the EEG signal of the brain when the patient had their eyes open
- 4 - Recording the EEG signal when the patient had their eyes closed
- 3 - Recording the EEG activity from the healthy brain area
- 2 - Recording the EEG from the area where the tumor was located
- 1 - Recording of the EEG signal of a patient having seizure activity

Comparison of EEG signals of all classes

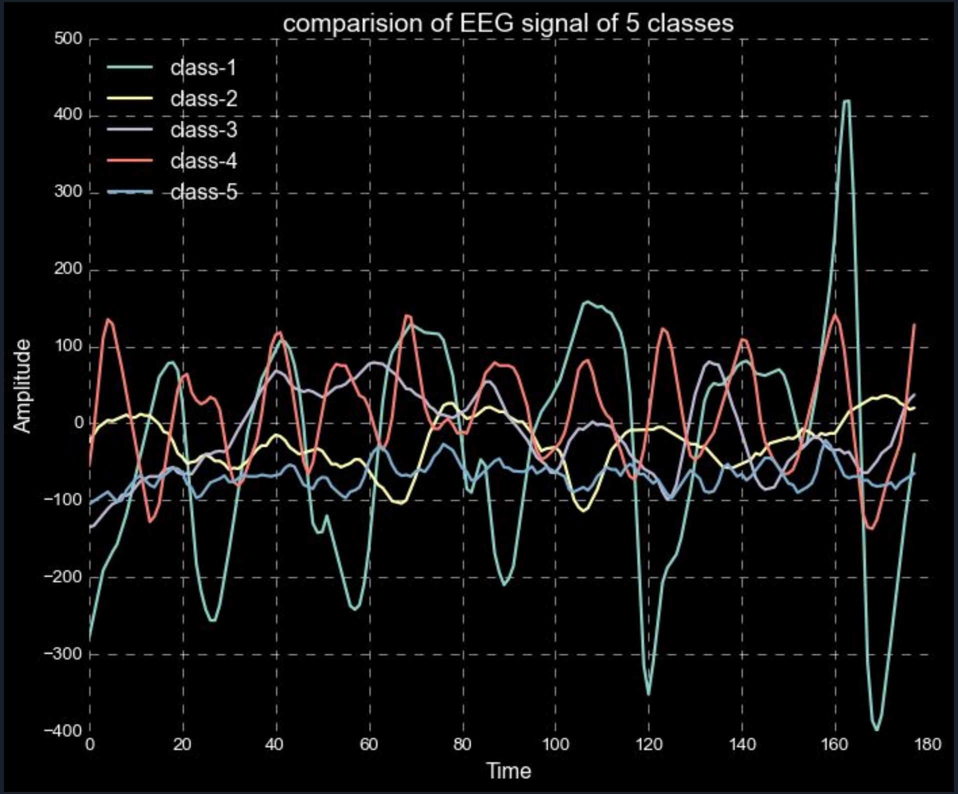


Fig-6: Plot of EEG for 5 classes

Data Modification

- All subjects falling in classes 2,3,4 and 5 are subjects who did not have epileptic seizure, only subjects in class 1 have epileptic seizure, so we have assigned label 0 for classes 2, 3, 4 and 5 and label 1 for class 1.
- After binary classification we have 9200 data samples of label 0 and 2300 data samples of label 1.
- Since the data is imbalance we balanced the data by using several sampling techniques.

Undersampling

In this technique we balance the dataset by reducing the number of samples in the majority class.

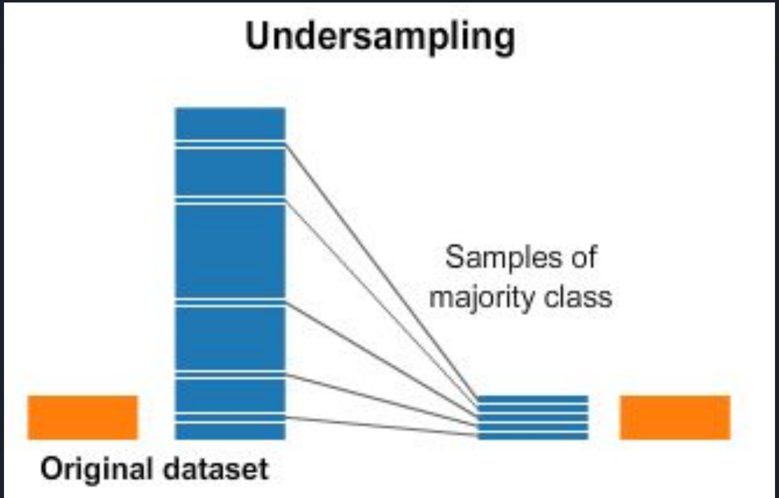


Fig-7: Undersampling

Oversampling

In this sampling method we balance the dataset by increasing the number of samples in the minority class by just creating copies of already existing samples

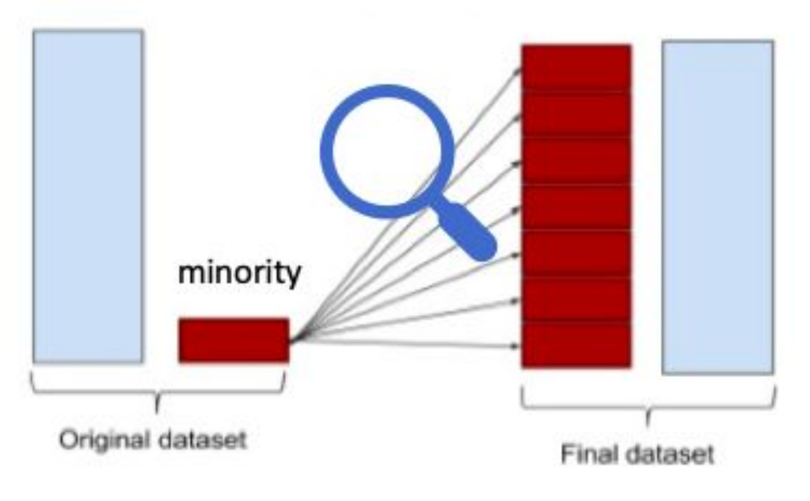


Fig-8: Oversampling

SMOTE

It's basically an oversampling method which uses k-nearest neighbors for generating new samples in order to balance the data.

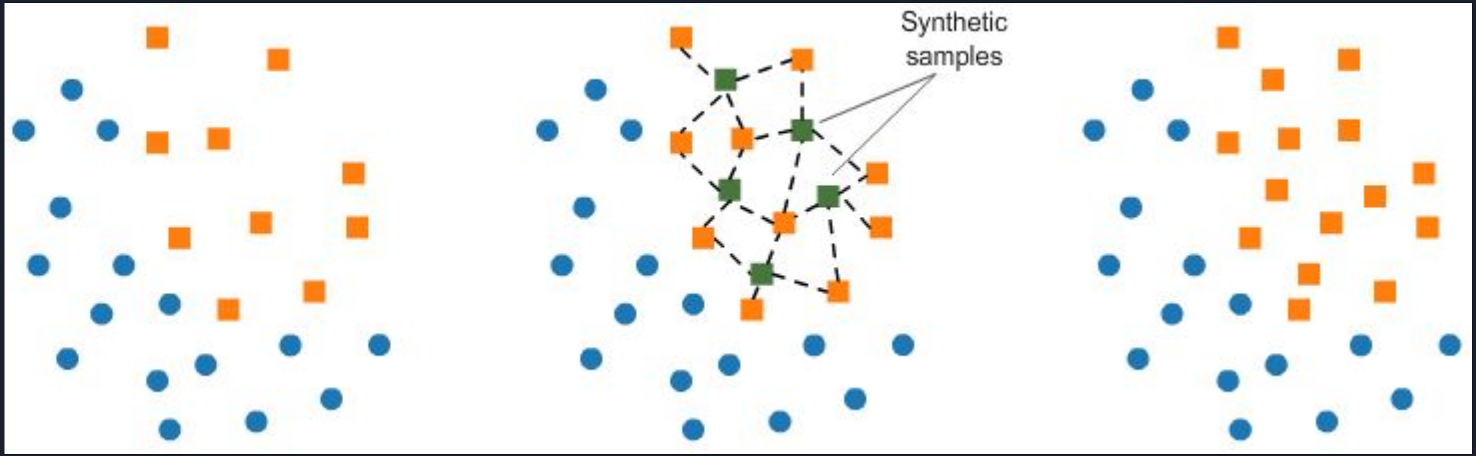


Fig-9: SMOTE

ADASYN

ADASYN or Adaptive Synthetic Sampling Approach is a sampling technique which is a generalization of SMOTE.It adjusts the decision constraints adaptively depending on difficult samples.

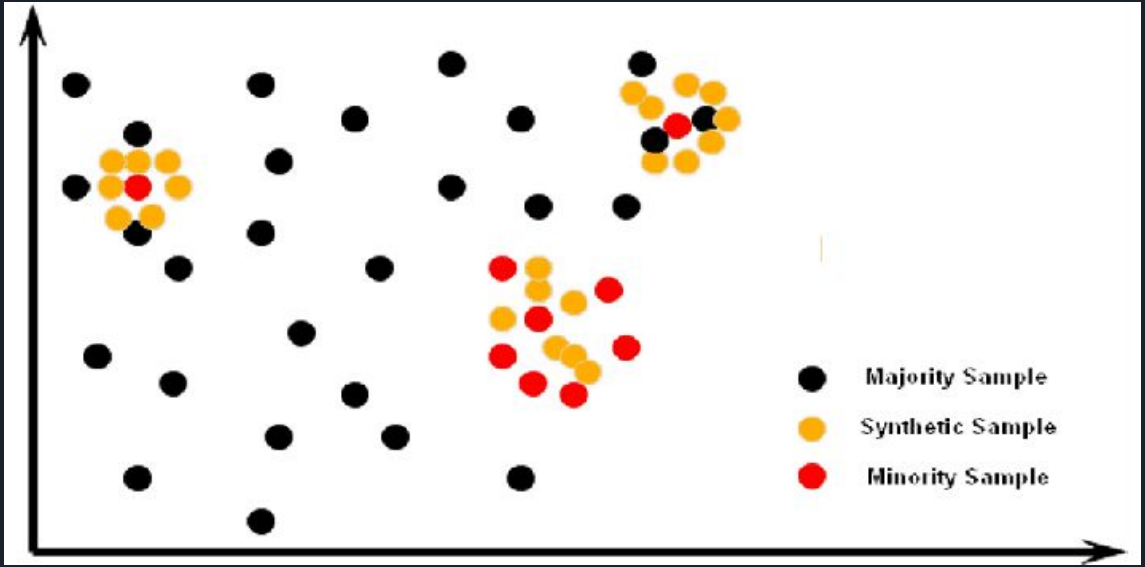


Fig-10: ADASYN

Random Oversampling

It creates duplicates by randomly selecting samples from minority class for data balancing.

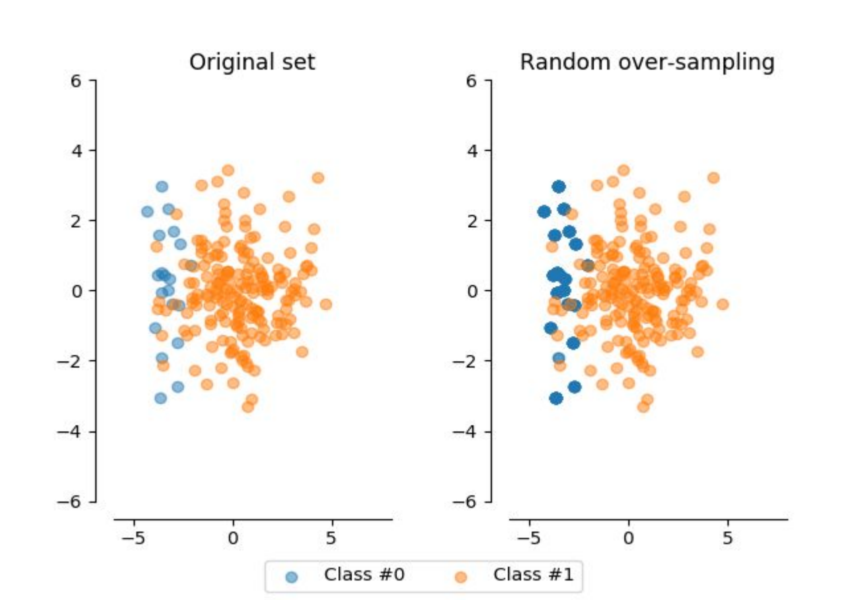


Fig-11: Random Oversampling

Comparison of EEG Signals

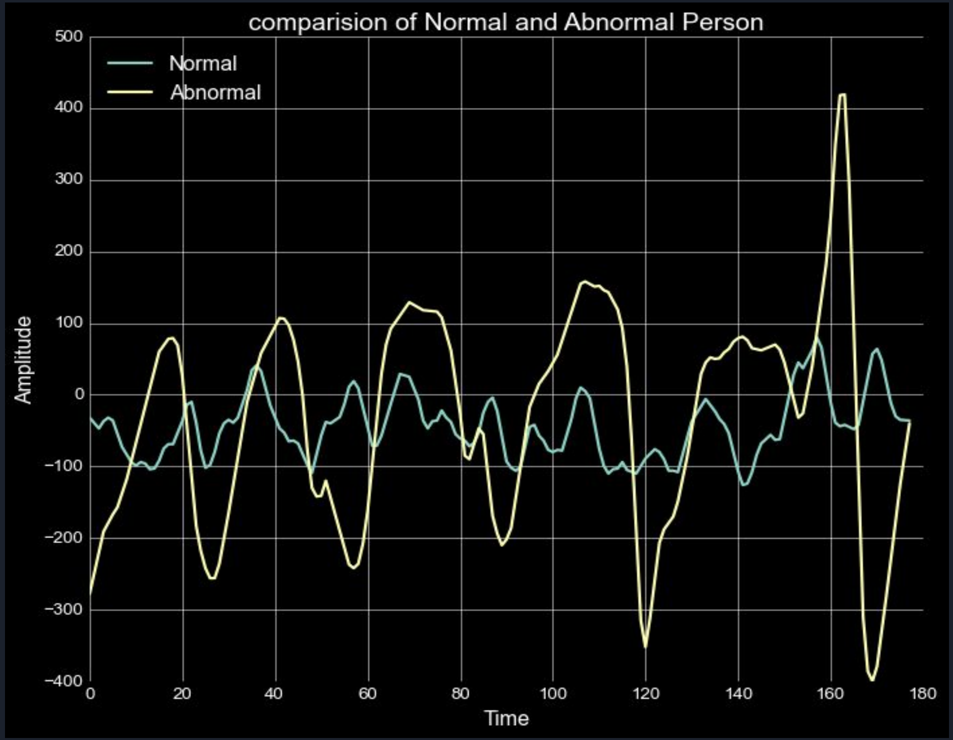


Fig-12: Comparison of EEG SIgnals

Normalisation of Data

Z-score Normalisation

In this normalisation technique every value in the dataset is normalised in such a way that the mean of all of values is zero and standard deviation is one.

$$v' = \frac{v - \overline{A}}{\sigma_A}$$

Training, Testing and Validation Split

Training and Testing split kept at a 70:30 ratio. So,

Number of samples in train set:	12880 samples
Number of samples in test set:	5520 samples

Now we further split the training dataset into a training and validation dataset at 80:20 ratio. So,

Number of samples in train set:	10304 samples
Number of samples in validation set:	2576 samples

CNN ARCHITECTURE

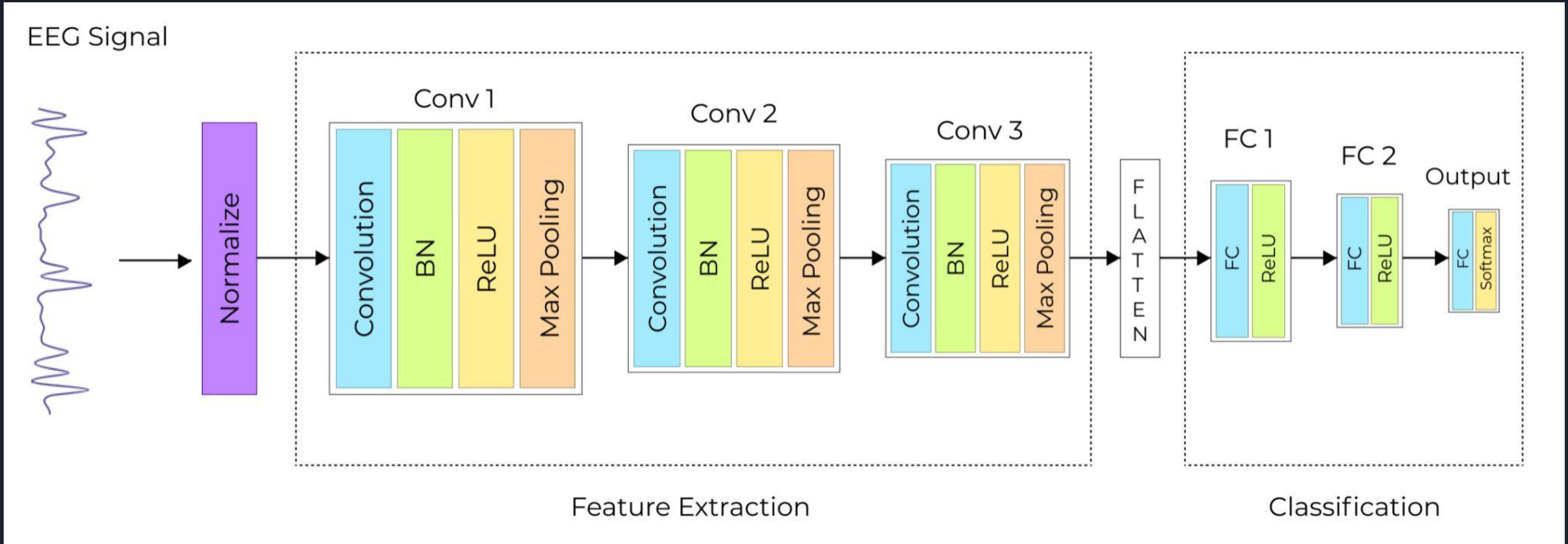
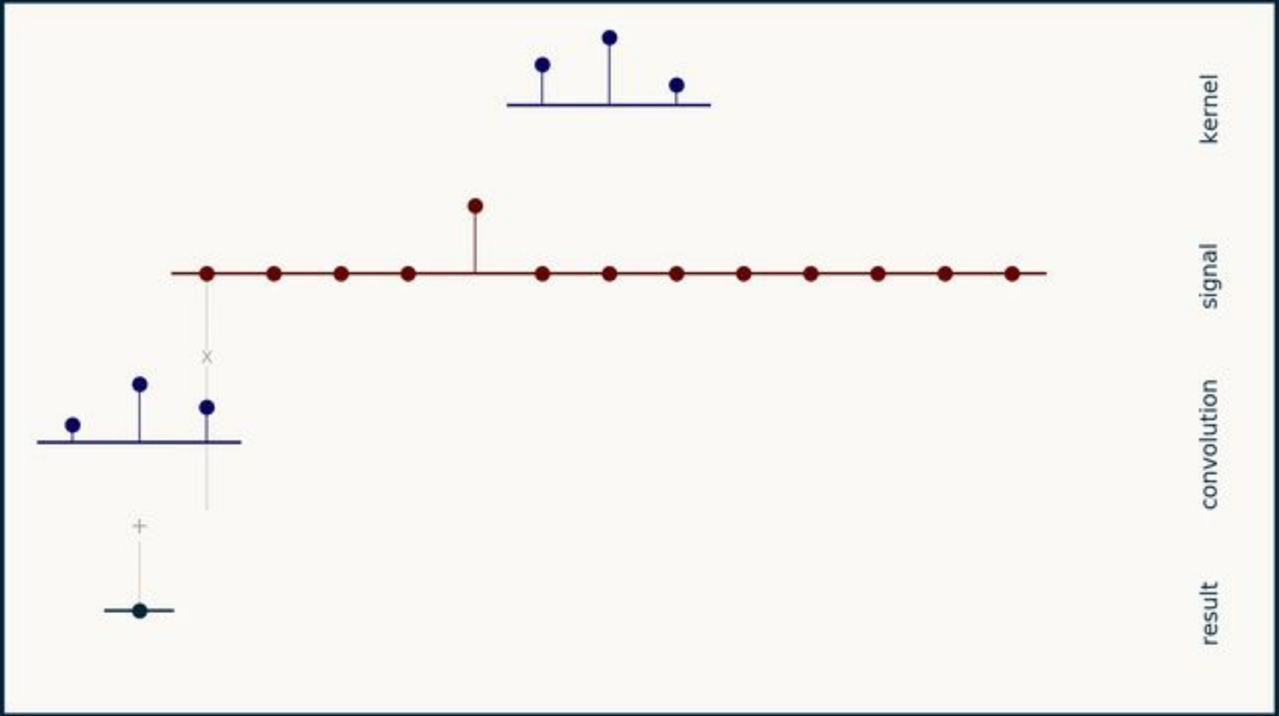


Fig-13: CNN Architecture

Convolution Block



- 1 D Convolution layer
- Batch normalisation layer
- Max pooling layer

Fig-14: Convolution Block

Batch Normalization

Step	Expression	Description
1	$z = \frac{x - mean}{std}$	Normalize output x from activation function.
2	$z * g$	Multiply normalized output z by arbitrary parameter g.
3	$(z * g) + b$	Add arbitrary parameter b to resulting product $(z * g)$.

Batch Normalization Process

Fig-15: Batch Normalization

Max Pooling

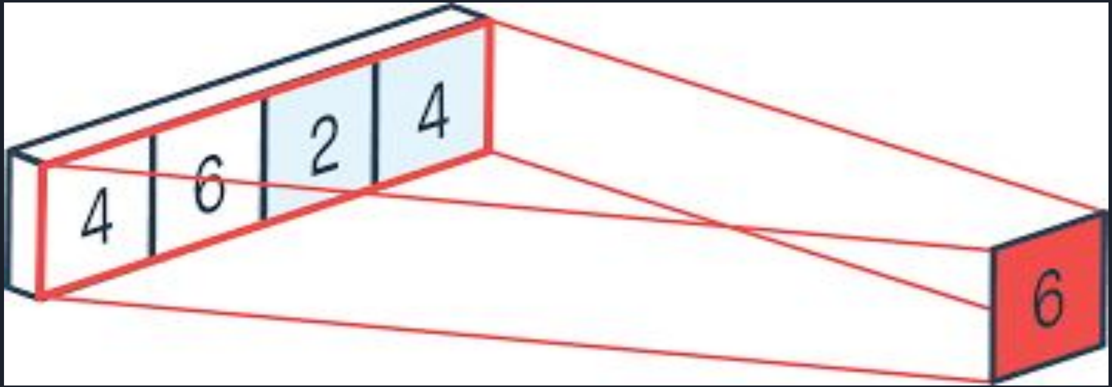


Fig-16: Max Pooling

Relu Activation Function

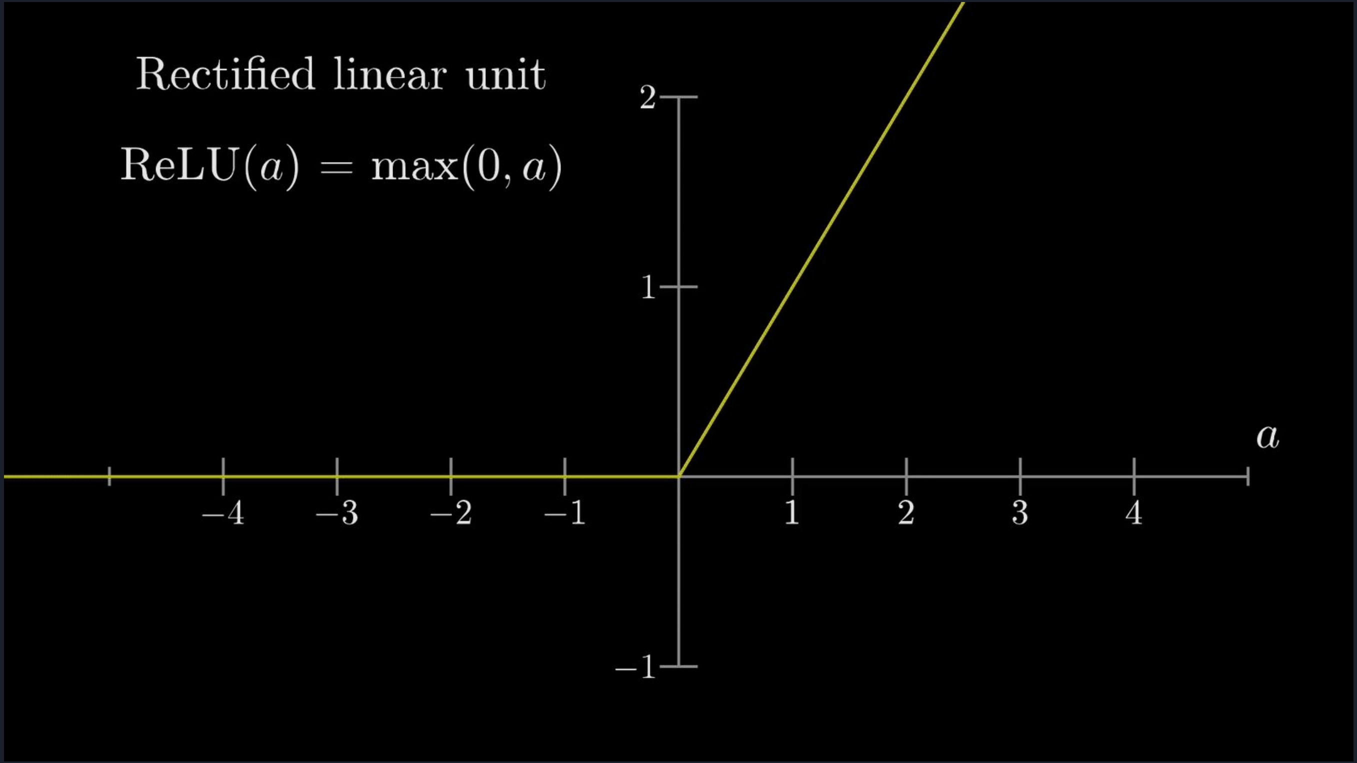


Fig-17: Relu Activation Function

Output Block

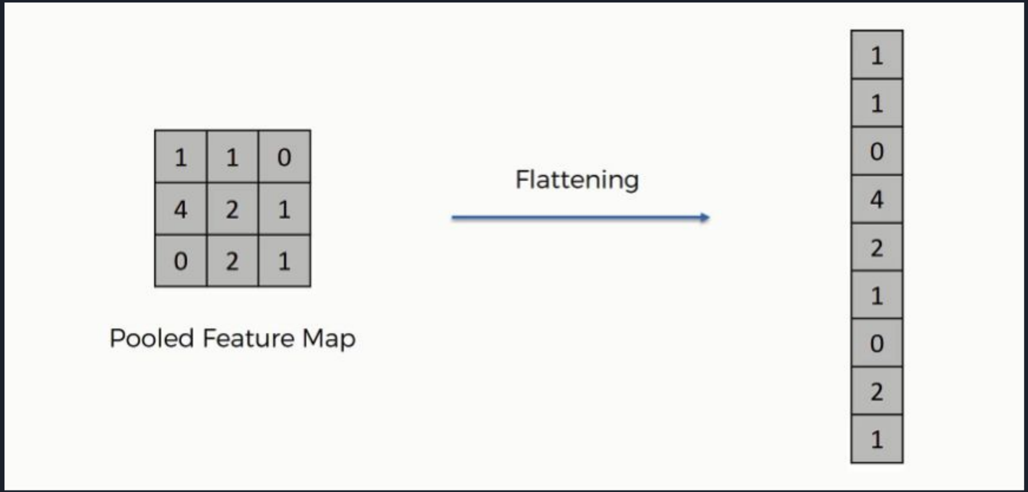
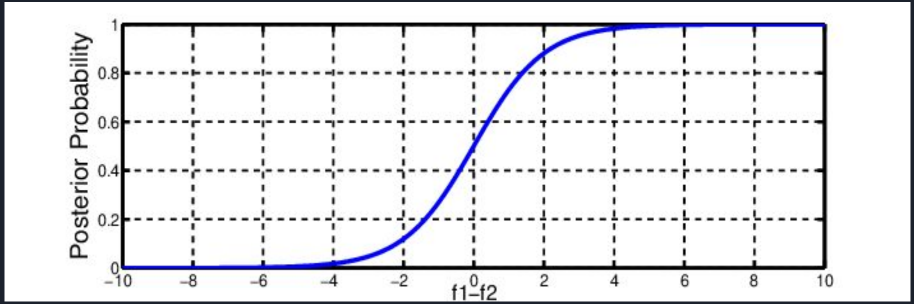


Fig-18: Output Block

- Flatten layer
- Dense layer
- Output layer
- Relu
- Softmax



Training

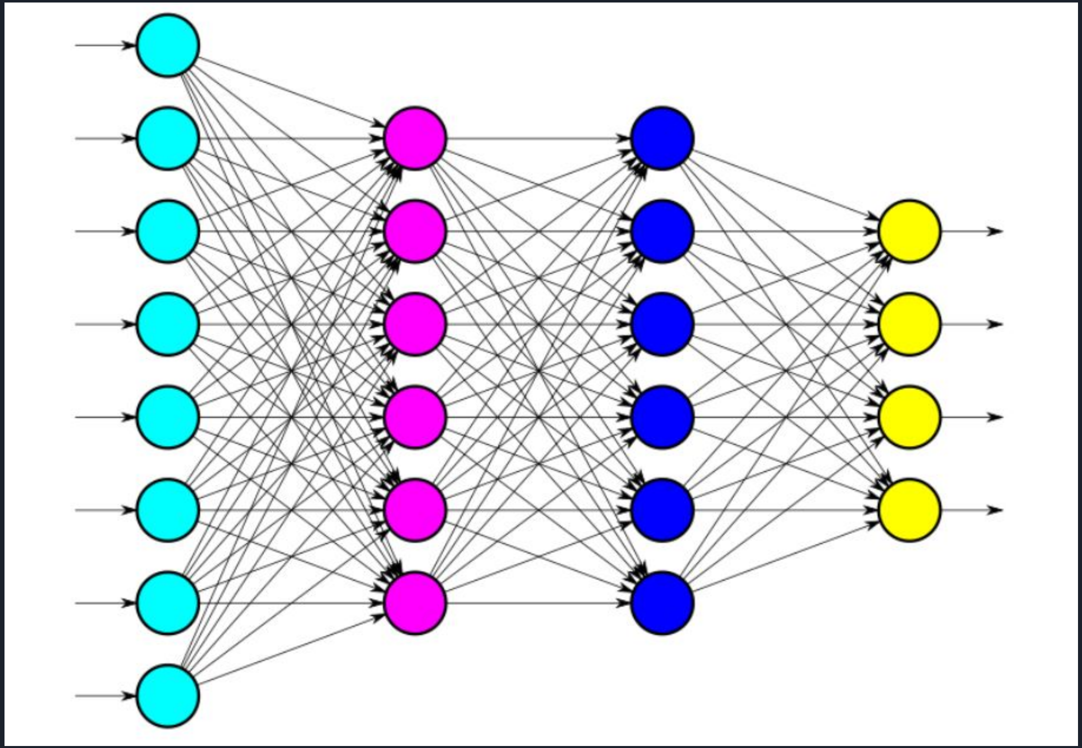


Fig-19: Training

- Adam optimizer
- Binary Cross entropy

Convolutional Neural Network

- 1 Input layer, 3 convolutional layer, 2 hidden layers and 1 output layer.
- Max-pooling layer to reduce computational cost and batch. normalisation layer for improving training and learning rate.
- Relu and Softmax as Activation functions.
- Adam as optimizer.
- No. of epochs = 30.

CNN + LSTM

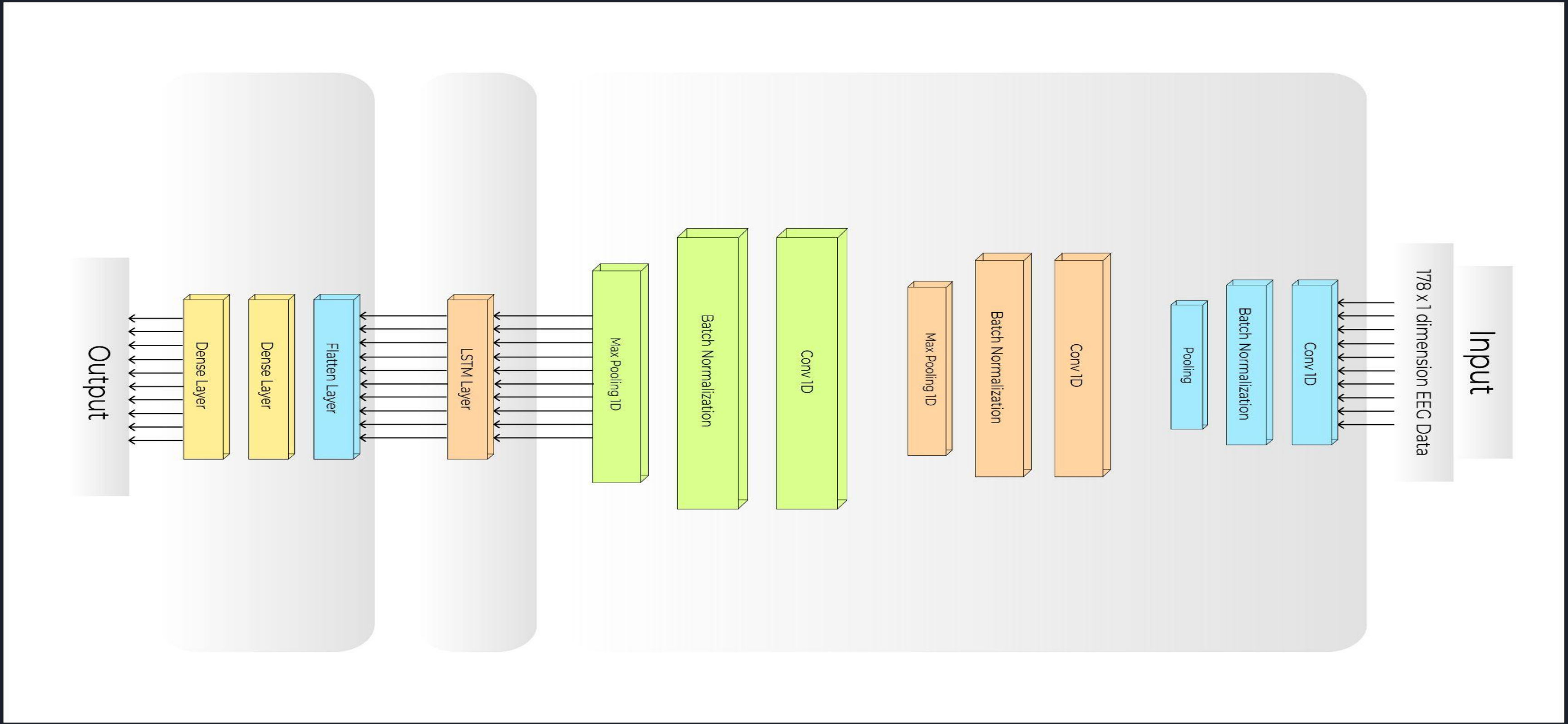


Fig-20: CNN + LSTM Architecture

RNN

RNN or Recurrent Neural Networks are basically neural networks that helps in finding the pattern in sequential data like time series data but it has certain shortcomings like vanishing gradient descent and short term memory.

LSTM

LSTM stands for long short-term memory networks,It's basically an extended form of RNN(Recurrent Neural Network) that overcomes the problems posed by RNN .It solves the problem of vanishing gradient and along with RNN it provides long term memory

The LSTM has three layers;

- input layer
- single hidden layer
- feedforward output layer

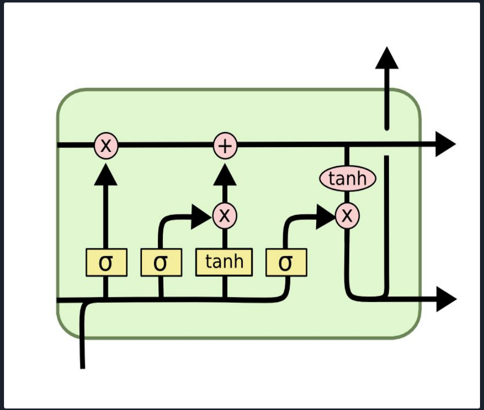


Fig-21: LSTM

RESULTS

Table-1: Accuracy Table of Different Models

Classes	Model	Data Balancing Type	Training Accuracy (%)	Testing Accuracy (%)
5	CNN	-	98.52	75.50
	CNN+LSTM	-	98.70	80.75
3	CNN	-	99.57	88.69
	CNN+LSTM	-	99.18	96.05
2	CNN	-	99.81	98.81
	CNN	Undersampling	99.73	97.39
	CNN	Oversampling	99.73	99.52
	CNN	SMOTE	99.92	99.31
	CNN	ADASYN	99.64	98.19
	CNN	Random Oversampler	99.73	99.38
	CNN	SVM SMOTE	99.63	99.29
	CNN	Borderline SMOTE	99.91	99.11

Final Accuracy

- Training Accuracy : 99.92 percent
- Validation Accuracy : 99.53 percent
- Testing Accuracy : 99.31 percent

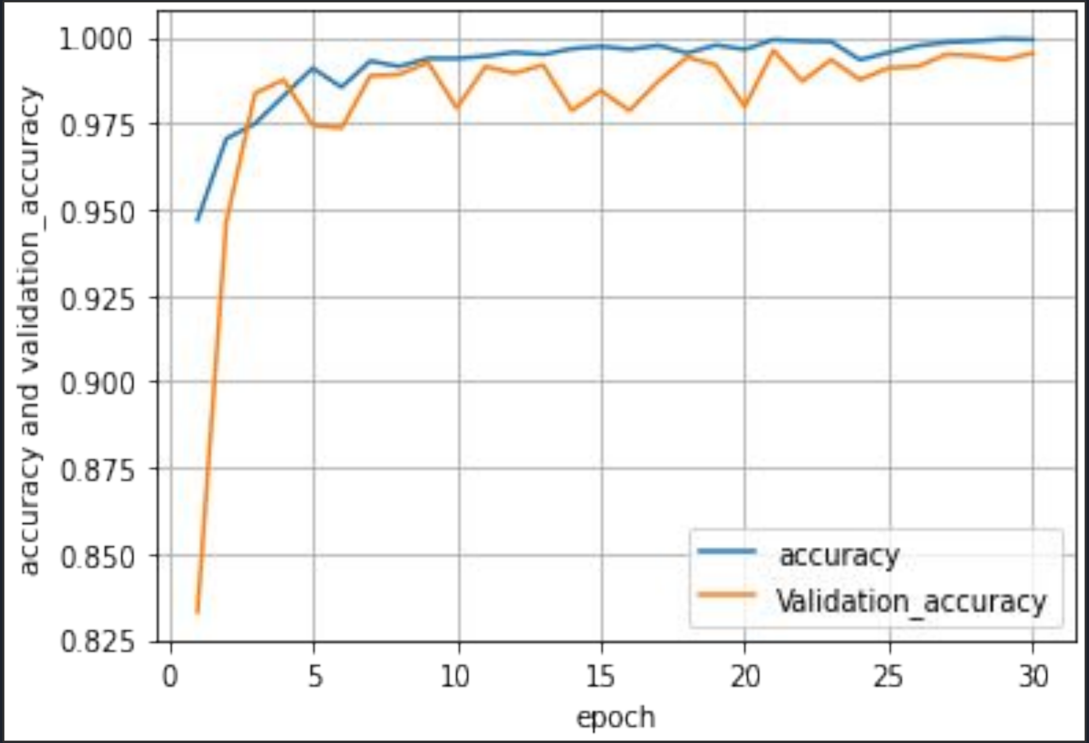


Fig-22: Training and Validation Accuracy

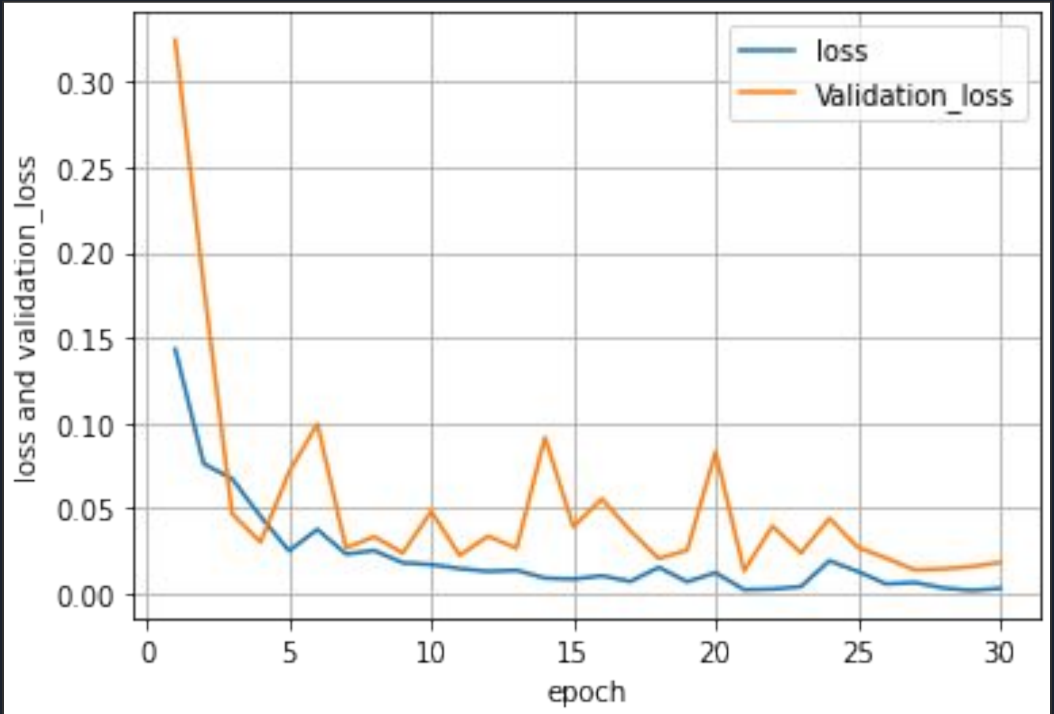


Fig-23: Training and validation loss

Table-2: Confusion Matrix

Binary Classification	Predicted Negative	Predicted Positive
Actual Negative	True Negative(TN)	False Positive(FP)
Actual Positive	False Negative(FN)	True Positive(TP)

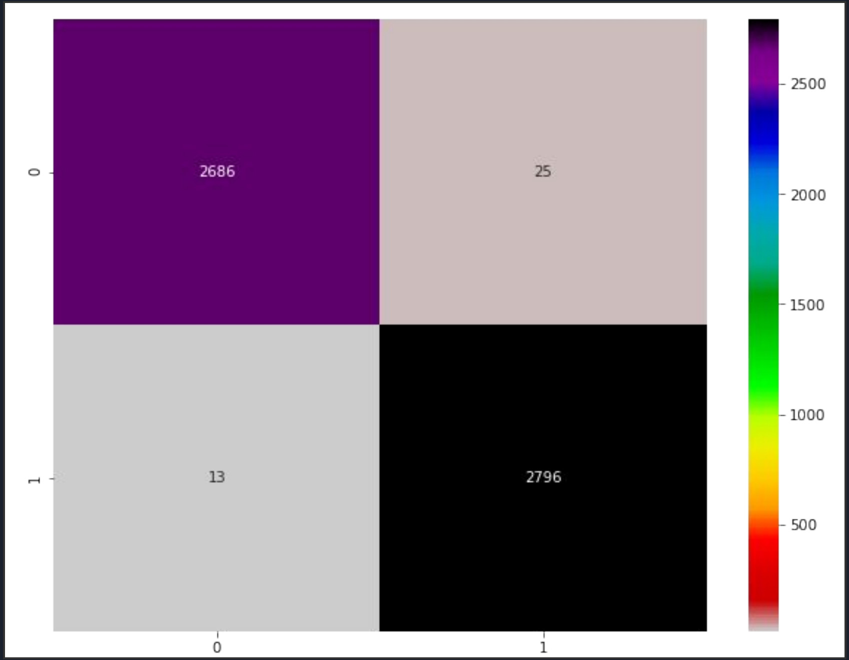


Fig-24: Confusion matrix

Conclusion

- Epilepsy remains incurable and there are measures taken to protect the patients from brain damage or physical injury in case of seizures.
- Traditional methods used earlier for detecting epilepsy were time consuming and sometimes inefficient but with the introduction of deep learning algorithms, detection is much more easier, accurate and faster.
- Deep learning methods allow the use of large datasets and improved detection accuracy than human counterparts.
- With 1-D CNN architecture, we got an accuracy of 99.31 percent for detecting epileptic seizure.

References

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2. Ullah, Ihsan, Muhammad Hussain, and Hatim Aboalsamh. "An automated system for epilepsy detection using EEG brain signals based on deep learning approach." Expert Systems with Applications 107 (2018): 61-71.
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5. Andrzejak, Ralph G., et al. "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state." Physical Review E 64.6 (2001): 061907.
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7. Mayo Foundation for Medical Education and Research (MFMER)
8. Harvard Health Publishing, Harvard Medical School

THANK YOU