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NANYANG TECHNOLOGICAL UNIVERSITY

SINGAPORE

CLASSIFICATION OF ELECTROGRAPHIC SEIZURES USING DEEP LEARNING APPROACH

KAUSHIK BHOWMIK

SCHOOL OF ELECTRICAL AND ELECTRONIC ENGINEERING

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Statement of Originality

I want to acknowledge that the work done in this dissertation is a consequence of work and research done by me and this work has not been provided to any other institute for the award of any degree.

Kaushik

05/09/2019 **Kaushik Bhowmik**

Supervisor Declaration Statement

I certify that I have checked the content of this dissertation which I supervised and acknowledge that it is free from plagiarism. I affirm that the work done for the completion of the dissertation is in a render with the ethical policies of Nanyang Technological University and the research finding presented in the dissertation are correct without any bias.

05/09/2019 **Assoc Prof Justin Dauwels**

Authorship Attribution Statement

I confirm that any material in this thesis is not from papers that are published in peer-reviewed journals or papers which are already accepted at conferences in which I am listed as an author.

Kaushik

05/09/2019 **Kaushik Bhowmik**

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Abstract

Seizures are referred to as a type of neurological disorder which is described as an unexpected, unvoluntary electrical disturbance in neurons of the brain cells resulting in the uncontrolled changes in the behavior, physical movements, feeling and consciousness level of patients. As neurologists classify seizures into two types which are electroclinical and EEG only seizures because for each type of seizure, the neurologists prescribe different kinds of medicines to the patients for their recovery and relief. And to make this classification between these two type of seizures, the neurologists have to go through the long EEG recordings of patients and even compare the EEG recording during the seizure event with the video of patient to make this classification which is very time consuming and even sometimes seizure events are of such low intensity that they can easily be missed by neurologists. These reasons motivated me to use the deep learning method to make this classification between these two types of seizures which will save a lot of time of neurologists.

In this project, I have used the Temple University Hospital dataset named (NEDC TUH EEG Seizure (v1.3.0)) and in this dataset, I have utilized the data from the folder “train_02”. The EEG recordings were made in the TCP montage (Temporal Central Parasagittal Bipolar Montage). Since it is the preferred way of viewing seizure data at Temple University Hospital. The EEG recordings at Temple University Hospital were recorded at different sampling frequencies 250Hz, 256Hz, 400Hz, 512Hz and for the uniform analysis I have resampled the data at 128Hz. In the (train_02) folder of the dataset, there are 126 seizures of the electroclinical type and 255 seizures of the EEG-only type. And then I have segmented each seizure into segments of 5 seconds duration, which resulted in a total of 88220 segments of the electroclinical type and 295960 segments of the EEG-only type and then after this for the balanced training. I randomly selected 88220 segments of data from 295960 segments. Then the seizures segments of the electroclinical and the EEG-Only type were then fed to the Deep Learning Convolutional Neural Network for the training of the network. The deep learning model consists of four 1-D convolutional layers, four

max-pooling layers, two dense layers and 1 flattening layer. The data is then split into training and test data in which 80% of data is used for training and 20% for testing. The model uses 3 fold analysis for better training of the model. The layers use “Relu” and “hard_sigmoid” as the activation function. In this model, I have used the ”Adam” optimizer and the performance of the model is monitored by the “Validation Accuracy”.

I have achieved an accuracy of 77.938% with this model and this is the first time that an attempt has been made by using the deep learning technique for doing the classification between electroclinical and EEG-Only seizures, which will save a lot of neurologist’s time which is consumed in doing this classification manually by comparing the EEG recording with the video of patient.

Acknowledgment

I am thankful to my supervisor Dr. Justin Dauwels, from the School of Electrical and Electronic Engineering at Nanyang Technological University for providing me this opportunity and guidance throughout the project. I would also like to express my gratitude to Dr. Yuvaraj Rajamanickam for patiently helping me throughout the whole project. With their support and guidance only I was able to complete the project successfully.

I am also thankful to my friends for their help which they provided me on clearing my doubts in the field of machine learning and deep learning because of which I could complete my project on time. As they always stood by my side to help me in all possible ways. Without their support and love, I could not have completed this thesis.

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Acronyms

TUH	Temple University Hospital
EEG	Electroencephalogram
TCP	Temporal Central Parasagittal Bipolar Montage
CNN	Convolutional Neural Network
ANN	Artificial Neural Network

Chapter 1

Introduction

This chapter describes information about the history of epilepsy, different types of seizures, the causes of seizures, EEG signal characteristics, complications due to seizures and different methods for diagnosis of seizures.

1.1 Epilepsy

Epilepsy is a neurological irregularity because of which the patient encounters unwanted seizures[4]. A seizure is a neurological disorder in which a patient encounters an unexpected increase of electrical activity in the neuron cells which can affect how a person appears or behaves during the time he encounters seizures[8].

The seizures in epilepsy can occur because of any of the multiple reasons among these some are like an injury in the brain or a parental history. But generally, the real cause is very hard to find and as a result of this, the real cause is still unknown.

Epilepsy patients can suffer from multiple seizure types and have multiple neurological problems also. After migraines, stroke and Alzheimer's disease, Epilepsy is observed as one of the most common neurological diseases.

According to Epilepsy Action Australia, worldwide more than 65 million people are suffering from epilepsy and 80% of the epileptic patients are belonging to developing nations[12]. Even in developed countries like the USA, every year 150,000 individuals are diagnosed with a kind of seizures.

Even, more than 20,000 Singaporeans are diagnosed with some kind of epileptic seizures.

1.2 Causes

The neuron brain cells are responsible for the creation, sending and receiving of electrical signals, during proper functioning of the brain's nerve cells but for some people due to their extra electrical activity in their brain neuron cells, this electrical signal transmission is disrupted which leads to the patient experiencing seizures.

The reason why anyone experiences seizure is due to the extra electrical activity in neurons due to which there is not a proper transmission of electrical signals between the neurons leading to seizures [4].

We know the electrical activity in the brain is a result of the complex changes in the chemical composition that occur in nerve cells. In normal conditions, this balance is maintained between cells that send the messages and the other neuron cells which stop these electrical signals which are referred to as messages. However, during seizures, either there is no or excessive electrical activity, causing a chemical imbalance between brain neuron cells which in turn leads to the chemical changes, which finally results in patients experiencing seizures.

1.3 EEG Signals

The EEG signals for an adult have an amplitude of around 10 µV to 100 µV and in the frequency range of 1-40Hz.

For Humans EEG signals arising from the chemical activity from brain cells are classified into four different bands

Delta(0.5 to 4Hz), Theta(4 to 8Hz), Alpha(8 to 13Hz) and Beta(13 to30Hz)[3].

The neurologists consider each band from the EEG signal important which gives information about a human’s physical condition.

As for the EEG signals which are in the time domain so to go for time-domain analysis is the most convenient option but if want to go for different analysis like frequency domain or time-frequency domain analysis[9]. Seizures mainly occur in the frequency range of 1-30Hz of EEG recordings.

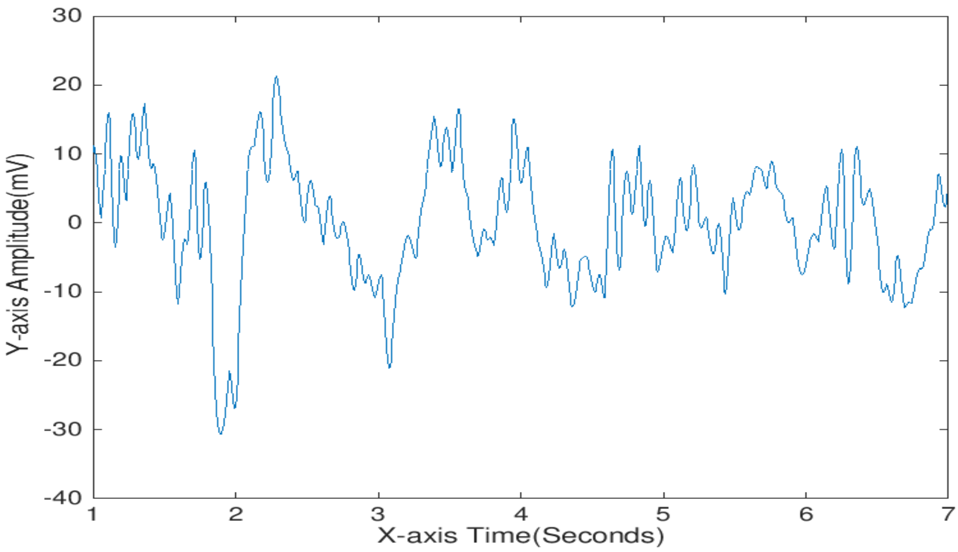


Figure 1.1: EEG Signal(Normal Case)

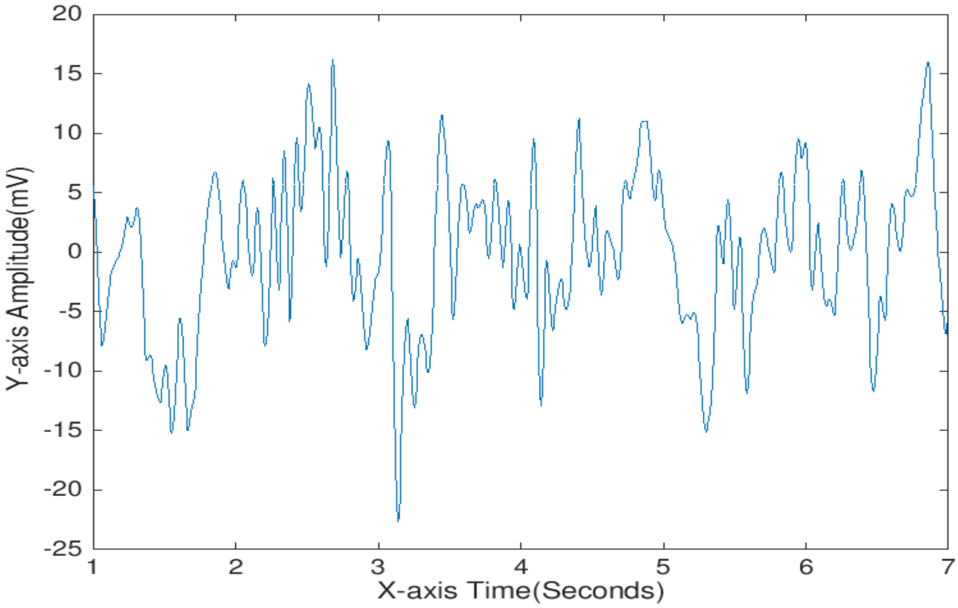


Figure1.2: EEG Signal Segment(During seizure)

1.4 Complications during seizures

As seizures are highly unpredictable this can create very dangerous circumstances which may be risky for the patients and also for others.

The most common risks are:

1. Falling, during seizures, patients have a very high chance of hurting their head or even hurting their different body parts.

2. Drowning, if the patient experiences seizures while in deep water then there is a very high chance of drowning if the patient is not accompanied by anyone.

3. Car accidents, during seizures, patients have no control over their physical or psychological actions which can be very threatening while the patient is driving a car or operating other equipment, this can pose danger to others also.

4. Pregnancy complications, if seizures occur during pregnancy can create a very risk for both the mother and the baby.

5. Emotional health issues, people suffering from the seizures are at a very high risk of having different types of psychological problems like depression and anxiety.

1.5 Epilepsy Diagnosis

Neurologist use different methods for the diagnosis of epilepsy which are:-

EEG Recording

This method is the most preferred and popular for testing of epilepsy diagnosis. This method requires the neurologist to place the sensors on the patient's head scalp so that to record the electrical activity in the brain. If doctors detect any abnormal activity in the EEG wave patterns, then there is a high chance that the patient is suffering from epilepsy.

Computerized tomography (CT) Scan.

In this method, doctors use X-rays to create images of the brain which helps the doctors to figure out the real cause of seizures among the other different causes of seizures, like tumors, bleeding, and cysts.

Magnetic Resonance Imaging (MRI).

This technique provides doctors with the opportunity to see the structure of the patient's brain. This method shows damaged tissue that leads to seizures.

Functional MRI (FMRI)

Functional MRI provides information about the part of the patient's brain which utilizes much more oxygen when the patient performs some basic tasks and based on these results doctors rule out the different areas which are not the cause of seizures origin in the patient's brain.

Magnetic resonance spectroscopy (MRS)

Being similar to MRI, MRS produces the image of the patient's brain which provides the doctor with the opportunity to compare how the various areas of brain function. In this type of MRI, the image of the whole brain is not shown at the same time which provides doctors with the opportunity to focus on a specific part of the brain which they want to analyze more.

Positron emission tomography (PET scan)

This test involves injecting radioactive material into the vein of the patient's arm which gets collected in the patient's brain. This collected radioactive material then provides the doctors with the opportunity for checking the damage by illustrating which parts of the patient's brain use how much of glucose from that we can come to know which part the brain is causing the extra electrical activity. The PET scan also provides information about the changes in the chemical state of the patient's brain and helps doctors to identify the problem.

Single-photon emission computerized tomography (SPECT)

This mentioned test helps to figure out the origin of seizures in the patient's brain. As in the PET scan, the doctor infuses a controlled amount of radioactive material in the vein of the patient. The doctor repeats this procedure when the patient is not experiencing any seizure and tries to conclude by analyzing the scans for both cases.

Neuropsychological tests

In this, the doctor will test the patient's vocal, thinking, and memory skills to conclude that which areas of the patient's brain are affected by seizures.

1.6 Different types of seizures

1. Focal seizures

These types of seizures occur because of the abnormal electrical activity from one part of the patient's brain. These seizures may or may not cause loss of alertness:

a. Focal seizures with impaired awareness, in this type of seizures, patients encounter a change or loss of awareness.

b. Focal seizures without loss of awareness, these types of seizures can cause a change in the patient's behaviour and consciousness. This type of seizures can lead to unwanted jerking of body parts.

2. Generalized seizures

These types of seizures involve all the areas of the brain.

The various types of generalized seizures are:

a. Absence seizures, Children mainly suffer from this type of seizure and this type of seizure is distinguished by gazing into space or by abrupt uncontrolled body movements like eye blinking or lip-smacking. These seizures may cause temporary loss of awareness.

b. Tonic seizures, these types of seizures primarily causes stiffening of the patient's muscles, in particular, the seizures affect muscles in the patient's back, arms and legs and which can eventually lead the patient to fall on the ground.

c. Atonic seizures, in these types of seizures, the patient suffers a loss of muscle control, resulting in sudden collapse or falling of the patient.

d. Clonic seizures, in these types of seizures, the patients suffer repeated jerking physical body part movements especially the neck, face, and arms.

e. Myoclonic seizures, in these seizures, the patient experiences sudden unwanted short term jerks and twitches in body parts.

f. Tonic-clonic seizures, in these seizures, the patient experiences a sudden loss of alertness, body hardening and shaking.

Chapter-2

Literature Review

Researchers for conducting their research on epileptic seizures for either detection, prediction or classification of seizures have used different methods which are based on the traditional recognition techniques, the morphological analysis, the template matching analysis, the parametric approaches, the independent component analysis, the artificial neural networks, the clustering techniques[4].

For all the different methods mentioned above, it involves calculating the features for the EEG signal segments and then performing various statistical tests that whether the set of features calculated for the EEG signal segments can discriminate between the classes required for the classification.

The commonly used features are peak frequency, maximum amplitude, entropy, skewness, kurtosis, Root mean square, Amplitude, Correlation dimension, mean amplitude, variance, morphological operators, non-linear energy operators, energy and power of EEG signals[5].

But for deep learning, the CNN method does not involve the calculation of any features of the EEG signal which is also an advantage for this method.

Here, I have used 1-D Convolutional Neural Network to classify between electroclinical and EEG-only seizure.

As 1D-CNN is very effective in extracting features from short (fixed length) segments from the overall signal.

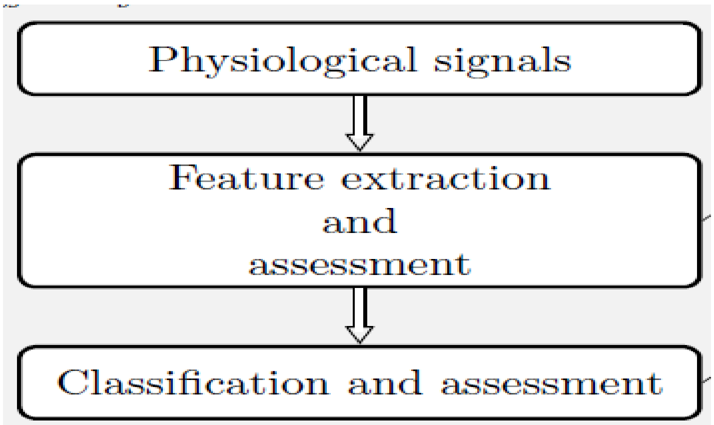


Figure 2.1: Machine Learning Methods

Chapter -3

Classification Problem

In this project, I made the classification of the electrographic seizures into the electroclinical and the EEG-only seizures.

I was interested to solve this classification problem because this classification till now is done by the neurologists manually which is a very time consuming and monotonous job to perform.

And even this process of doing the classification involves comparing the EEG reading and video of the patient. Even sometimes clinical manifestations are very minute which can be missed by the expert. And regarding the classification of electrographic seizure classification, the experts sometimes may have different opinions also[8].

Electrographic seizures can be classified into two types:

Electroclinical seizures

It is also called convulsive or clinically evident seizures from the medical literature, it is observed that this type of seizure can last for any duration.

EEG-only seizures

It is also referred to as Non-convulsive or sub-clinical seizures which are generally seen to occur for the duration of 10s or more.

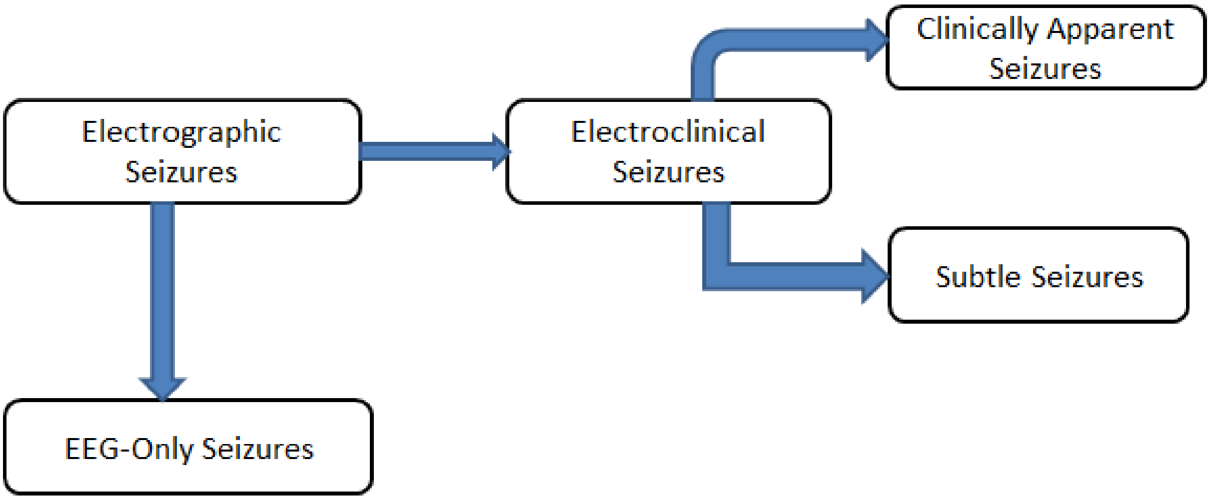


Figure 3.1: Classification Problem

Chapter-4

TUH Database

This chapter explains about the TUH dataset. The version of the TUH dataset used for the project, the seizure classification types and the seizure start time and the stop time of each EEG signal.

Here, I have utilized the TUH database version-“NEDC TUH EEG Seizure (v1.3.0)”. In the TUH database, hospital experts have divided the database into training and testing data. For the training and the testing of the deep learning model, I have utilized the “train_02.tar.gz”.The data in this folder was present in the European Data Format. The data in these files are recorded for different patients and different sessions.

The data was recorded in the TCP montage.

TUH in addition to the dataset has also provided the “seizures_v30r.xlsx” which mentions various information like file name, seizure start time, seizure stop time and seizure type.

For the classification problem in my project, I have classified the electroclinical and the EEG-only seizures.

The data in the TUH database is recorded in different sampling frequencies which are 250 Hz, 256 Hz, 400 Hz, 512 Hz and for the uniform analysis I have resampled the data at 128Hz.

There are 126 seizures of the electroclinical type and 255 seizures of the EEG-only type. And then I have segmented each seizure into segments of 5 seconds duration, there are a total of 88220 segments of the electroclinical type and 295960 segments of the EEG-only type and then for the balanced training I have randomly selected 88220 segments of data from 295960 segments, the seizures segments of both type will be fed to the Deep Learning Convolutional Neural Network for the training of network.

The TCP montage is the preferred way of viewing the seizures from EEG signals.

The channel configuration for the TCP montage is defined as follows:

montage = 0, FP1-F7: EEG FP1-REF -- EEG F7-REF

montage = 1, F7-T3: EEG F7-REF -- EEG T3-REF

montage = 2, T3-T5: EEG T3-REF -- EEG T5-REF

montage = 3, T5-O1: EEG T5-REF -- EEG O1-REF

montage = 4, FP2-F8: EEG FP2-REF -- EEG F8-REF

montage = 5, F8-T4 : EEG F8-REF -- EEG T4-REF

montage = 6, T4-T6: EEG T4-REF -- EEG T6-REF

montage = 7, T6-O2: EEG T6-REF -- EEG O2-REF

montage = 8, A1-T3: EEG A1-REF -- EEG T3-REF

montage = 9, T3-C3: EEG T3-REF -- EEG C3-REF

montage = 10, C3-CZ: EEG C3-REF -- EEG CZ-REF

montage = 11, CZ-C4: EEG CZ-REF -- EEG C4-REF

montage = 12, C4-T4: EEG C4-REF -- EEG T4-REF

montage = 13, T4-A2: EEG T4-REF -- EEG A2-REF

montage = 14, FP1-F3: EEG FP1-REF -- EEG F3-REF

montage = 15, F3-C3: EEG F3-REF -- EEG C3-REF

montage = 16, C3-P3: EEG C3-REF -- EEG P3-REF

montage = 17, P3-O1: EEG P3-REF -- EEG O1-REF

montage = 18, FP2-F4: EEG FP2-REF -- EEG F4-REF

montage = 19, F4-C4: EEG F4-REF -- EEG C4-REF

montage = 20, C4-P4: EEG C4-REF -- EEG P4-REF

montage = 21, P4-O2: EEG P4-REF -- EEG O2-REF

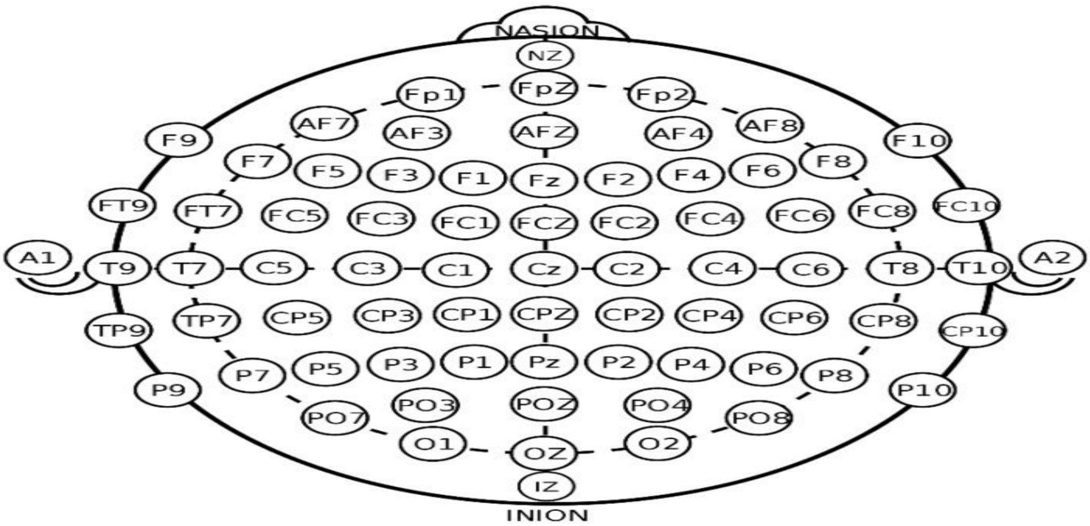


Figure 4.1: The 10-20 System [3]

Chapter-5

Preprocessing

This chapter provides information about the preprocessing steps which have been taken to preprocess the data before the EEG signal data is given to the deep learning model.

Steps involved in preprocessing.

1. Filtering

   A zero phase 4^{th} order Butterworth bandpass filter(IIR) between 1-30 Hz is employed.
2. Downsampling

   As the different EEG signals are sampled at different frequencies 250 Hz, 400 Hz, 256 Hz and 512 Hz. So, for uniform analysis, all the EEG signals are resampled to 128 Hz.
3. Montage: The TCP montage is employed since it is the preferred way of viewing the seizure data at TUH. The montage is defined as FP1-F7, F7-T3, T3-T5, T5-O1, FP2-F8, F8-T4, T4-T6, T6-O2, T3-C3, C3-CZ, CZ-C4, C4-T4, FP1-F3, F3-C3, C3-P3, P3-O1, FP2-F4, F4-C4, C4-P4, and P4-02.
4. Extraction of the seizure part from the EEG signals from the different channels.
5. Seizure segmentation involves dividing the EEG signals into segments of 5 seconds each, which will be utilized for the training of the deep learning model.
6. For balanced training, the number of segments from each class are made equal.
7. Cross fold validation analysis:

   Here, I have used the cross- fold analysis to perform the training of the model, so that effective training of the model is carried out.

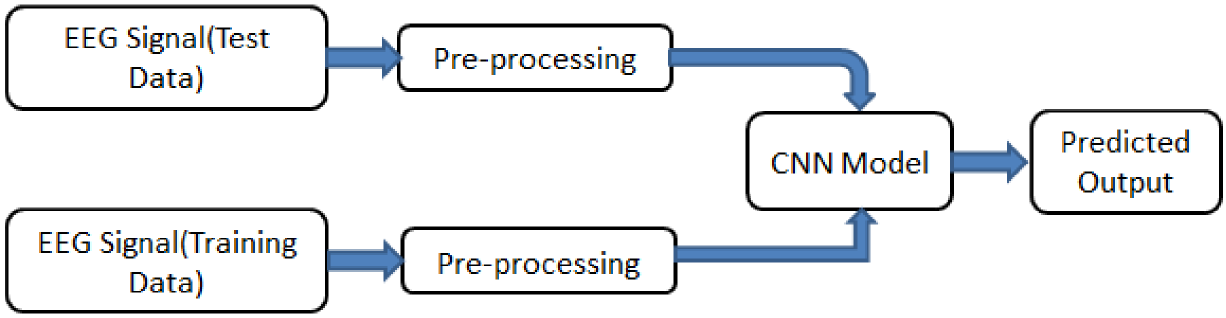


Figure 5.1: Working Methodology

Chapter-6

Deep Learning

This chapter describes the theoretical concept of deep learning, the architecture of the convolutional neural networks and the different parameters for judging the performance of the model.

Deep learning as compared to the other methods is a relatively newer method for the training of a multi-layer neural network. But this technique is popular because of producing good results with images and that is why this method is very popular and is used for handling various problems related to computer vision and taking inspiration from the good results it has produced to handle the problems in the research area of computer vision. I have used it for the classification of seizures in my project.

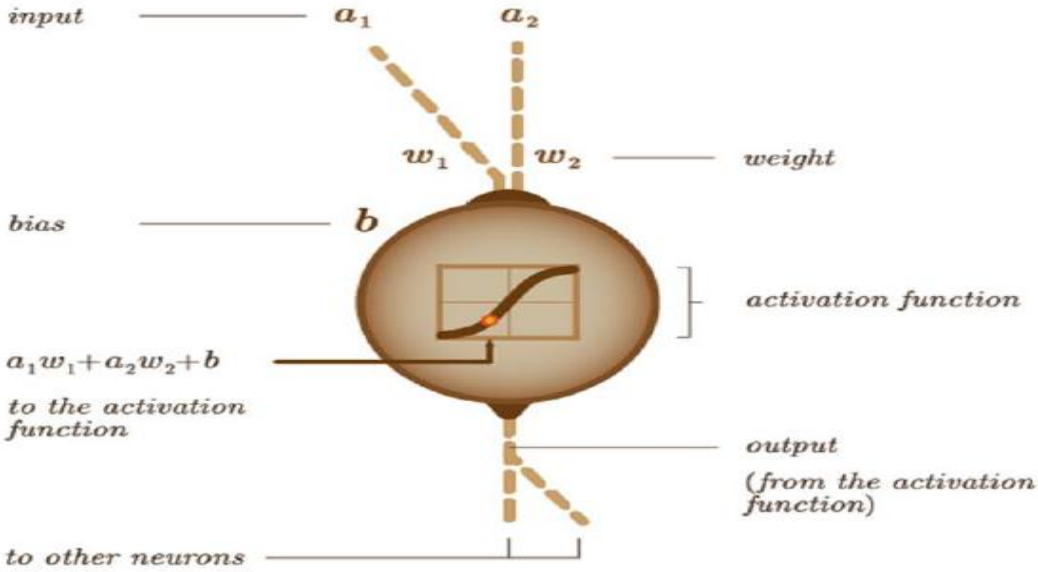


Figure 6.1: Neuron Structure[5]

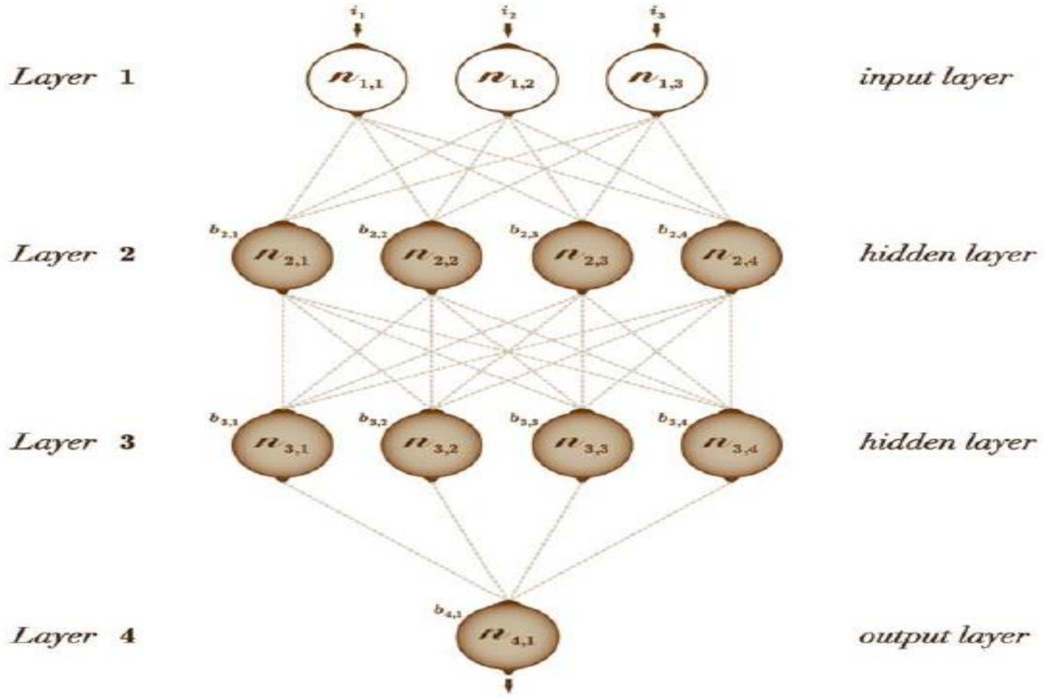


Figure 6.2: Traditional ANN[5]

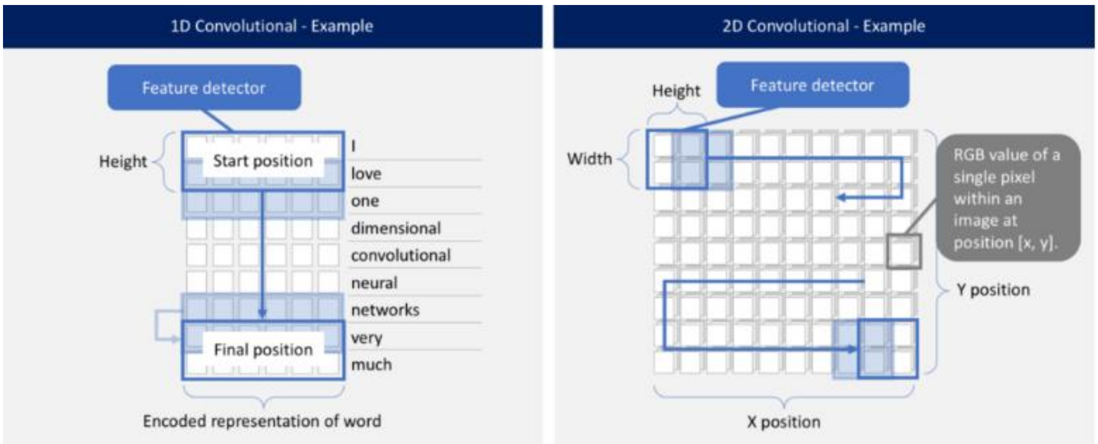


Figure 6.3: 1D and 2D CNN[13]

6.1 Convolutional Neural Networks

Convolutional Neural Network mimics the behavior of the brain’s visual cortex similarly like many neurons, which have a very small local receptive field. The convolutional neural network is popular because of its good performance in image recognition. Nowadays they are being used in a lot of fields like image search engines,self-driving cars, voice recognition, and many more fields.

CNN is a deep learning algorithm that is very popular because of its good performance in the field of image classification area. CNN uses kernel technique which involves relative space position relation which in turn reduces the number of training parameters thus increasing the performance and training speed.[1]

As CNN architecture has an input layer, convolutional layers, pooling layer, and fully connected layer.

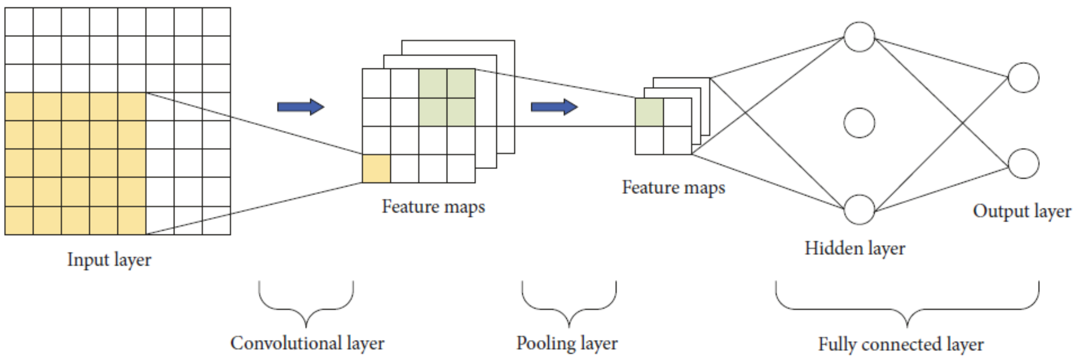


Figure 6.4: The CNN Architecture[6]

Filters

It is the way of representing the neuron's weight as a small image of the receptive field[5].

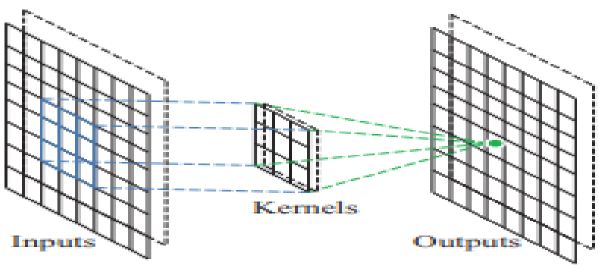


Figure 6.5: Kernel Operation[6]

Description of different layers-

Input layer

This layer receives the input data and then the data is transformed into a unified form so that the data can be delivered to the next layer[1].

Convolutional Layer

This layer processes data and this layer the weights for kernels are trained which in turn is required to increase the accuracy for the given data.

Sub-Sample Pooling

This layer helps in reducing the number of training parameters and more importantly it helps in preventing overfitting of the network.

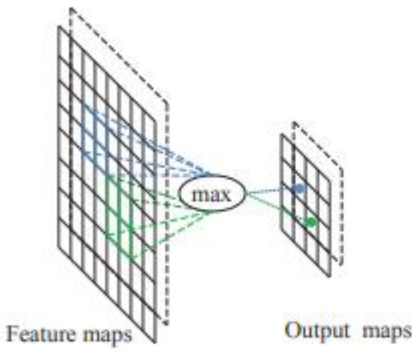


Figure 6.6: Pooling Operation[6]

Fully Connected Layer

In this layer, all the neurons in the current layers are connected to the neurons of the earlier layer, as data progresses through the different layers of the model, the size corresponding to the output feature map keeps on decreasing. And at the classification layer, every feature vector comprises only one neuron cells which later on becomes a 1-D feature vector[2].

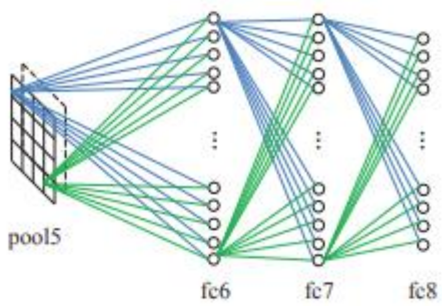


Figure 6.7: Fully Connected Layer Operation[6]

Different Optimization functions

Gradient Descent

Gradient descent, which is considered as the generic optimization algorithm is being used to optimize a function by progressively moving in the direction of the steepest gradient. It is defined by the negative slope for finding the most optimal solutions to a cost function. The basic idea for Gradient Descent is to vary the parameters iteratively so that to minimize the cost function.

In machine learning, this technique is used very commonly to update the parameters of the model for optimizing the cost function.

The size of the steps is a very important parameter in Gradient Descent which is determined by the learning rate hyper-parameter. If the learning rate is kept very small, this will take the algorithm to go through a lot of iterations to converge to the optimal solution for the optimization function, which will take a long time.

On the other hand, if the learning rate is very large, this may cause the algorithm to diverge away from the optimal solution for the optimization problem with larger and larger values, thus failing to find an optimal solution.

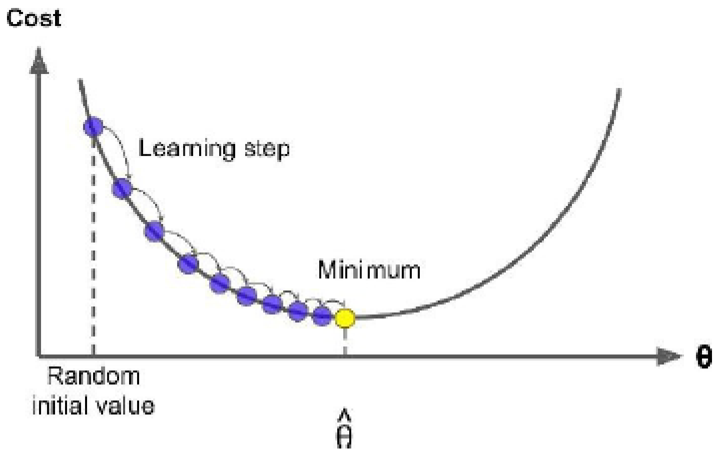


Figure 6.8: Gradient Descent Working[14]

Momentum Optimization

This method is proposed by Boris Polyak in 1964.

In contrast to regular Gradient Descent which simply takes small regular steps down the slope, Momentum Optimization takes much more time to reach the optimum solution.

Nesterov Accelerated Gradient

One small variant to Momentum optimization, proposed by Yuri Nesterov in 1983, is always faster than vanilla Momentum optimization. The idea of Nesterov Momentum optimization, or Nesterov Accelerated Gradient (NAG), is to measure the gradient of the cost function not at the local position but slightly ahead in the direction of the momentum.
This small tweak works because in general the momentum vector will be pointing in the right direction, so it will be slightly more accurate to use the gradient measured a bit farther in that direction rather than using the gradient at the original position, the Nesterov update ends up slightly closer to the optimum. After a while, these small improvements add up and NAG ends up being significantly faster than the regular momentum optimization. NAG always speeds up training compared to regular Momentum optimization.

AdaGrad

The AdaGrad algorithm achieves the optimum solution by scaling down the gradient vector along the steepest dimensions. This optimization utilizes an adaptive learning rate which helps it in updating the solution more directly toward the global optimum. The benefit is that it requires much less tuning of the learning rate.

RMSProp

As AdaGrad slows down a bit too fast and ends up never converging to the global optimum, the RMSProp algorithm removes this demerit by accumulating only the gradients from the most recent iterations as opposed to all the gradients since the beginning of training. It does so by using exponential decay.

Adam Optimization

Adam Optimization, which includes the ideas of momentum optimization and RMSProp just like momentum optimization it, keeps a record of an exponentially decaying mean of the earlier gradients, and just like RMSProp, it keeps a record of an exponentially decaying average of the past squared gradients.

Dropout Layer

It is considered as the most popular regularization technique for the deep neural networks which was proposed by G. E. Hinton in 2012. The concept of dropout layer is very simple that during each training step, each neuron (including the input neurons but excluding the output neurons) has a chance of being "dropped out" which means it will be completely ignored during this training step, but it may or may not be active during the next step. The dropout rate is generally set to 50%. The neurons are not considered for dropping after the training.

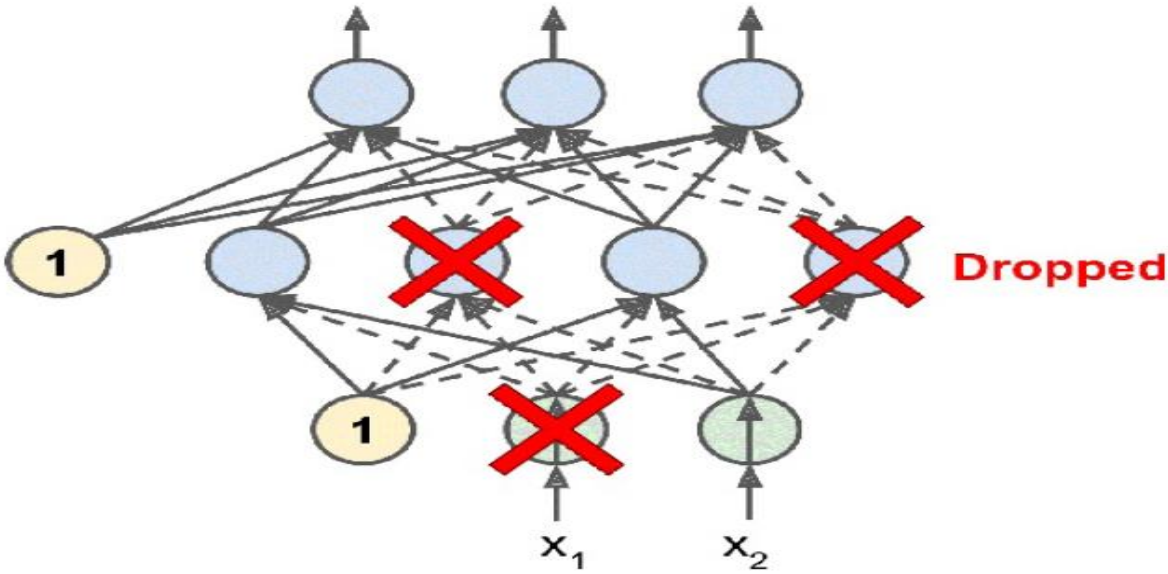


Figure 6.9: Dropout Layer[15]

Early Stopping Criteria

To avoid over-fitting of the training set, it would be best to satisfy the early stopping for a good solution which involves just interrupting the training when the model's performance on the validation set starts dropping.
This technique has always been used by various researchers during training the model as their stopping criteria.

Different Activation Functions

1. Sigmoid or Logistic

   This activation function can be mathematically be represented as

   f(x) = 1 / 1 + exp(-x) .

   The Range of this function lies between 0 and 1.

   This activation function leads to an S-shaped curve.

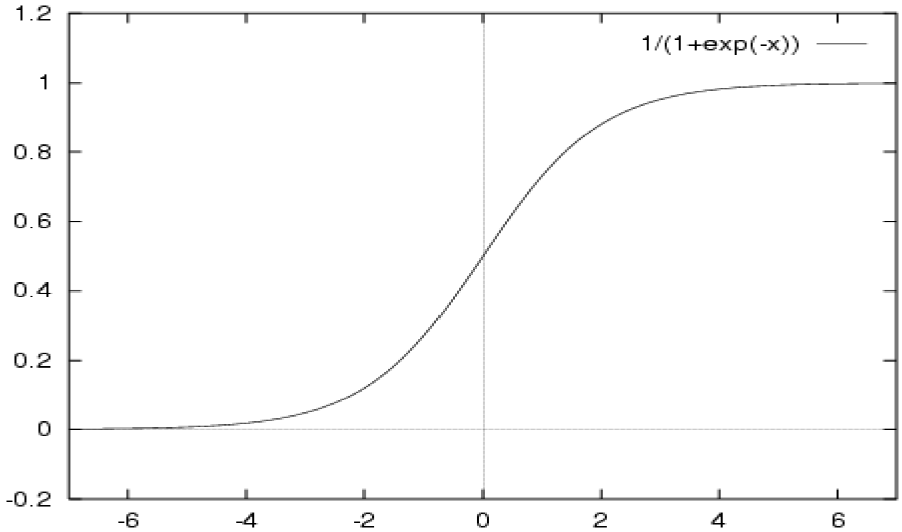


Figure 6.10: Sigmoid Activation Function

2. Tanh-Hyperbolic tangent

This activation function can be mathematically be represented as f(x) = 1-exp(-2x) / 1 + exp(-2x). The output of this mathematical function is zero centered because the range of this function is between -1 and 1. Optimization using this activation function is easier because of this reason, this activation function is preferred by the researchers over the sigmoid activation function. But even then this has some limitation which is called a vanishing gradient problem.

3. ReLu -Rectified linear units

This activation function is the most preferred by the researchers in the past couple of years because recently researchers from the community showed that this activation function converges six times faster as compared to the Tanh function.

It can be represented mathematically as.

R(x) = max(0,x) if x < 0

R(x) = 0 and if x >= 0 ,

R(x) = x.

4). Linear Function:-

The Linear activation function has the equation very similar to that of a straight line y = ax.

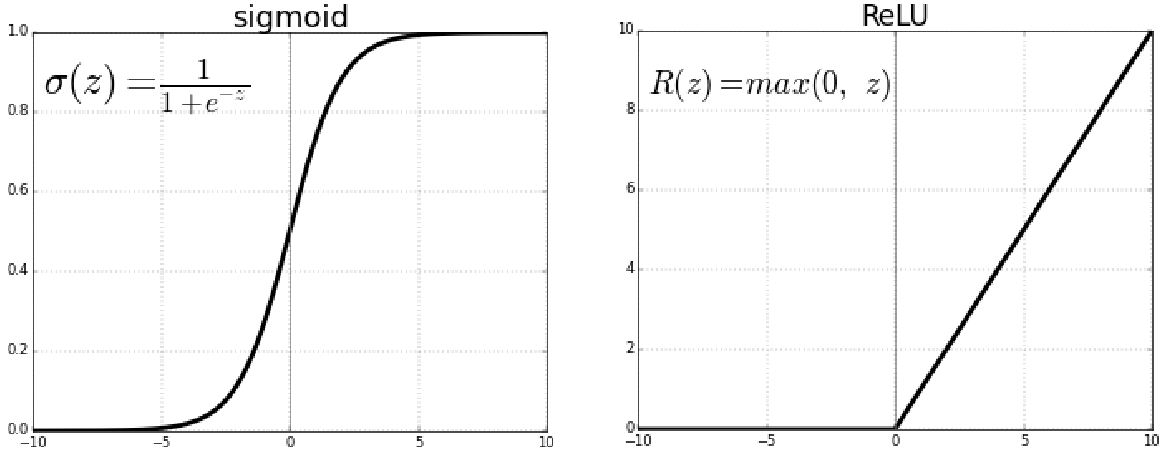


Figure 6.11: Sigmoid And ReLU Activation Function

5. Leaky ReLU

This activation function was developed by the researchers to solve the dying ReLU problem. The leak helps in providing an increase in the range for the ReLU activation function.

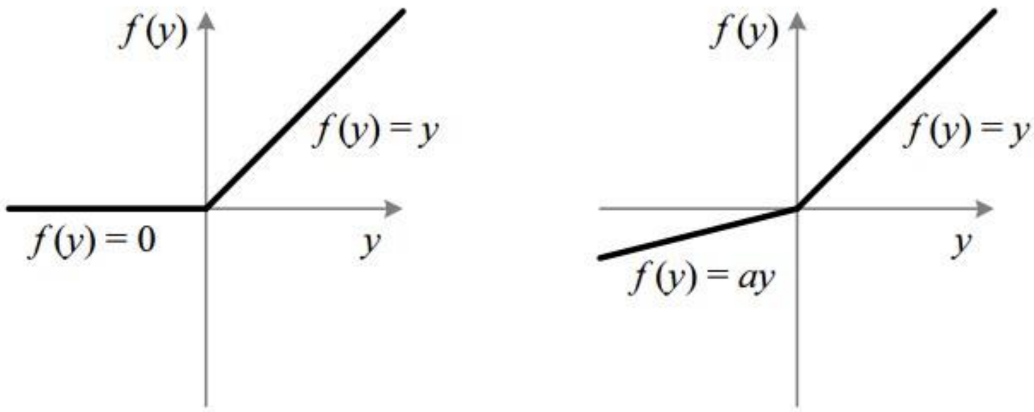


Figure 6.12: ReLU v/s Leaky ReLU

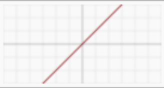
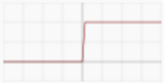
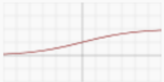
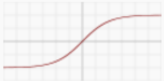
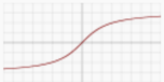
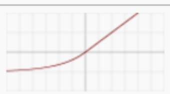
Name	Plot	Equation	Derivative
Identity		$f(x) = x$	$f'(x) = 1$
Binary step		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x \neq 0 \\ ? & \text{for } x = 0 \end{cases}$
Logistic (a.k.a Soft step)		$f(x) = \frac{1}{1+e^{-x}}$	$f'(x) = f(x)(1 - f(x))$
TanH		$f(x) = \tanh(x) = \frac{2}{1+e^{-2x}} - 1$	$f'(x) = 1 - f(x)^2$
ArcTan		$f(x) = \tan^{-1}(x)$	$f'(x) = \frac{1}{x^2+1}$
Rectified Linear Unit (ReLU)		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
Parameteric Rectified Linear Unit (PReLU) [2]		$f(x) = \begin{cases} \alpha x & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} \alpha & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
Exponential Linear Unit (ELU) [3]		$f(x) = \begin{cases} \alpha(e^x - 1) & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} f(x) + \alpha & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
SoftPlus		$f(x) = \log_e(1 + e^x)$	$f'(x) = \frac{1}{1+e^{-x}}$

Figure 6.13: The tabular form of popular activation functions

Different performance parameters

Confusion Matrix

For evaluating the performance of a classifier Confusion matrix is the best way to judge the performance of a classifier. The main aim behind calculating the confusion matrix is that it gives information about the number of times instances of one class has been predicted as the other class by the model.

To calculate the confusion matrix, it is required to first have a set of predictions so as they can be compared to the actual targets.

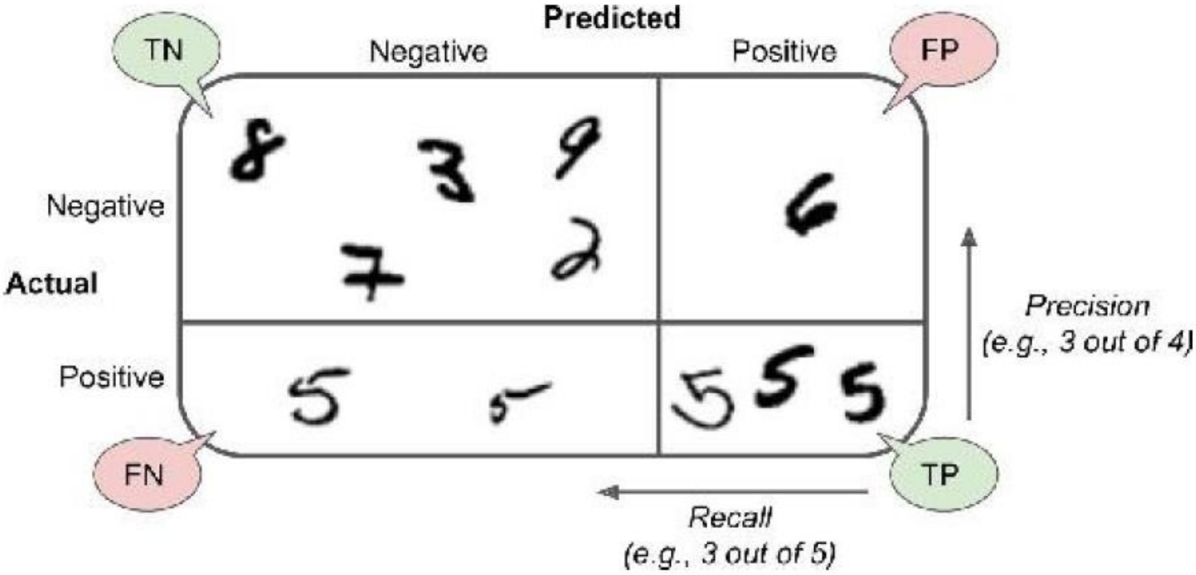


Figure 6.14: Classification Matrix[15]

The parameters which are calculated to judge the performance of a classifier are

Precision

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

TP is the number of instances, which are considered true positives and FP is the number of instances, which are considered false positives.

Recall

It is also referred to as sensitivity or true positive rate (TPR). It is defined as the ratio of positive instances that are correctly detected by the classifier.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

FN represents the number of instances that are considered False Negatives.

F1 Score

It is also another parameter to judge the performance of a classifier which includes combining both precision and recall into one performance parameter.

The F1 score is defined as the harmonic mean of precision and recall. As the regular mean gives equal emphasis to all values, the harmonic mean provides higher weight to the low values. Due to this, the classifier produces only a high F1 score only when precision and recall both of them have high values.

$F_1 = 2 * (\text{precission} * \text{recall})/(\text{precission} + \text{recall})$

It favors classifiers that have similar precision and recall.

The most important thing to take care of is that increasing precision reduces recall, and vice versa which is called the precision/recall trade-off.

Specificity

The specificity of a model is defined as

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

In this classification problem, if the electroclinical seizure is classified as True class and EEG-Only seizures are classified as False Class then TN represents EEG-Only seizures instances wrongly classified as an electroclinical seizure. TP represents electroclinical seizure instances classified as electroclinical only FN represents EEG-Only seizures instances wrongly classified as electroclinical seizures FP represents electroclinical seizure instances wrongly classified as EEG-Only seizures.

Chapter-7

Model And Results

The model consists of four 1-D Convolutional layers, four Maxpooling layers, two dense layers, and one flattening layer.

The data for each class is labeled manually.

The whole data is split into 80% training data and 20% testing data and after that 3 fold analysis method is used for better utilization and training of the deep learning model.

The model utilizes the batch size of 20000 samples with epochs equal to 150 and in the model validation accuracy is chosen as the stopping criteria with the patience of 10 iterations in each fold during training and “Adam ” optimizer is chosen as the optimization function for the model.

After this CNN model is provided with the testing data and corresponding to that the model makes a prediction and corresponding to that confusion Matrix and other parameters for evaluating model performance is calculated.

The 1-D Convolutional Neural Network is giving the classification accuracy of 77.938% and the value of recall is 0.80266. The precision value is 0.5148. The F1-Score is 0.6269. The specificity value is 0.255.

S.No.	Parameters	Value
1.	Classification Accuracy	77.938%
2	Recall	0.80266
3.	Precision	0.5148
4.	F1-Score	0.6269
5.	Specificity	0.255

Table 1- Model Performance Parameters

The Classification Matrix is given by $\begin{bmatrix} 4309 & 13364 \\ 3476 & 14139 \end{bmatrix}$

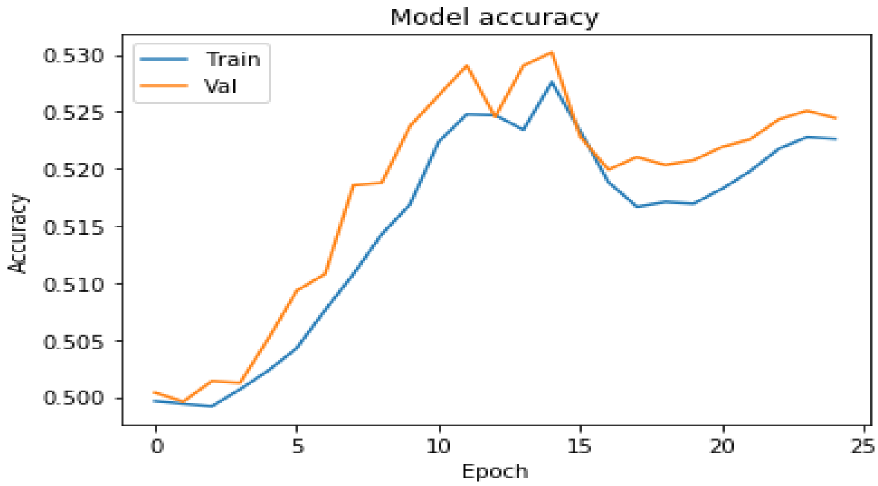


Figure 7.1: Model Accuracy in Fold-1

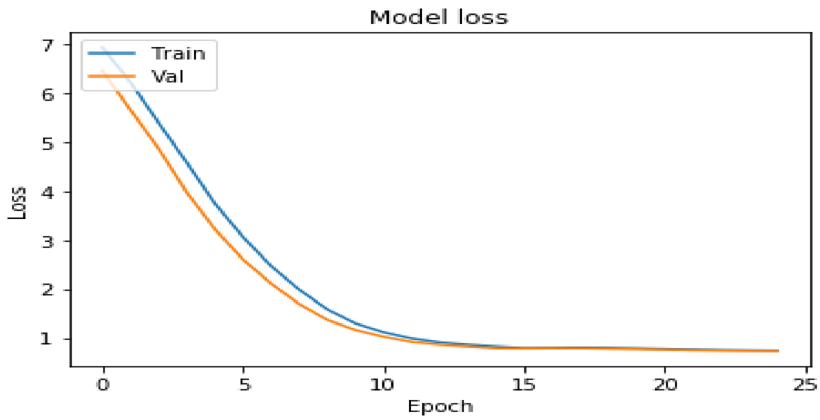


Figure 7.2: Model Loss in Fold-1

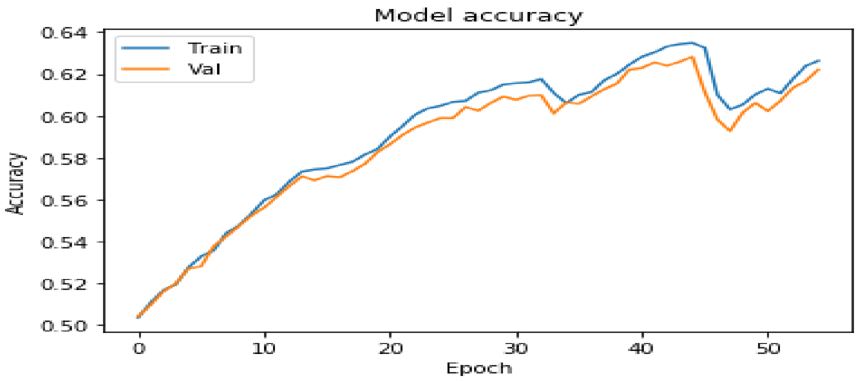


Figure 7.3: Model Accuracy in Fold-2

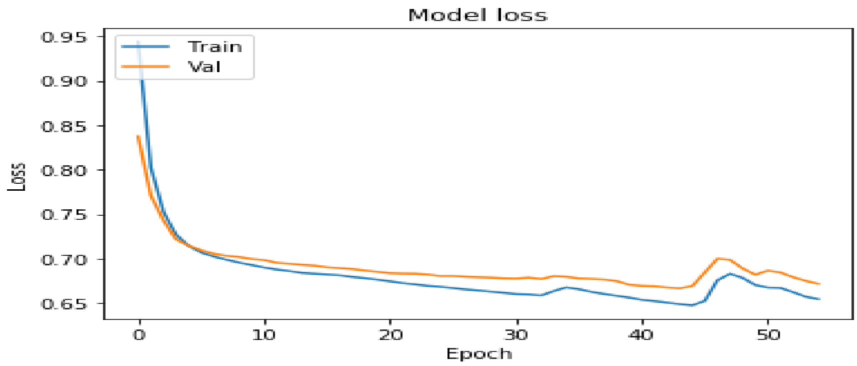


Figure 7.4: Model Loss in Fold -2

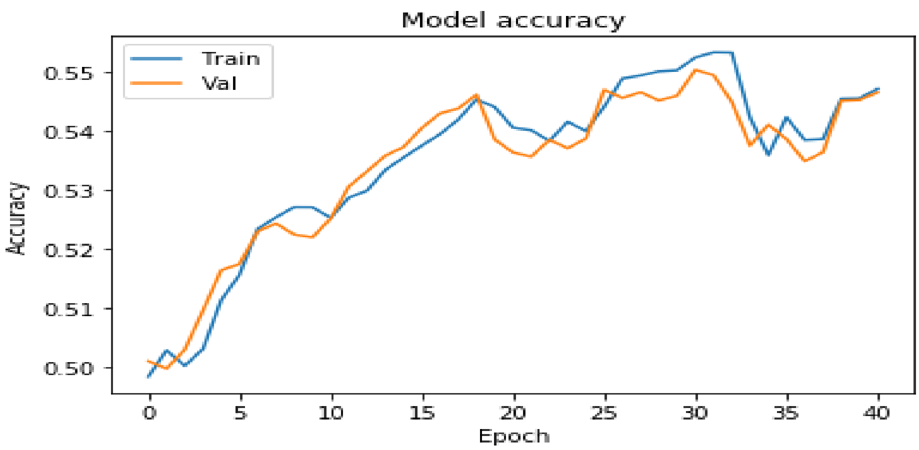


Figure7.5: Model Accuracy in Fold-3

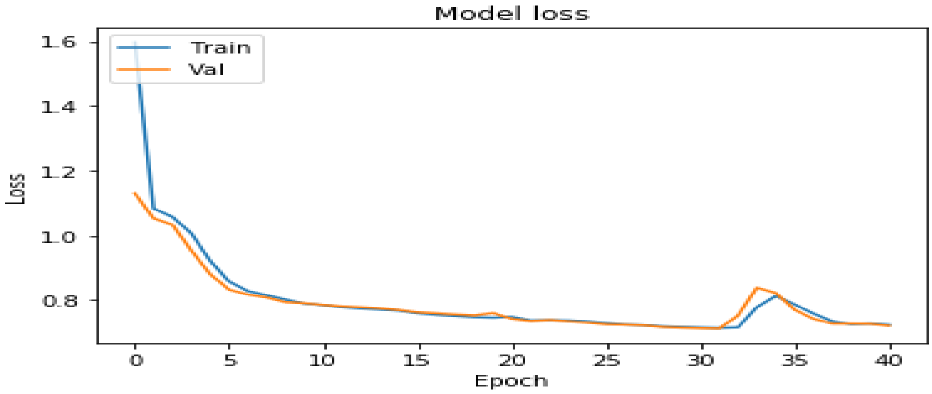


Figure 7.6: Model Loss in Fold-3

Chapter-8

Conclusion

I have used the deep learning 1-D Convolutional Neural Networks for making the classification between the electroclinical and the EEG-Only seizures. I have achieved a classification accuracy of 77.938% and this is the first time that the deep learning technique has been used for doing this classification between the electrographic seizures and the EEG-Only seizures. This model can save a lot of time for the physicians, as for this classification the doctors are required to compare the long EEG-recordings of the patient with the video of the patient which is very time-consuming.

And I believe that the deep learning technique is a much better way for doing this classification as compared to the tradition machine learning methods because the traditional machine learning methods involves calculation of the different sets of features for the EEG signal segments and then conducting various statistical tests on different features calculated to check whether the features are able to make the classification or not. But for the deep learning classification method, we are not required to calculate any kind of features.

The limitations of the model are that during the training of the model the whole TUH dataset was not utilized. For better training of the model, better techniques can be tried like 2-D and 3-D Convolutional Neural Networks. Also, better artifacts management techniques should be used which can handle the noises caused by various reasons like loose electrodes, body movements etc.

Chapter-9

Future Work

The future work in this aspect would be to train the model on a much bigger and diverse dataset so that the model can generalize well to the testing data. Secondly, we can use better techniques for the removal of noises from EEG signals which will also take into account the various noises like loose electrode placement, body movements. Lastly, we can use better techniques like 2-D and 3-D Convolutional Neural Networks for getting better results.

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