Prediction of Epileptic Seizure Based on Deep Learning Methods

by

Sazzad Mahmud Tusher
16301091
Israth Jahan Nafi
17101263
Iffat Immami Trisha
16101097
Minhajul Abrar Faisal
16301196
Alimul Hasan Jami
17201150

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Declaration

It is hereby declared that

1. The thesis submitted is our own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

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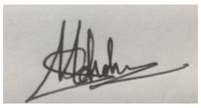
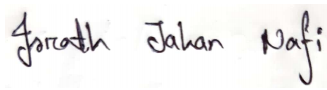
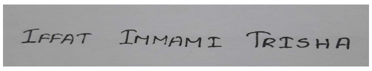
Student's Full Name & Signature:



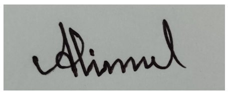
Sazzad Mahmud Tusher
16301091



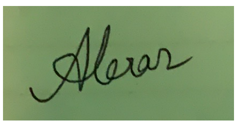
Israth Jahan Nafi
17101263



Iffat Immami Trisha
16101097



Alimul Hasan Jami
17201150



Minhajul Abrar Faisal
16301196

Approval

The thesis titled "Sentiment Analysis on Mobile Operators' Customer Review" submitted by

1. Sazzad Mahmud Tusher (16301091)
2. Israth Jahan Nafi (17101263)
3. Iffat Immami Trisha (16101097)
4. Minhajul Abrar Faisal (16301196)
5. Alimul Hasan Jami (17201150)

Of Summer, 2020 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of B.Sc. in Computer Science and Engineering on October 9, 2020.

Examining Committee:

Supervisor:
(Member)

Zavid Parvez

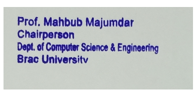
Digitally signed by Zavid Parvez
DN: cn=Zavid Parvez, o=Brac University, ou=CSE, email=zavid.parvez@bracu.ac.bd, c=US
Date: 2020.10.16 12:16:30 +06'00'

Dr. Mohammad Zavid Parvez
Assistant Professor
Department of Computer Science and Engineering
Brac University

Program Coordinator:
(Member)

Dr. Md. Golam Robiul Alam
Associate Professor
Department of Computer Science and Engineering
Brac University

Head of Department:
(Chair)



Mahbub Alam Majumdar
Professor and Dean
Department of Computer Science and Engineering
Brac University

Abstract

An epileptic seizure is a period when there is a rapid burst of intense electrical activity in the brain of a person. A person's behavior or movement might be change because of epileptic seizure attack. Patients may face different types of seizure. Different seizure attacks occur from different parts of brain. In many cases, seizure attack duration might be 30 seconds to less than two minutes. If a seizure attack cross the 5 minutes time duration then it will be a medical emergency case. Different circumstances can be the cause of seizure attack. The after effect of stroke can be a seizure attack. Severe head injury can be a cause of seizure attack. Any type of infection like as meningitis can be a cause for seizure attack. The specific facts that cause seizure are difficult to identify. Epileptic seizure can cause long lasting effect on human body like as hypertension, sleeping disorder etc.Prediction of epileptic seizure at the very early age can save an epileptic patient from these problems.In this research work,we proposed an epileptic seizure prediction method. In the model we proposed, we used Deep Learning model to predict epileptic seizure.We used Convolutional Neural Network(CNN),which is a section of deep neural network. Here Convolutional Neural Network is used for analysis the EEG signals. There are different phases of seizures. They are preictal, ictal, interictal. The seizures are sudden and unpredictable in nature. This is one of the most concerning aspects of epileptic seizure. The extraction of feature method and classifier using techniques are very much time consuming for classify ictal and interictal EEG signals. Deep learning can extract the features. In the dataset, there are epileptic EEG signals. The results from the procedures illustrate that proposed model can provide better performance over existing methods. Deep learning method used to make the model more time convenient.

Keywords: Epileptic seizure, EEG signals, Convolutional Neural Network, Deep Learning, preictal, ictal, interictal.

Dedication

We are grateful to our parents for their countless sacrifices and utmost care. Without their guidance and prays we would have been lost. This book is dedicated in a heartfelt way to our parents, who deserve all the respect and honour for any of our success in life.

Acknowledgement

First of all, we are thanking almighty Allah for enabling us to complete our thesis. After that, we want to express our deepest love and respect to our supervisor Dr. Mohammad Zavid Parvez for introducing us with deep learning. Without his constant support and direction, it was quite impossible to complete our thesis on time. His excellent supervision made our work easier. At the same time, we would like to thank the department of computer science and engineering of BRAC University for providing us with an excellent thesis lab where we got high configuration computer that accelerated our progress of thesis work. Moreover, we are grateful to our parents for providing their effort in every single day. Without their care and support, we would not able to complete this. Finally, we are expressing our thanks to our friends for sharing knowledge with us. They made it easy to learn different algorithms and visualize our work more clearly.

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Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

AI Artificial Intelligence

ANN Artificial Neural Network

CNN K-Nearest Neighbors

DL Deep Learning

EEG Electroencephalogram

ML Machine Learning

NLP Natural Language Processing

NN Neural Network

$ReLu$ Rectified Linear Unit

RNN Recurrent Neural Network

SNR Signal to Noise Ratio

SVM Support Vector Machine

Chapter 1

Introduction

A seizure is commonly known as epileptic seizure. Epileptic seizures occur because of excessive abnormal brain neuron activity. The after effects of epileptic seizure attack may vary from person to person. Some people may face shaking in the body. Some may fell unconscious. This is known as tonic-clonic seizure. Some may face memory loss for a time period. This is known as absence seizure. In many cases of epileptic seizure, the seizure attack duration is not more than two minutes. To come back to normal life, it takes some time.Seizures may be provoked and unprovoked. Less amount of sugar in blood, less portion ofsodium in blood, fever, infection in brain may hinder for provoked seizures. People may face unprovoked seizures without any known cause. Irregular sleeping disorder, high stress may hinder unprovoked seizures. Acute brain diseases and previous seizure attack may hinder epilepsy. 10 people among 100 face at least one epileptic seizure attack. In a year, 3.5 per 10000 people face provoked seizure attack. Moreover 4.2 per 10000 people face unprovoked seizure attack in a year. About 50Genetic influence.
Head trauma.
Brain conditions.
Infectious diseases.
Prenatal injury.
Developmental disorders.

Risk Factors:
Certain factors may increase your risk of epilepsy:
• Age.
• Familyhistory.
• Headinjuries.
• Stroke and other vasculardiseases.
• Dementia.
• Brain infections
• Seizures in childhood

In past cases, different algorithms of detection method for epileptic form EEG data had proposed [1]. Some epileptic seizure detection model used hand-engineered methods to execute feature extraction. Like as, time-frequency domain, non-linear signal analysis and so on [1]. They proposed that, after extraction of features, the features send to classifier for classification process, this helps to detect different

EEG signals [2] . In other paper they used the discrete wavelet method for feature extraction and after that trained in support vector machine [3] showing that SVM approach can detect epilepsy and further diagnosis [1]. Intheotherpapertheyshowed-hybridmodelto improve the SVM parameters based on genetic algorithm and optimization ofparticle swarm, showing that the proposed model is an efficient tool for neuron scientists for detection of epileptic seizures using EEG [3].]. These methods do not dismiss the necessity of manual feature selection [1]. We proposed a model where complex feature extraction is not required to perform classification. Deep Learning plays an important role in this model. We used convolutional neural network to predict epileptic seizure. With the help of EEG signals differences of voltage changes between electrodes can be measured, as it senses ionic current, which flow in brain.[[1]. Epileptic seizure detection with the help of EEG signals requires continuous examination by physician.Moreover, experts sometimes report different opinions on the diagnostic results [1]. Some proposed automatic computer based method for epilepsy diagnosis [2]. Some proposed model used time and frequency domain in EEG signals. Some focused on the methods based on spatial properties analysis of EEG signals in the time, frequency domains. The model already applied in inter-ictal and ictal recordings and share same objective of localizing the brain structure subsets involved in paroxysmal activity [1]. Some proposed a frequency domain based on genetic algorithm feature search method that gives good extensibility [2]. Therefore, we used Deep Learning to predict epileptic seizure. Here, we used EEG signals directly as input into the convolutional neural network (CNN).Here we don't need to extract features. We performed our model using CHB-MIT database.

1.1 Problem Description

Epileptic seizure affected patients found all over the world. A huge number of projects are working day and night to get rid from this epileptic seizure issues. Brain is one of the most important parts of human body. Unfortunately epileptic seizure is strongly related to brain. Excessive amount of abnormality in brain result in epileptic seizure. Epileptic seizure can attack at any age of both male and female. Patient feel terrible shake in body at the time of seizure attack. Babies may also face seizure attack. Seizure attack may create severe health issues. Seizure attack varies person to person. It can last two to five minutes. Low blood sugar, high fever, consuming alcohol, low blood sodium, stress, infection in brain parts are the main reasons of seizure attack. More than 10% people face epileptic seizure at least once in their lifetime. Sometimes because of seizure attack patient may lose muscle movement for quite long time. Patient became unconscious. When neurons of the brain act abnormally then epileptic seizure occurs. There is pre-ictal, ictal and post-ictal period in epileptic seizure. As epileptic seizure create quite bad effect in human brain, some measures must have to take to get rid from this. People are trying to detect epileptic seizure in the lowest amount of time to secure patients health. They try to detect epileptic seizure with high accuracy. People can face different types of epileptic seizure. People must have to visit doctor immediately if the seizure last more than 5 minutes. Severe damage of health can be occurring because of epileptic seizure. Epileptic seizure affected patient must have to maintain regular checkup. Chronic epileptic seizure attack is quite dangerous.

1.2 Objective and Motivation

Epileptic seizure can cause long-lasting affect in human body. People may face hypertension, sleeping disorder, muscle problem and many other health issues because of epileptic seizure. The result of a survey shows that, the person whose age is 65 or upper is suspected to increase from 16.9% (2004) to 29.9% (2050). [3] Epileptic seizure can also cause memory loss and nerve breakdown. Every year a large no of patients face this seizure attack. If a system can visualize the seizure attack at earlier, then the damage of health of affected person can be reduced. If something can predict epileptic seizure at the very early stage, then it will be possible to take proper medication. People become helpless at the time of epileptic seizure attack. Epileptic seizure has some different stages. They are divided into pre-ictal, ictal, inter-ictal and post-ictal. Pre-ictal stage is the most significant stage to predict epileptic seizure. EEG signals are also important to predict epileptic seizure. The previous time of seizure attack is most important. If one can predict that an epileptic seizure will occur right after, then the person will be more conscious. Thus it will help people to save their life. By seeing the abnormal brain signal epileptic seizure can predict. Some researchers work to detect the epileptic seizure with higher accuracy. But it will be much more effective for the patient if epileptic seizure can predict beforehand.
The main objectives of our research paper are:
• The foremost objective of this paper is to predict epileptic seizure quickly with higher accuracy
• In this project we used deep learning method to predict seizure
• We gave more focus on accuracy alone with easier method.

1.3 Thesis Overview

Epileptic seizure prediction is quite difficult as it requires pre-ictal state's signal. To analyzing the EEG signals also strenuous for the researchers. Comparing different EEG signals is quite hard. We show some related research works in this field in chapter two. We discuss all the background study which is necessary for our work. In chapter four we will discuss about our proposed model. We show a workflow to give a clear representation of our model. We discuss about the data which we used for our work. In chapter five we discuss about the implementation of our work and also analysis the result of our proposed model. And lastly in chapter six we discuss about the future dimension of our model and conclude the thesis paper.

Chapter 2

Literature Review

In the paper [4] S. Tofiq proposed a framework which can learn directly from the given data without extracting feature set. Most of the models are based on features extracted from the EEG recordings. Electroencephalogram (EEG) is one of the most successful methods to record brain wave pattern. But feature extracting from EEG is time consuming and also need more manpower. Deep neural network supports the learning directly from the data with extracting the feature set. In their proposed model EEG signal which came from brain, segmented into four segments. Also train the long- and short-term memory network. Deep learning model separately feed each into seizure classifier and also ignore the connection between them. The researcher's use 5 folds cross validation for evaluating the performance of their proposed model. Their proposed model tested on 21 patients with different ages. Preprocessing and processing are two significant folds of this method. The total accuracy achieved for this method is 97.75%.
In the paper [5] M. Z. Parvez proposed a method of seizure prediction based on by extracting global and local features. These features extract from preictal, ictal and interictal periods of EEG signals. Phase correlation between two consecutive epochs of EEG signal use for extracting global signals. On the other hand, fluctuation and deviation of EEG signals use for extracting undulated local signal. A regularization technique is being used on the classified output to reduce the false alarm. Data formulation, UGF extraction, ULF extraction, classification, postprocessing these steps used in this method. This proposed method gives high prediction accuracy. This is 97.7%.
In the paper [6] S. M. Usman proposed a reliable method of both preprocessing and feature extraction. This method can predict epileptic seizures sufficient time before onset of seizure starts and also give true rate. In the method empirical mode decomposition applied for preprocessing and feature extraction like time and frequency domain. It can detect the start of preictal state; this is the state which starts few minutes before onset of seizure. Ictal and preictal states are very useful for predicting epileptic seizures. With the help of the method epilepsy affected patients will get enough time for proper medication. This model faces enough success rates.
In the paper [7] M. Shanir proposed an automatic seizure detection algorithm based on two statistical features in time domain. To identify normal and epileptic EEG signals classifier is being used. The classifier is trained with at least 60% of seizures. The work is to distinguish between normal and ictal states of brain using EEG signals. This is done by using one second non-overlapping window. Mean and Mini-

mum energy value extracted from each epoch for constructing feature vector. Then linear classifier can be able to classify normal and seizure epochs. Data which are used to test the method is pediatric EEG. The accuracy of the proposed model is quite satisfactory.
In the paper [8] H. Daoud proposed a seizure prediction technique based on Deep Learning method. In the proposed system feature extraction and classification process both are combined into single automated system as well as raw EEG signals used as input which further reduce the computation problem. In the field of seizure prediction process time is very important factor. Early prediction of the incoming seizures has a great influence on epileptic patients' life. The main purpose of this model is to accurately detect the preictal brain state and differentiate it from interictal state as fast as possible and make it applicable for real time. Deep learning methods are used to extract features which increase the classification accuracy and prediction time. The proposed model achieved high accuracy of 99.6% and lowest false alarm rate.
In the paper [9] Y. Yuan proposed a multi-view Deep Learning model to capture abnormality of brain from multi-channel epileptic EEG signals. Now a day, from multi-channel EEG signal detection of epileptic seizure is very much popular. In the proposed model at first generate EEG spectrograms using short-term Fourier transformation (STFT) to represent time frequency. They use stacked sparse denoisingautoencoders (SSDA) to learn multiple features of EEG channels. SSDA based channel selection procedure implanted in the method to reduce the dimension of intra-channel feature. Lastly by concatenate learned multi features and applying fully connected SSDA with Softmax classifier in order to learn the cross-patient seizure detector. This model achieved accuracy while conducting the experiment on EEG dataset. This model is highly effective in detecting the epileptic seizure.
In the paper [10] V. Bajaj proposed a method for classification of electroencephalogram signal by using empirical mode decomposition process. EMD method generates intrinsic mode function, which used as a set of amplitude and frequency signal. Amplitude modulation bandwidth and frequency modulation bandwidth used as input to least square support vector machine for classifying normal and seizure EEG signals. The proposed method gives better performance in the field of classifying seizure and non-seizure EEG signals.
In the paper [11] Y. Park proposed a patient-specific algorithm for epileptic seizure prediction by using various features of spectral power from electroencephalogram signals (EEG) and support vector machine (SVM) classification. This method consists of preprocessing, feature extraction, SVM classification and post processing. Cost friendly SVM classifier is used for classifying the preictal and interictal samples. Kalman Filter used to post process SVM classification output. This proposed method achieved high sensitivity of 97.5% with fewer false alarms.
In the paper [12] L. D. Lasemidis proposed an adaptive epileptic seizure prediction method. In this method an adaptive procedure is introduce to analyze long term EEG signal recordings only when the first seizure occurs. Global optimization is applied for selecting the groups of electrode sites. The adaptive seizure prediction algorithm was tested on intracranial EEG recordings. This method can reduce false prediction rate.
In the paper [13] R. Hussein proposed an epileptic seizure detection system based on Deep Learning approach. From the authors opinion epilepsy is another severe brain

disorder after migraine problem. Others methods are EEG based seizure detection system which may face many challenges in real life. As seizure patterns vary across patients and also EEG signals are non-stationary signals. EEG data are prone to various noise types which negatively affect the accuracy. To overcome these problems authors proposed a model which is based on Deep Learning method and it can learn automatically discriminative features of EEG. Long Short-term memory (LSTM) is used to learn the representation of normal and seizure EEG signals. Then this are fed into Softmax for training and classification. This proposed model is very much appropriate for noisy and real-life situation whereas other methods are not appropriate for noisy situation.

In the paper [14] R. Meier, H. Dittrich, A. Schulze-Bonhage, and A. Aertsen proposed a model with automatic online and real time epileptic seizure detection. This model can detect epileptic seizures in long term EEG. They extract seven features to analyze the EEG dataset. For preprocessing raw EEG dataset must be filtered. Mean sliding variance holds the temporal change of the designated EEG signal. Normalize the data by using SVM. They applied radial basis function kernel in the SVM. When SVM rated three feature data samples as ictal in sliding window then will refer as detection of epileptic seizure. They count seizure morphology diversity which improves the performance of detection process. This model ensures early detection method and reliable one. This model supports low computational cost and good performance to detect epileptic seizure.

In the paper [15] S. Bugeja, L. Garg, and E. E. Audu proposed an easy process of data acquisition, feature extraction to detect epileptic seizure quickly. They used CHB-MIT dataset. To detect epileptic seizure they create simple training set acquisition. It fastest the training slot of classifier. For feature vector design they used multilevel wavelet. For feature classification they used SVM and ELM. They approached high sensitivity. They tested their model on dataset of 22 patients EEG signals.

In the paper [16] M. Kaleem, A. Guergachi, and S. Krishnan discussed about the use of empirical mode decomposition in epilepsy diagnosis and also detection of EEG seizure. In this model they used Bonn University EEG dataset. For EEG data preprocessing they used band-pass filtering method. To select the features they used kruskal- wallis feature ranking. SVM classifier is used for classification. They proposed a non-stationarity quantification method for early detection of seizure. The accuracy of this proposed model is quite high.

In the paper [17] A. Kumar and M. H. Kolekar proposed an epileptic seizure prediction model using machine learning method. They used discrete wavelet transform to analysis EEG signal time frequency. They use discrete wavelet to decompose EEG signals to sub sections. For decomposition they used db6 and coif4 wavelets. In the SVM classifier they used kernel functions to classify EEG signals with and without seizure. The accuracy of the proposed model is quite high.

In the paper [18] M. Bandarabadi, C. A. Teixeira, J. Rasekhi and A. Dourado proposed an epileptic seizure prediction model. IN this proposed model they used relative spectral power features to predict the epileptic seizure. Predicting epileptic seizure at very early age is very important. Their proposed model shows much more improved results in the field of epileptic seizure prediction. They showed the efficiency by choosing features. They predicted 75.8% test seizures. Early prediction of epileptic seizure can save a seizure attack patient. They used SVM to identify

preictal and non preictal state.
In the paper [19] Kitano, L. A. S., Sousa, M. A. A., Santos, S. D., Pires, R., Thome-Souza, S., & Campo, A. B. used unsupervised learning to predict epileptic seizure. They used CHB-MIT EEG signal dataset. They used non-overlapping 4s window to segment EEG data. SOM is well known for multidimensional characterization. Increase of window number produces high performance classifier. They proposed a patient specific prediction method. They consumed low processing time. The accuracy of the proposed model is quite high.
In the paper [20] M. Parvez and M. Paul proposed a model to predict epileptic seizure. EEG signals play most important in epileptic seizure prediction. They proposed a method which contains EEG signals spatiotemporal relationship. They used phase correlation to execute their method. Preictal refers before time of seizure onset. Interictal refers the time in between two corresponding seizures. One can attack by multiple seizures. This model shows the change of EEG signals reference and current vectors. This method shows low false alarm. This proposed model can predict epileptic seizure with high accuracy.
In the paper [21] M. Niknazar, S. Mousavi, B. V. Vahdat, and M. Sayyah proposed an epileptic seizure detection method using recurrence quantification. They used recurrence quantification analysis on the EEG signal recordings and their sub sections. They used wavelet decomposition. They used 70% of samples of training data. The other 30% of samples used as test data. The subbands of EEG signals optimized separately. The accuracy of this proposed model is quite good.
In the paper [22] A. R. Naghsh-Nilchi and M. Aghashahi proposed an epileptic seizure detection model based on eigen system spectral estimation. In this model they also used multiple layer perceptron. They divided EEG signals into subbands. They completed the feature extraction process from these subbands. They performed complexity measure and standard deviation. Multiple layer perception neural network rank the signals according to normal or seizure affected. They used public database of EEG signals. It can make real time detection. This model holds quite high accuracy. The computational speed is good. This method is low misclassifying.
In the paper [23] Y. Song and P. Li'o proposed an epileptic seizure detection approach. In their model they extracted features by using sample entropy. They used extreme learning machine. It's a high standard of learning machine. They focus on the training period of classification. They tried to get high accuracy as well as less training time. They mainly focus on high speed learning. They used 10 fold cross violation. They obtained 95.67% accuracy.
In the paper [24] Acir, N., Oztura, I., Kuntalp, M., Baklan, B. and Guzelis, C. proposed an automatic epileptiform event detection model using artificial neural networks. They establish three stage procedures for automatic detection. In first stage they classify EEG peaks by using discrete perception. In the second stage they separated peaks by using artificial neural network. At the last stage of the system they integrated multichannel information.
In the paper [25] Chandaka, S., Chatterjee, A. and Munshi, S. showed a cross correlation aided support vector classifier. To classify EEG signals this classifier used. For the problems related to binary classification support vector machine used. This model shows a pattern recognition technique. For feature extraction cross correlation used. This method achieved high classification accuracy.

Chapter 3

Background Study

3.1 Types of Epileptic Seizure

Epilepsy is a neurological condition including the mind that makes individuals more helpless to having repetitive, unwarranted seizures. It happens when a rupture of electrical impulses in the brain cross their usual limits. Sometimes people get confused about which seizure he/she has. Because there are many types of seizure which are Focal Impaired Awareness Seizures, Bilateral Tonic-clonic seizures, Focal Aware Seizures, Absence, Tonic-clonic, Atonic, Clonic and Tonic seizures. Figure 3.1 shows the types. Focal Aware Seizures are also called simple partial seizures, which starts from single side of the brain but the person remains alert and also can interact. That is why previously this were called partial seizure. Then it starts the person loss the awareness of their surroundings. Then comes Focal Impaired awareness seizure which also starts in one side of the brain but people don't have control on their surroundings. This kind of seizure gives and warning before it occurs. Next, starting from one side of the brain, the seizure spreads to other side as well is called bilateral Tonic-Clonic seizure. Similarly, absence seizure also cause disability to awareness but it starts from both side at the same time.

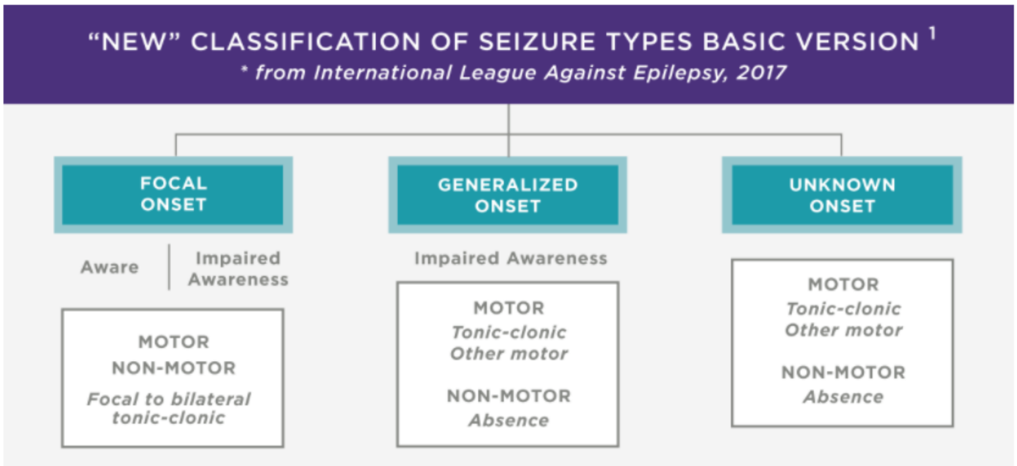


Figure 3.1: Different types of seizure

Though a tonic-clonic seizure starts from both sides, it may start from and one side and spread to the both side as well. In the stage of Atonic seizures people loss the muscle tone, which may lead drive their body and head to go limp. Clonic seizure causes jerking of the body. On the other hand during Tonic seizure the body, legs or arms might get tensed. Myoclonic seizures basically refers brief shock-like jerk of muscle or muscles. Gelastic seizures make people laugh in an uncontrolled way while Dacrystic seizures cause for uncontrolled crying but both of them are partial which means both of them start from one side of the brain. The hypothalamic hamartoma (HH) people are mainly seen to be affected with this kind of seizures. Furthermore, febrile seizures is mostly noticed in children aged 3 months to 5 or 6 years which may have genetic connection with his/her predecessors. For example, if any of the close relatives' like- Parents, siblings or any other have had febrile seizure, the child is a bit more likely to have them.

3.2 Phases of epileptic seizure

There are some phases after the seizure which indicate when the seizure is going to occur, the duration of seizure and the post condition of seizure. The phases are given below:

3.2.1 Pre-ictal

Pre-ictal mental manifestations as a rule comprise of group of indications going before captures of variable length, going from a couple of moments as long as three days. Such indications, despite the fact that not described by any distinguishable surface EEG change, most likely speak to the statement of basic epileptic movement. Prodromal states of mind of gloom or fractiousness may happen hours to days before a seizure and are regularly soothed by the spasm. Various creators brought up that conduct changes are the most much of the time announced pre-ictal side effects, being portrayed by peevishness or diminished resilience and enduring a few hours. These manifestations for the most part intensify in seriousness closer to the hour of the seizure and dispatch roughly 1 day after the seizure, despite the fact that sometimes side effects may endure for up to 3 days after the seizure. As of late, a commonness of pre-ictal dysphoric indications in patients with epilepsy has been accounted for. It appears, hence, significant for clinicians to ask about these wonders, since they can't be identified by rating scales or surveys.

3.2.2 Ictal

Ictal is the actual period of seizure. By this time people who are affected with seizure will feel some physical changes in their body. All things considered, it's now that the electrical tempest in the individual's cerebrum roars to life. During this time, if the person's body is connected to a medical device the device will definitely show metabolic, cardiovascular and EEG changes, which is shown in figure3.2. The patterns and the shapes help the neurologists to find out the type of the seizure.

3.3 Brain parts

The brain is a combination of millions of nerve cells and neurons, which generates electrical impulses and messages to provide feelings, movement, thoughts, control of

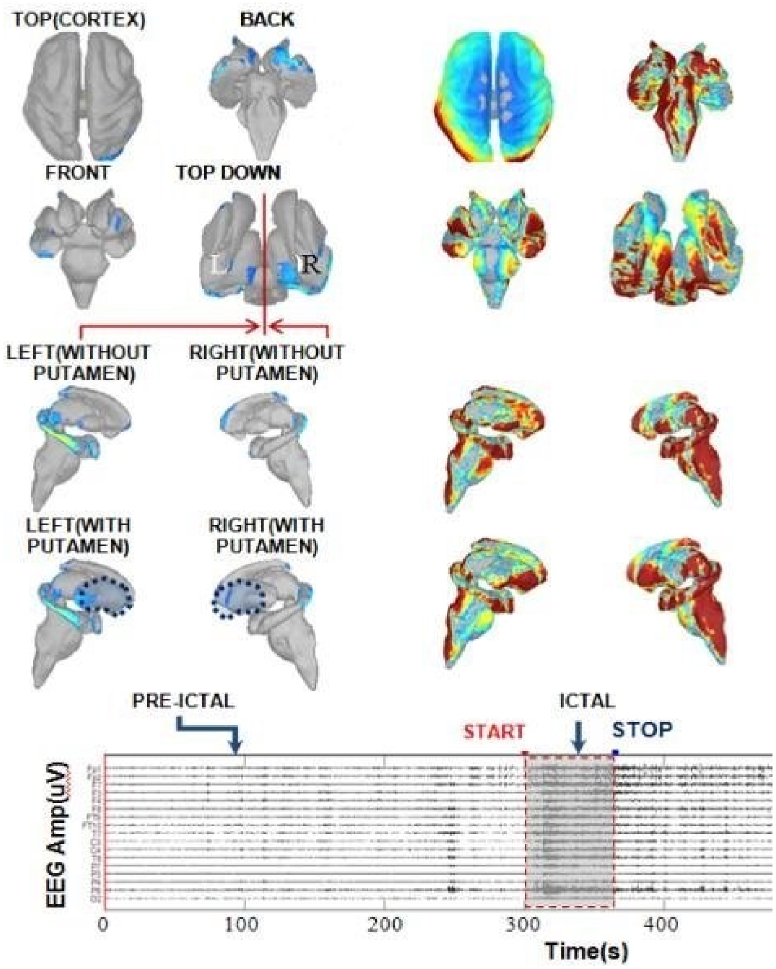


Figure 3.2: Pre-ictal and ictal phase in different sides of brain

body and sensations.

3.3.1 Regions of brain

The brain is basically divided into two portions one is left and the other is right, which is called hemisphere. But the hemisphere which is situated in the right handles functionalities connected to left part and the left one handles right part of the body. The view of different parts of brain is shown in the fig 3.3.

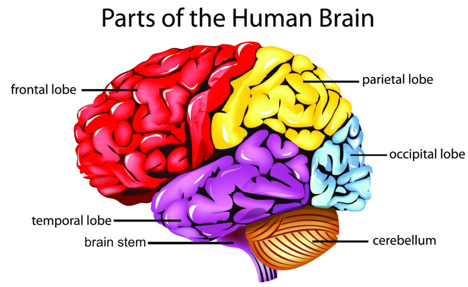


Figure 3.3: Different regions of brain

Brain Stem

The brainstem is the back aspect of the cerebrum (See fig: 3.3), persistent with the spinal cord. In the human cerebrum, the brainstem is made out of the midbrain, the pons, and the medulla oblongata. The midbrain is nonstop with the thalamus of the diencephalon through the tentorial notch, [3], [5], [26] and at times the diencephalon is remembered for the brainstem. The brainstem is a little part of the mind, making up just around 2.6 percent of its all-out weight [3], [5], [26]. It has the basic function of managing cardiovascular and respiratory capacity, assisting with controlling pulse and breathing rate. It likewise gives the principle engine and tactile nerve gracefully to the face and neck by means of the cranial nerves. Ten sets of cranial nerves originate from the brainstem. Other jobs incorporate the guideline of the focal sensory system and the body's rest cycle. It is additionally of prime significance in the movement of engine and tangible pathways from the remainder of the mind to the body and from the body back to the brain [3], [5], [26]. These pathways incorporate the corticospinal plot (engine work), the dorsal segment average lemniscus pathway (proprioception and fine touch), and the spinothalamic lot (torment, tingle, and unrefined touch) [27], [28].

Cerebellum

The cerebellum is one of the most significant part of the brain. Although,it is small even in some creatures littler than the cerebrum [29], for example, the mormyrid fishes it might be as extensive as or even larger. In people, the cerebellum assumes a significant part in engine control. It might likewise be engaged with some psychological capacities, for example, consideration and language just as passionate control, for example, directing apprehension and delight responses, [30] yet its development related capacities are the most decidedly settled. The human cerebellum doesn't start development, yet adds to exactness,precise planning, coordination and : it gets contribution from tactile frameworks of the spinal string and from different pieces of the mind, and incorporates these contributions to adjust engine activity. Cerebellar harm produces issues in fine development, balance, stance, and engine learning in humans [26], [30].

Cerebrum

The cerebrum is the biggest and generally created of the five significant divisions of the mind which contains two sides of the equator, the left and the right, associated by a heap of nerve filaments called the corpus callosum. The cerebrum coordinates the cognizant or volitional engine elements of the body. Harm to this territory of the cerebrum can bring about loss of solid force and accuracy as opposed to add up to loss of motion. The essential tangible zones of the cerebral cortex get and measure visual, hear-able, somatosensory, gustatory, and olfactory data. Every side of the equator of the mammalian cerebral cortex can be separated into four practically and spatially characterized projections: frontal, parietal, temporal, and occipital where every lobe is responsible for controlling specific functionalities.

Frontal Lobe

Frontal lobe is considered as the biggest of four major lobes in the brain. It is noticed at the frontal side of each hemisphere (See figure 3.4). There is a portion in the brain which is called frontal cortex which covers the frontal lobe and pre-frontal cortex covers the front part of frontal lobe. It plays an important role in memory, motivation, attention and multiple other daily task. All mammals contain a frontal lobe but the size and complexity vary from species to species. Mostly, children are seen to be affected by seizure in this region of the brain, affecting the functions that these region controls.

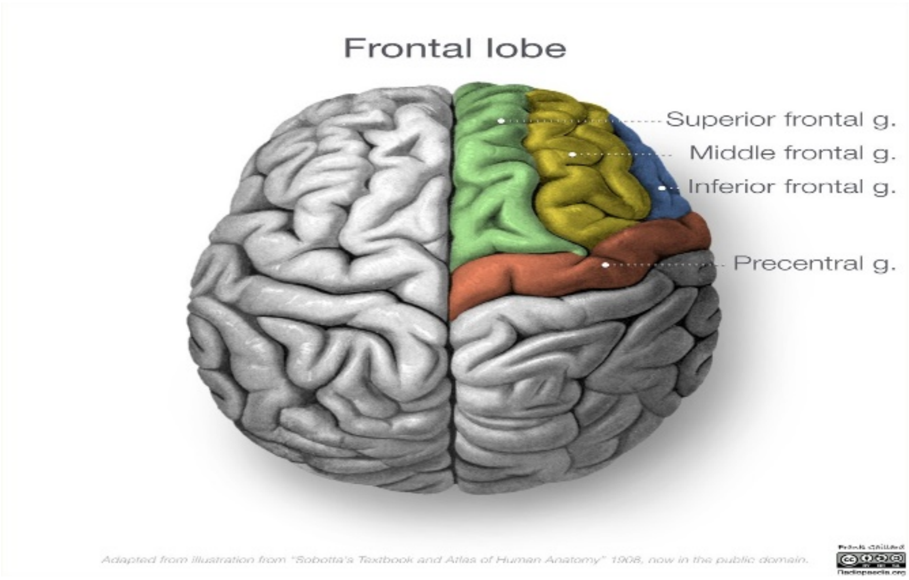


Figure 3.4: Frontal Lobe

This is one of the most common types of epilepsy that people suffer from because of neurological disorder where clusters of brain send abnormal signals. Various kinds of reason such as- Unusual brain tissue, infections, injuries, strokes, tumors or other conditions may cause for frontal lobe seizures. Since a lot of functionalities are related to these lobes, any abnormalities in this region have some noticeable symptoms which may last for 30 seconds or less. Symptoms causes for frontal lobe may include - head and eye movement to one side, complete or partial responsiveness, difficulty in speaking, unusual body posture, repetitive movements like bicycle pedaling (See figure 3.5) [31].

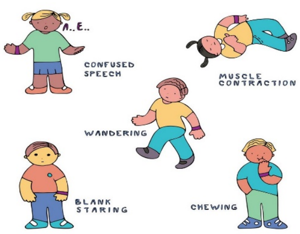


Figure 3.5: Symptoms of frontal lobe seizures

Parietal Lobe

The parietal lobe is essential for a tactile framework involving fringe receptors, neural pathways, and neurons of a few supraspinal focuses (cerebellum, basal ganglia, parietal projection) that cycle visual and somatosensory data. The somatosensory modalities incorporate proprioception (e.g., view of body and appendage positions), interoceptive tangible modalities, for example, temperature and torment recognition, and contact. Traditionally, contact has been characterized as an exteroceptive sense. Notwithstanding, in acknowledgment that touch discernment depends on a few modalities, the term substantial faculties is likewise generally utilized. It is realized that the parietal flaps intercede exteroceptive and proprioceptive recognition, while interoceptive sensations are likewise connected with initiations of the privilege separate cortex. One of the essential parts of the parietal cortex lies in the combination of somatosensory and visual data that is required for development arranging and control. Furthermore, explicit territories of the parietal lobe are applicable for psychological cycles, for example, understanding perception, and intelligent and numerical reasoning. One of the principal far reaching records of parietal projection work was distributed in 1953 by the British nervous system specialist Macdonald Critchley whose experiences depended to a great extent on the investigation of patients with parietal injuries. From that point forward, various specialists endeavored to connect practices with parietal and subcortical neural movement in people and creatures utilizing a variety of psychophysical, electrophysiological, and mind imaging strategies

Occipital lobe

. The occipital flap is one of the four significant mind projection sets in the human cerebrum. The occipital flap is so named in light of the fact that it rests underneath the occipital bone of the skull. It is likewise the littlest of the projections. There are really two occipital lobes — one on every half of the globe of the mind. The focal cerebral gap partitions and isolates the projections. The occipital flaps are situated on the back aspect of the upper cerebrum. They sit behind the transient and parietal projections or more the cerebellum, isolated from the cerebellum by a layer called the tentorium cerebelli. The outside of the occipital flap is a progression of folds, including edges called gyri and dejections called sulci. Since there is no arranged structure to the occipital projection, researchers utilize these sulci and gyri to recognize the region of the flap. When all is said in done, the occipital flap manages parts of vision, including:

- separation
- color determination
- profundity observation
- Memory data, etc.
- object acknowledgment

Dysfunction in the occipital projection may cause different generous dysfunctions, for instance, erratic vision, inconvenience standing, and visual weakness. A couple of conditions, for instance, epilepsy, may in like manner have an interface with brokenness in the occipital projection.

Temporal lobe

The temporal lobe of the cerebrum is regularly alluded to as the neocortex. It shapes the cerebral cortex related to the occipital flap, the parietal projection, and the frontal flap. It is found principally in the center cranial fossa, a space found near the skull base [6]. It is foremost to the occipital projection and back to the frontal flap. It is discovered second rate compared to the sidelong crevice, otherwise called the Sylvian gap or the horizontal sulcus. The transient projection partitions further into the prevalent worldly flap, the center fleeting projection, and the mediocre worldly flap. It houses a few basic cerebrum structures including the hippocampus and the amygdala. Furthermore, TL plays an important role functioning couple of things as follows:
• Speech perception.
• Hearing.
• Speech production.
• Visual.
• Social [6], [32].
Alongside, Harm to the hippocampal locale, amygdala as well as their interconnections can cause posttraumatic stress problem (PTSD), Alzheimer ailment and temporal lobe epilepsy [6], [33].

3.3.2 Changes in Brain due to Seizure

Seizures can happen anywhere in the cerebrum as figure: 3.4, however in kids they habitually happen in the worldly and frontal projections, influencing the capacities that these areas control. A locale of specific significance in grown-ups with epilepsy, however less so in kids, is the mesial, or center, part of the fleeting projection. What changes occurs in different parts of the brain has described in the below:

Changes in Hippocampus in Epilepsy

Hippocampus assumes a significant part in cognizance and it is engaged with minute-to-minute psychological processing [34]. Hippocampus and related regions were accounted for to be influenced basically in epilepsy, particularly transient projection epilepsy, which is more normal in adults [35]. It was accounted for that repetitive seizures may cause hippocampus harm all through the lifetime of the patient. Structural (histological) and utilitarian changes happen in hippocampus in epilepsy. Histological changes incorporate particular and broad hippocampal neuronal misfortune in CA1 and CA3 locales and around the end folium where the cells of CA2 district are spared [1], [36]. In different sorts of epilepsy, neuronal misfortune can be seen in all hippocampal zones. Aside from neuronal misfortune and gliosis, granule cell scattering in dentate gyrus is additionally seen in epilepsy. Atrophied hippocampus is accounted for to be liable for seizures, and careful expulsion of hippocampus is accounted for to improve the condition [1], [37].

Changes in Basal Ganglia in Epilepsy

The capacity of basal ganglia in scholarly limits is settled. Prior assessments guessed that basal ganglia limits as a part of a modulatory control system over seizures rather

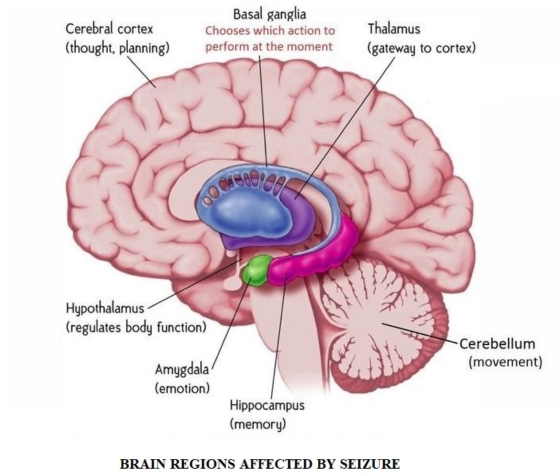


Figure 3.6: Changes in Brain due to Epilepsy

than a spread pathway. Albeit no specific epileptic electroencephalography changes were seen in basal ganglia, commitment of basal ganglia in scattering of epileptic activity was accounted for. Dopamine is represented to remember for the control of seizures related to such an epilepsy [38]. Adequately, upheld seizures cause damage of substantianigra norms reticulate (SNR) and globuspallidus. Curiously, epilepsy has been represented to have talk relationship with Parkinson's affliction as event of seizures is less in patients with Parkinson's ailment. Seizures may incite reformist microanatomical changes in putamen of the two sides of the equator [39]. As the SNR accepts a huge capacity in the change of seizures, the seizures may be treated with high-repeat instigation of SNR.

Changes in Piriform Cortex in Epilepsy

Cortical, subcortical neuronal associations accept a key capacity in age, upkeep, and spread of epileptic development. The piriform cortex (PC) and amygdala make seizures due to engineered and electrical prompting and as an enhancer of epileptic activity when seizures are delivered elsewhere. Helper varieties from the standard were found in PC in frontal projection epilepsy [29].
MR imaging reported that the PC amygdala is comprehensively hurt in steady common flap epilepsy patients, particularly in those with hippocampal decay. Changes in the PC are obligated for complex fragmentary seizures, i.e., the most notable sort of seizures in human epilepsy [40].v

Changes in Hypothalamus in Epilepsy

The relation between the hypothalamic mass and the various sorts of seizures is still unknown [41]. Sex steroid hormone pivot variations from the norm happen all the more usually in individuals with epilepsy. Arrival of sex steroid hormones is constrained by the hypothalamic–pituitary–gonadal hub; the prescriptions used to treat epilepsy can effectsly affect guideline of these hormonal frameworks. The adjustments in the hormone may prompt hypogonadism and sexual brokenness and are connected to polycystic ovary condition, decline in fruitfulness and labor rate, untimely menopause, and thyroid problems. It might likewise cause hormonal prophylactic collaboration. Endogenous hormones can impact seizure seriousness and recurrence, bringing about catamenial examples of epilepsy. Women who are taking antiepileptic drugs have expanded danger of maternal and fetal entanglement; henceforth, great arranging and successful caring is important during and after the pregnancy. Epilepsy and rest have corresponding connections, absence of rest may prompt seizures, and seizures antagonistically influence the rest design. Treating rest issues, which are conceivably brought about by or added to by chemical imbalance, may affect well on seizure control and on daytime behavior [42]. In almost 33% of patients, the event of seizures was during the rest state. This is brought about by a close connection between the physiological condition of rest and the obsessive cycle hidden epileptic seizures. Subsequently, control of seizure can improve rest. Seizures, antiepileptic medications, and vagus nerve incitement all impact rest quality, daytime readiness, and neurocognitive function. Cold and shudder and piloerection are uncommon ictal signs in central epilepsies and are regularly connected with an epileptic seizure center inside the fleeting projection. Hypothalamic injuries can affect thermoregulation; consequently, temperature dysregulation is normally seen during epileptic condition [43].

Changes in Cerebellum in Epilepsy

Part of cerebellum in discernment and conduct is well documented. Cerebellar rot was represented in patients with epilepsy. In spite of the fact that peri-ictal changes in cerebellar perfusion was found in epilepsy, its pledge to cerebellar rot was least [44]. Cerebellar induction especially in front fold and thalamic region is represented to be incredible in patients with seizures [45].

Changes in olfactory cortex in Epilepsy

Primary olfactory cortex (piriform cortex) is integral to olfactory ID and is an epileptogenic structure. Epilepsy seems to cause a summed up decline in olfactory working albeit expanded affectability may happen in some epileptic patients eventually in the pre-ictal period. Other tactile modalities are likewise influenced by the epileptic cycle which, now and again, includes limbic-related fleeting flap structures. A critical number of the olfactory deficits as of late credited to common projection resection truly exist preoperatively. Confusions in taste and offensive transmissions are connected with hyperresponsiveness of neurons, which may explain why most epilepsy-related olfactory airs are portrayed as awful. Fascinating equivalents exist between the effects of the neuroendocrine system on seizure activity and olfactory capacity [46].

Changes in amygdale in Epilepsy

Following actuation of amygdale, a full scope of experiential signs is found in patients with fleeting projection fold epilepsy. Specific amygdalotomy has wind up being an effective treatment for temporal fold epilepsy. Horizontal amygdala is a core of the amygdala that tasks to the fleeting neocortex and hippocampus. Rat considers have demonstrated that unconstrained releases happen in the horizontal amygdala of epileptics. In two patients, interictal spikes, spike-wave, and polyspike buildings were watched intraoperatively in the amygdala; notwithstanding, proof of its source from the amygdale is lacking [47]. Recent exploration in people have demonstrated that amygdala sores may hinder particular areas of effect and discernment, which are identified with the examination of enthusiastic and social criticalness of tactile occasions. Harm to the amygdala may cause a wide scope of shortfalls in the examination of enthusiastic and social hugeness of tangible occasions despite the fact that these deficiencies are frequently factor and still inadequately understood [48].

3.4 EEG signals

There are some characteristics to define them. Utilization of thick gatherings of cathodes including varieties of 128, 256 and 512 anodes which are joined to head has expanded the extent of EEG recording capacities. And yet enhanced, highlighted and pertinent EEG signals are a lot of basic for improving the nature of the presentation assessments. Analysts have use time and space highlights like entropy, power range, singular recurrence groups, coefficients, and autoregressive. The electroencephalogram (EEG) is an account of the electrical movement of the mind from the scalp [1]. EEG ID includes an immediate assessment by a specialist just as a lot of time and exertion. Furthermore, specialists with various degrees of demonstrative experience likewise report discrepant perspectives on the results of the conclusion. There are many types of EEG signals such as delta, theta, alpha, and beta.

Delta

The frequency of delta is 3Hz or more [28]. It has the lowest wave with highest amplitudes. It is discovered to be happened centrally with sub cortical injuries and diffuse sores too with general conveyance. It is found as conspicuous frontally in grown-ups and furthermore back in kids.

Theta

Theta has a recurrence of 3.5 to 7.5 Hz and is delegated "moderate" movement [28]. Disregarding the way that It has all the earmarks of being customary in kids who are up to 13 years and moreover in their rest, found sporadic in attentive adults. It may occur as an appearance of focal sub cortical wounds and can moreover be found in diffuse disarray.

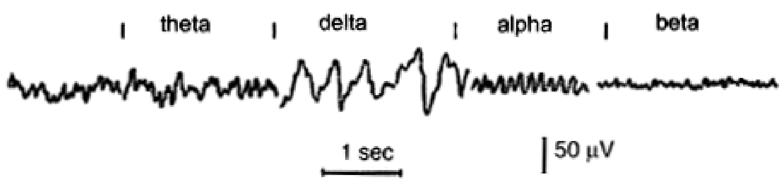


Figure 3.7: Different types of EEG signals

Alpha

The signal is Alpha if the frequency is within 7.5 to 13Hz [28].As cerebrum has different sides, it is found in the back bit of the head in each side. It has a higher abundancy in the predominant side and furthermore observed when we close our eyes and furthermore during unwinding. Then again it vanishes while opening our eyes and being alarmed by deduction and computing. It is found in the whole life yet generally following thirteen years.

Beta

When the frequency is 14Hz or greater is call Beta signal[28]. It is found in both sides of the brain but specially seen on the frontal side. It shows a dominant rhythm in alert or anxious or open eyed people.

3.5 Deep Learning

Deep Learning was evolved from ANN, and now it is a vital area of Machine Learning. Deep Learning models use hierarchical systems for connecting their layers. These models use simple linear or non-linear equations to attach the outputs among layers. They make use of low-level functions to transform into higher-level abstract features. They maintain track of the increasingly abstract representations of the input data and have the capability to frequently learn about those factors.

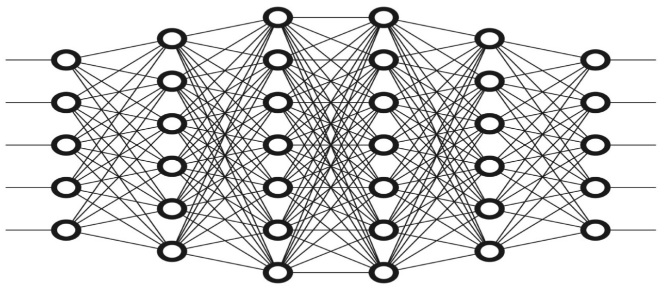


Figure 3.8: Deep Learning Model

From Figure 3.8, DL works particularly way better than machine learning when it comes to fathoming complicated issues, like discourse acknowledgment, picture classification, NLP. Deep Learning makes utilize of a colossal amount of parameters which makes the training time tremendous. Classical Profound Learning strategies suggest utilizing ANN, CNN, RNN and their changed adaptations. The soft max classifier is executed upon the profound NN methods to infer the classification yield [49].

3.6 Neural network

A multilayered network which is basically used to do predictions, classifications and so forth is called neural network.It is a technique for building a PC program that gains from data. It is put together incredibly openly with respect to how we think the human mind functions. Regardless, an assortment of program ”neurons” are made and related together, allowing them to send messages to one another. Another, the organize is asked to enlighten an issue, which it attempts to do again and again, each time bracing the affiliations that lead to triumph and diminishing those that lead to dissatisfaction. For a more point by point presentation to neural systems, Michael Nielsen’s (Neural Networks and Deep Learning) could be a great put to begin. A NN has an input layer, which presents all of the input information and they are passed on to the enactment work after relegating person weights to each of the inputs. The actuation work applies the desired methods to produce the yield that’s afterward passed straightforwardly to the yield layer [50].

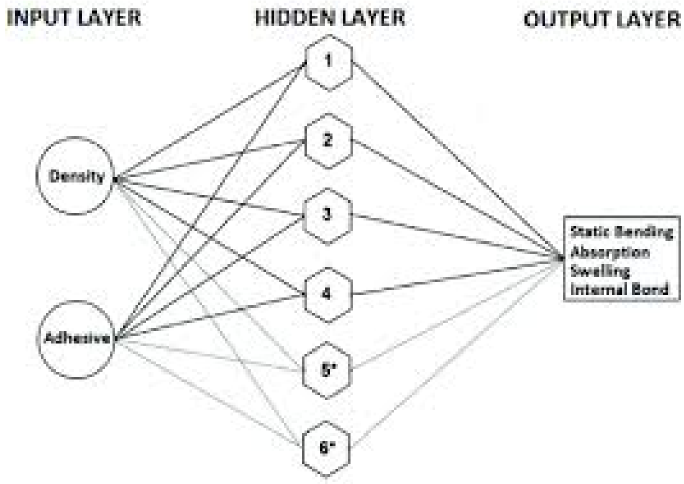


Figure 3.9: Neural Network

Chapter 4

Proposed Model and Implementation

4.1 Workflow

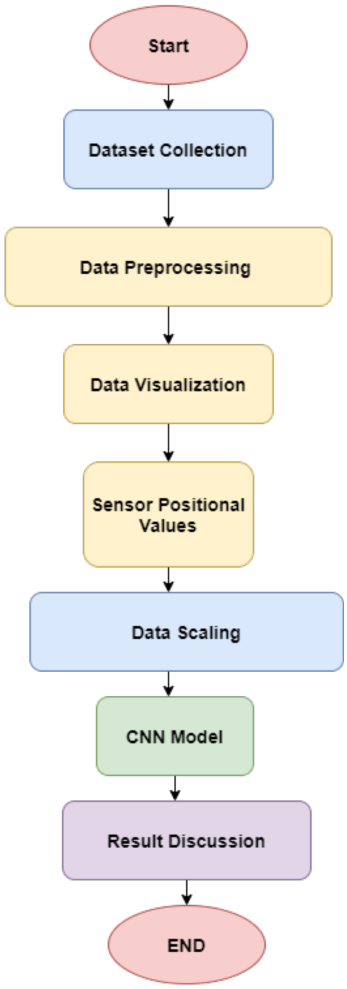


Figure 4.1: Workflow

4.2 EEG Signals

The electroencephalogram (EEG) could be a recording of the electrical movement of the brain from the scalp. The recorded waveforms reflect the cortical electrical movement. Flag concentrated: EEG action is very small, measured in micro-volts (mV).So we are reaching to utilize EEG to record the electrical action of the brain. The data is put away within the dataset and we have headed to the proposed show and the execution right after finding the dataset.

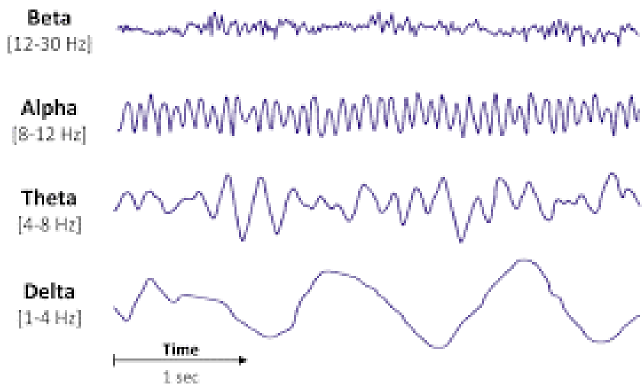


Figure 4.2: EEG Signals

Data was taken from different parts of the brain with several electrodes.

4.3 Data Collection

For our venture named Epileptic seizure prediction, we required a dataset. In our venture we utilize CHB-MIT Scalp EEG Database. [51] The database is openly accessible therapeutic inquire about information. In this collection, the records contain a list of .edf records. This dataset is utilized for epileptic seizure forecast [52].

4.3.1 Data description

The Recordings of EEG signals was collected into 23 cases from [53] 22 subjects where there were 5 males whose age was between 3-22 and 17 females with the age between 1.5-19. (Case chb21 was gotten 1.5 a long time after case chb01, from the same female subject.)

SEX	COUNT OF SEX
MALE	5
FEMALE	17

Figure 4.3: Gender of patients

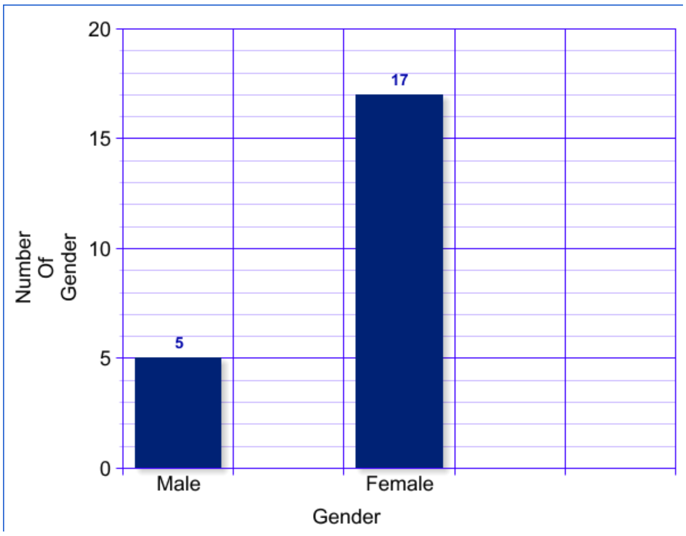


Figure 4.4: Gender Descriptions

All signals were sampled at 256 samples per second with 16-bit resolution. Most files contain twenty three electroencephalogram signals (24 or twenty six during a few cases). The International 10-20 system of electroencephalogram conductor positions and terminology was used for these recordings. during a few records, different signals are recorded, like Associate in Nursing cardiogram signal within the last thirty six files happiness to case chb04 and a cranial nerve nerve stimulation (VNS) signal within the last eighteen files happiness to case chb09.

Type Of Signal	Numbers
EEG	23
ECG	36
VNS	1
DUMMY	5

Figure 4.5: Types of signals

In some cases, up to five "dummy" signals (named "-") were interspersed among the electroencephalogram signals to get Associate in Nursing easy-to-read show format; these dummy signals may be neglected.
there are 664 .edf files where 129 files contains single or multiple seizures. [54] These records totally include 198 seizures (182 in the original set of 23 cases).

4.4 Pre-Processing

At that point we have to do pre-processing which is fundamentally the filtering of information of the dataset. We cruel there could be number of information in dataset which we don't require or those are undermined or wrong information. So, we must channel the dataset and select information which we require. In hone, measured EEG

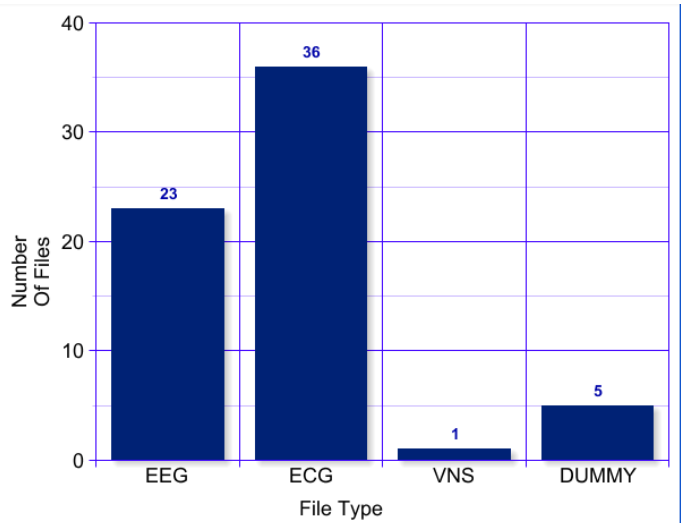


Figure 4.6: Signal Descriptions

Type Of Files	Numbers
EDF	535
SEIZURE	129

Figure 4.7: Types of files

information are regularly adulterated with diverse sorts of clamor. Such commotion adversely modifies the EEG waveform shapes and extremely influences the location precision of epileptic seizures.

4.5 Feature Extraction

Feature extraction includes diminishing the number of assets required to portray an expansive set of information. When performing investigation of complex information one of the major problem's stems from the number of factors included. Investigation with an expansive number of factors by and large requires an expansive sum of memory and computation control; too it may cause a classification calculation to overfit to preparing tests and generalize ineffectively to modern tests. Highlight extraction may be a common term for methods of building combinations of the factors to induce around these issues whereas still portraying the information with adequate exactness. We are going utilize flag preparing approaches for include extraction.

4.6 Convolutional Neural Network

Convolutional Neural Systems (CNN) are one of the celebrated profound manufactured Neural Networks. CNNs are built from learnable weights and predispositions. CNNs are used in picture acknowledgment, picture clustering and classification, question discovery, etc. CNNs utilize or maybe less preprocessing when compared to other calculations of image processing. Any pictures of specific regions are passed

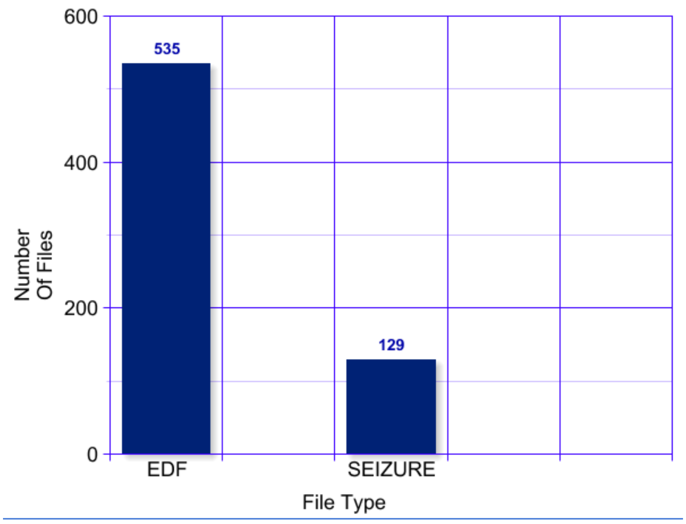


Figure 4.8: Visual Displays of files

through the convolutional layers and show up the extreme discovery result. This illustrates consolidates a few layers named The Bit, Pooling and the Totally Related Layer (FC Layer) through which various pictures or areas are prepared by feeding them into the arrange [54].

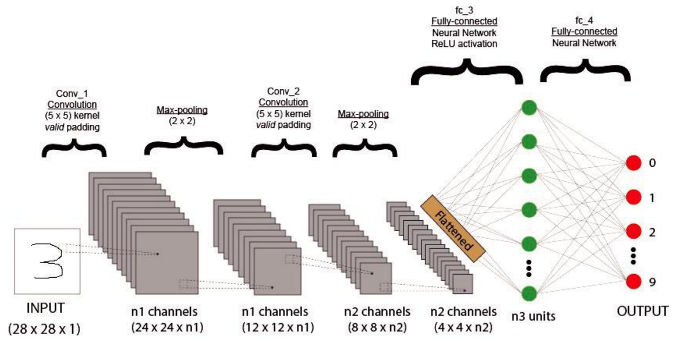


Figure 4.9: Convolutional Neural Network

4.7 Reasons of using CNN

Though neural networks have been around for the past 50 a long time, there have been basic progressions inside the zone of convolutional neural networks within the afterward past. This area covers the focuses of intrigued of utilizing CNN for image recognition.

4.8 Learning Features

The most include of CNNs is the highlight learning. The utilization of CNNs are propelled by the reality that they can memorize pertinent.

4.8.1 Activation function

The activation function could be a node that's put at the conclusion of or in between Neural Systems. They offer assistance to choose in case the neuron would fire or not.

4.8.2 ReLu

In case of utilizing a step work our classification would have been a straight one. As our information is linear which suggests, we are going viably back propagate the errors and have various layers of neurons, we have utilized the ReLu actuation function. In mid-layer, the amended linear activation is the default activation when building multilayer Perceptron and CNN. It changes the linear frame into a non-linear form. It is utilized in covered up layer to generate testing accuracy. It can be spoken to as,

$$f(x) = max(0; x) \tag{4.1}$$

It sets anything less than or equal to 0 (negative numbers) to be 0 and it keeps all the same values for any values 0.

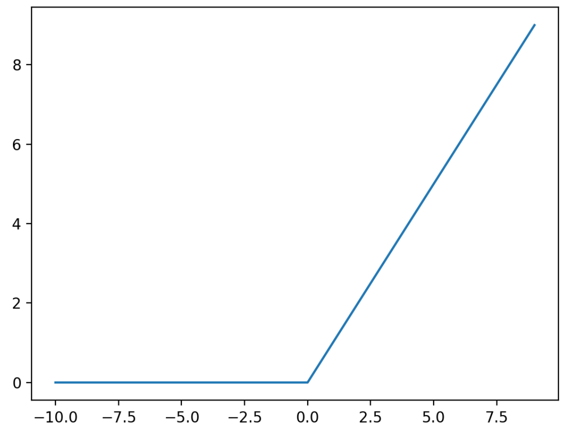


Figure 4.10: ReLu Curve

From the figure 4.3 we can notice that the function we have used for representing our prediction model. We have used ReLu as we have a linear classifier. We are using only two classes and so we have used this ReLu. The other reason for using ReLu is it solves the problem of vanishing slope issues. It also permits the model to learn in a faster and perform in a better way which leads the experiment to have a better accuracy.

4.8.3 Softmax

For binary classification and testing accuracy making we have used the Softmax Activation function in output layer. Softmax enactment work comes around in a multi class likelihood dispersion over your target classes. Numerically the softmax function is appeared underneath, where z i the inputs to the output layer (on the off chance that you have got 10 output units, at that point there are 10 components in z). And once more, j files the output units, so j = 1, 2... K.

$$f_i(\vec{d}) = \frac{e^{a_i}}{\sum_j e^{a_j}} \tag{4.2}$$

4.8.4 Convolutional Layer: Conv2D

The convolutional 2-D layer applies skimming convolutional filters to its input.In our model, we converted 2D to 3D using convolation2dlayer.The dimensions is determined by the filter size and parameter of the Keras deep learning Conv2D. In this case, the kernel size (1,1) is used and activation is ReLu function. Each time we used this layer the 3rd dimension value is increased by 2 times. Kernel size is used to reduce the size.Finally, it will decrease the size of data to extract the important information.

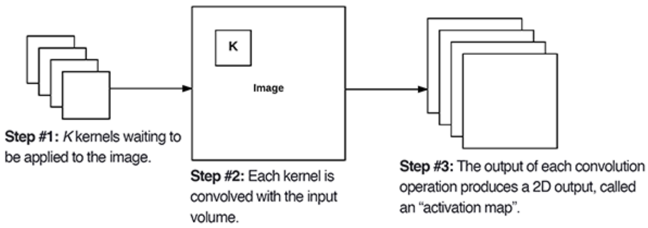


Figure 4.11: Convolutional Layer: Conv2D

4.8.5 MaxPooling2D

It down-samples/reduce the input representation by taking the maximum value by poolsize for each dimension. Pool size is the Integer or tuple of 2 integers, window size over which it is going to take the maximum (2, 2) will take the max value over a 2x2 pooling window.

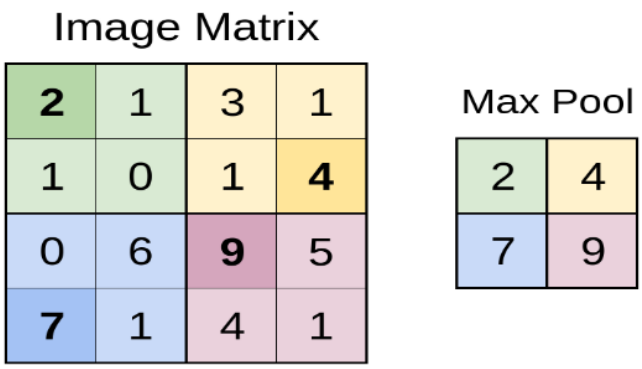


Figure 4.12: MaxPooling2D

In our first sequential model, we used 1x1. Then, in the second one the value is 2x2.

4.8.6 Dropout

Dropout is such a procedure used to avoid over fitting in a model. We placed the dropout layer after activate function for all activation functions in the both models.

```
model = Sequential()
model.add(Conv2D(8, kernel_size=(1, 1),activation='relu',input_shape=input_shape))
model.add(Conv2D(16, (1, 1), activation='relu'))
model.add(Conv2D(32, (1, 1), activation='relu'))
model.add(Conv2D(64, (1, 1), activation='relu'))
model.add(MaxPooling2D(pool_size=(1, 1)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(32, activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(8, activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(2, activation='sigmoid'))
model.compile(loss=tf.keras.losses.binary_crossentropy,
              optimizer=tf.keras.optimizers.RMSprop(),
              metrics=['accuracy'])
```

Figure 4.13: Dropout with 25% Rate

If one layer gets a sensor value which is unusually large it will increase the chance of getting wrong output. In orderto avoid that it will make random combinations. The shuffle parameter will shuffle the training data before each epoch.In this way the layer will prevent from being biased by any particular sensor value which is larger than others.

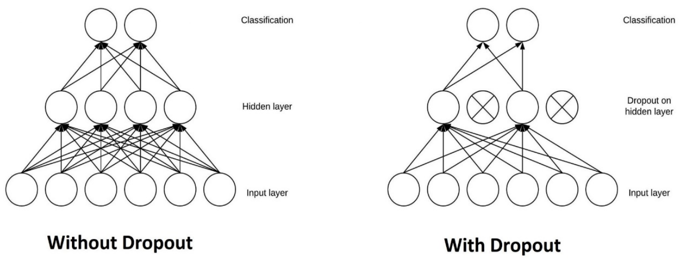


Figure 4.14: With and Without Dropout Scenario

4.8.7 Flatten

Flattening converts the data-set into a one-dimensional array for inputting it to the following layer. In order to form a single long feature vector,we have flattened the output of the past layer. For further processing, It is attached to the final classification model.

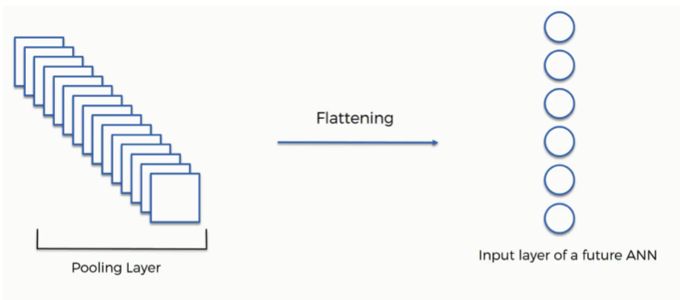


Figure 4.15: Flatten Layer

4.8.8 Dense

Dense layer refers the traditional deeply connected neural network layer. It is added after the convolution and pooling layer.

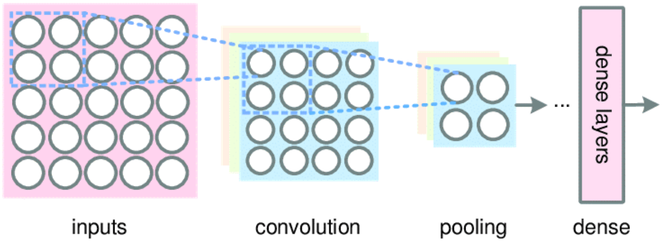


Figure 4.16: Dense Layer

It performs as a matrix vector multiplication. The matrix elements are the trainable parameters which will be modified during back propagation procedure.Which will give us a x dimensional vector as output. This layer is applied to transform the dimensions of out vector. From mathematical point of view, it applies scaling,rotation, translation etc. to the vector.In the layer addition part of first model, we added multiple dense Layer and reduce the value from 64 to 2.

4.9 Implementation

We divided the whole data and took 80% data for train left 600(20%) samples for test. Then, used categorical convert to get better accuracy.The data model is passed to the CNN architecture which utilizes architecture similar to ResNet-18. In the Sequential model we used convolutional 2D, MaxPooling2D, Dropout, Flatten, Dense layer. Here is the data visualization of files (See Figure: 4.17).

Subject	Age/Gender	Seizure Events	Total Ictal Time (secs)	Total Inter-ictal Time (secs)
chb01/chb21	11, 13 (F)	11	641	263461
chb02	11 (M)	3	172	126751
chb03	14 (F)	7	402	136366
chb04	22 (M)	4	378	561414
chb05	7 (F)	5	558	139813
chb06	1.5 (F)	10	153	240075
chb07	14.5 (F)	3	325	241044
chb08	3.5 (M)	5	919	71084
chb09	10 (F)	4	276	244043
chb10	3 (M)	7	447	179612
chb11	12 (F)	3	806	124416
chb12	2 (F)	27	989	73466
chb13	3 (F)	12	535	118232
chb14	9 (F)	8	169	93405
chb15	16 (M)	20	1992	142004
chb16	7 (F)	10	84	68297
chb17	12 (F)	3	293	75310
chb18	18 (F)	6	317	127932
chb19	19 (F)	3	236	107480
chb20	6 (F)	8	294	99043
chb22	9 (F)	3	204	111376
chb23	6 (F)	7	424	95177
chb24	NR (NR)	16	511	76134
Total	-	**185**	**11125**	**3515935**

Figure 4.17: Data visualization of chb01/chb21

Then we have taken the input data from channel/ sensor which were attached to the brain. Then the channels are converted to data frames P8-O2 675, CZ-PZ 675, T8-P8 675, T7-P7 675, FZ-CZ 675, ..., CZ 13, 01 13, T7 13, P7 13, LOC-ROC 11. Then to show the sensors value we have taken chb01_18 as example.

Channel	P8-O2	CZ-PZ	T8-P8	T7-P7	FZ-CZ	C3-P3	P4-O2	C4-P4	FP1-F7	F3-C3	F4-C4	P7-O1	FP2-F8
Time													
0	-192.429794	18.949940	0.976801	-6.837607	-44.346764	8.791209	-75.213676	-116.630035	35.360195	11.916972	25.982906	16.214897	-28.717949
0	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360
0	-0.586081	-0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	-0.195360	0.195360	0.195360	0.195360	0.195360	0.195360
0	-6.837607	-1.758242	-0.195360	0.195360	-0.586081	-0.195360	-2.930403	-3.711844	-0.195360	0.195360	0.195360	0.195360	-1.758242
0	-0.195360	1.758242	0.195360	0.195360	0.586081	0.195360	-1.758242	1.367521	0.195360	0.195360	0.195360	0.195360	0.195360

Figure 4.18: Sensor data of chb01_18

Here we have shown the values of the sensors which were found from the sensors which is shown in the figure 4.19. Then we have found out the sensor position of head and plotted in a scalp image like figure 4.20.

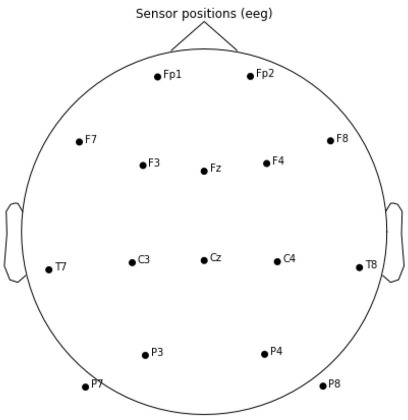


Figure 4.19: Sensor position

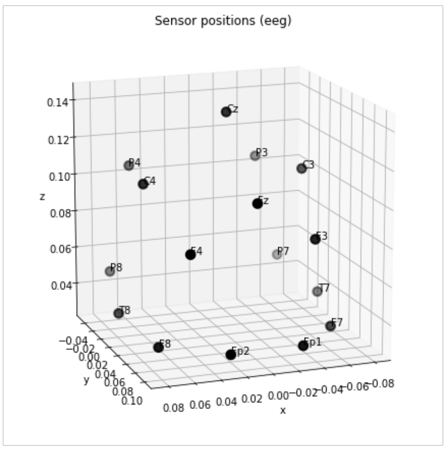


Figure 4.20: Sensor positions to have EEG signals

Then we have taken the chb01_12 sensor values and got the inter-ictal and the ictal period value from the sensors. When we represented it visually, we saw that the sensors age giving different values and visuals.

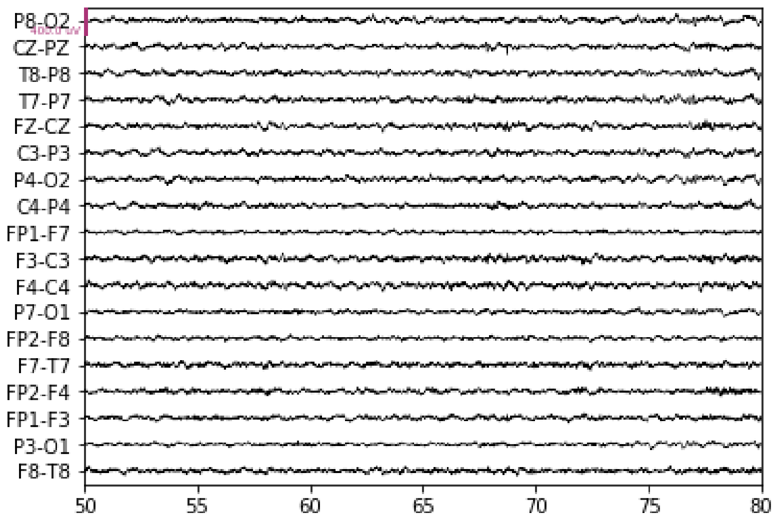


Figure 4.21: Inter-ictal period sensor reading

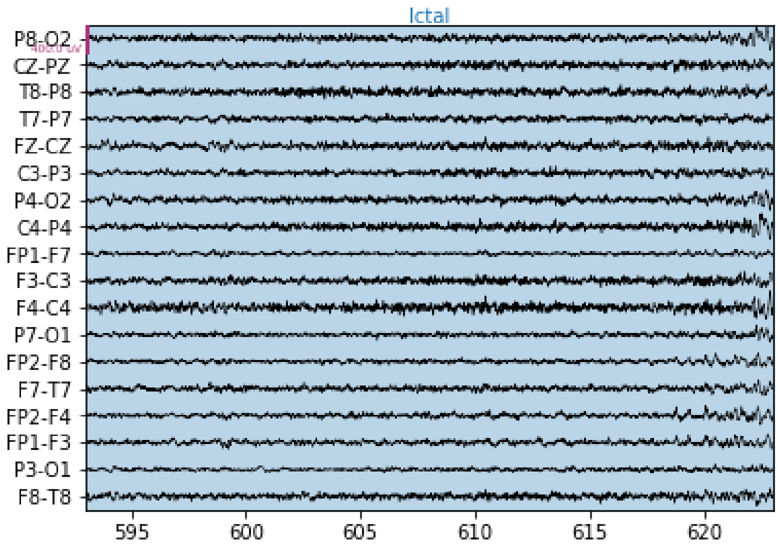


Figure 4.22: Ictal period sensor reading

Then we trimmed the datasets into training data (80%) and test data (20%). For that we have used tensorflow framework used for machine learning applications like neural network and also to build data models. We fixed batch size 128 for our dataset. We have taken 128 data points for at a time to train them. We have taken only 2 classifiers, one is either seizure and the other is not have seizure. That is why we have taken the num_classes=2. We have set the epochs number to 100, which means we will iterate the dataset 100 times. We have converted the x_train, y_test to categorical in order to get better accuracy. We have chosen sequential model. We have added conv2D with Kernel size (1, 1) and activation function ReLu. We have added conv2D for four times and each time increased the value of z-dimension by 2 times. Then we added MaxPooling2D with pool_size (1, 1). To avoid model overfiting we use dropout and the rate of dropout was 0.25 which means it will set 25% on input to zero each time.
To change the dimension of input we have used dense. It was basically used for

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 256, 2, 8)	72
conv2d_1 (Conv2D)	(None, 256, 2, 16)	144
conv2d_2 (Conv2D)	(None, 256, 2, 32)	544
conv2d_3 (Conv2D)	(None, 256, 2, 64)	2112
max_pooling2d (MaxPooling2D)	(None, 256, 2, 32)	0
dropout (Dropout)	(None, 256, 2, 32)	0
flatten (Flatten)	(None, 16384)	0
dense (Dense)	(None, 64)	2097216
dropout_1 (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 32)	2080
dropout_2 (Dropout)	(None, 32)	0
dense_2 (Dense)	(None, 8)	264
dropout_3 (Dropout)	(None, 8)	0
dense_4 (Dense)	(None, 2)	18

Figure 4.23: Summary of layers

making multidimensional input to single 2-dimensional input. Then again we used epochs size 30 because with 100 epochs we got the accuracy 82%. But in this case, with 30 epochs we got 92% of accuracy.

Chapter 5

Result Analysis

For training we have used batch size of 128 and epoch 30, 100.

5.1 Model Loss & Model Accuracy for epoch 100

The result of 100 epoch is given in Figure: 5.1

```
Epoch 97/100
21000/21000 [==============================] - 1s 36us/sample - loss: 0.4027 - accuracy: 0.7871 - val_loss: 0.3872 -
val_accuracy: 0.8067
Epoch 98/100
21000/21000 [==============================] - 1s 36us/sample - loss: 0.4040 - accuracy: 0.7855 - val_loss: 0.3618 -
val_accuracy: 0.8175
Epoch 99/100
21000/21000 [==============================] - 1s 34us/sample - loss: 0.4021 - accuracy: 0.7886 - val_loss: 0.3753 -
val_accuracy: 0.8050
Epoch 100/100
21000/21000 [==============================] - 1s 34us/sample - loss: 0.4046 - accuracy: 0.7871 - val_loss: 0.3639 -
val_accuracy: 0.8217
Test loss: 0.3639336057504018
Test accuracy: 0.82166666
```

Figure 5.1: Model Loss & Model Accuracy for epoch 100

From the above figure (Figure: 5.1), we can see using 100 epochs we got test loss 36% and test accuracy 82%.
The result of 100 epoch is given in Figure: 5.1

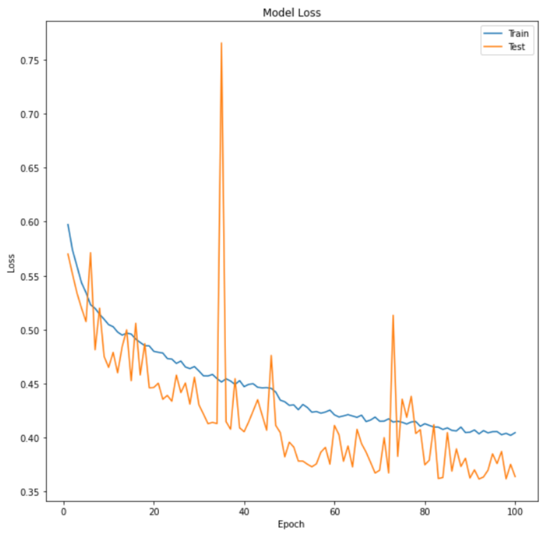


Figure 5.2: Changes in train and test using loss function

From the above figure (Figure: 5.2), we can observe the changes in train and test using loss function.

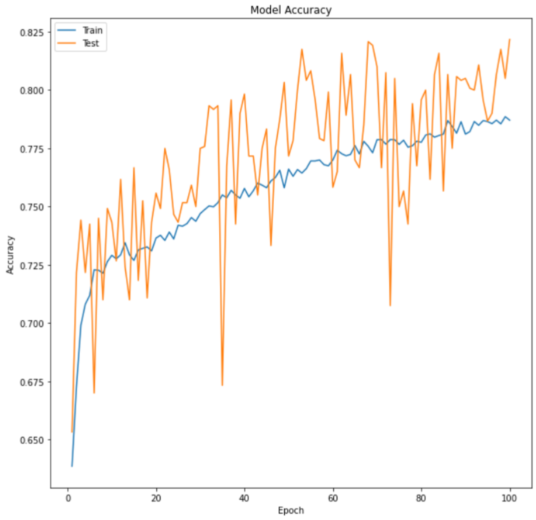


Figure 5.3: Changes for Accuracy by plotting from Train

In the above figure (Figure: 5.3), changes for accuracy function is shown by plotting from train.

5.2 Model Loss & Model Accuracy for epoch 30

The result of 30 epoch is given below:

```
165/165 [==============================] - 125s 758ms/step - loss: 0.1571 - accuracy: 0.9002 - val_loss: 0.1847 - val
_accuracy: 0.8723
Epoch 27/30
165/165 [==============================] - 125s 756ms/step - loss: 0.1573 - accuracy: 0.9101 - val_loss: 0.1709 - val
_accuracy: 0.8823
Epoch 28/30
165/165 [==============================] - 124s 754ms/step - loss: 0.1516 - accuracy: 0.9090 - val_loss: 0.1593 - val
_accuracy: 0.9055
Epoch 29/30
165/165 [==============================] - 126s 761ms/step - loss: 0.1431 - accuracy: 0.9232 - val_loss: 0.2098 - val
_accuracy: 0.9120
Epoch 30/30
165/165 [==============================] - 125s 760ms/step - loss: 0.1494 - accuracy: 0.9268 - val_loss: 0.1905 - val
_accuracy: 0.9202
Test loss: 0.19045889139175415
Test accuracy: 0.9202666579246521
```

Figure 5.4: Model Loss & Model Accuracy for epoch 30

From the above figure (Figure: 5.4), we can see using 100 epoch we got test loss 19% and test accuracy 92%. Which is 10% increase in test accuracy.

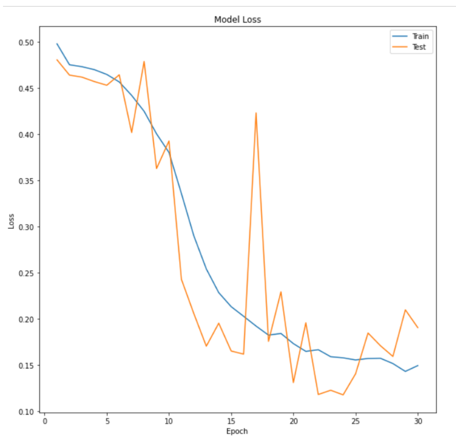


Figure 5.5: Changes in train and test using loss function

From the above figure (Figure: 5.5), we can observe the changes in train and test using loss function.

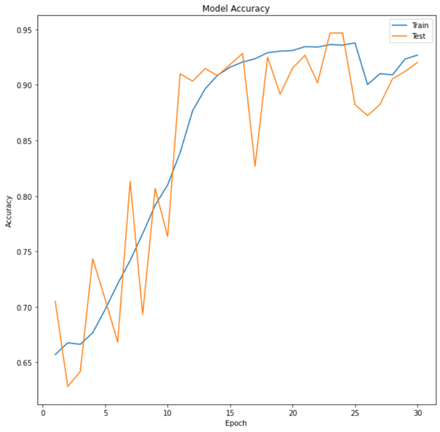


Figure 5.6: Changes in train and test using Accuracy function.

In the above figure (Figure: 5.6), changes for accuracy function is shown by plotting from train.

5.3 Loss Function

Loss Function is used in Neural networks to evaluate the loss of a certain model in order to update the weights to lessen the loss on the later evaluation process.It plays vital role to in producing optimum and faster results.Before implementing loss function, we have to add "sigmoid" as activation function.Activation function is implemented to alter the vectors before calculating the loss during the training phase. It suppresses a vector in the range of (1, 1).

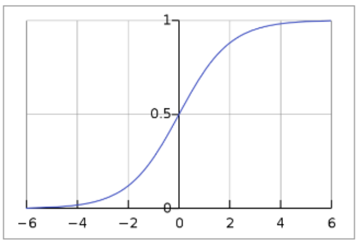


Figure 5.7: Loss function

For a same prediction, different loss function will give non-identical errors. The difference between the predicted output and actual the output is the error. Which is calculated in learning networks. In out model, we used binary cross entropy loss function. Which will evaluate the losses in one iteration. Then, the weights will be changed for next iteration in order to get better result.

5.4 Summary

In the final train part, we used epoch 30 and at the end of 30 epoch we got 92% accuracy, 19% loss. Which is 10% better accuracy than the previous attempt and the loss is dropped significantly by 17%.

```
Epoch 1/30
165/165 [==============================] - 128s 777ms/step - loss: 0.4978 - accuracy: 0.6571 - val_loss: 0.4805 - val_accur
acy: 0.7050
Epoch 2/30
165/165 [==============================] - 126s 764ms/step - loss: 0.4752 - accuracy: 0.6677 - val_loss: 0.4640 - val_accur
acy: 0.6283
Epoch 3/30
165/165 [==============================] - 124s 754ms/step - loss: 0.4731 - accuracy: 0.6663 - val_loss: 0.4618 - val_accur
acy: 0.6417
Epoch 4/30
165/165 [==============================] - 125s 758ms/step - loss: 0.4699 - accuracy: 0.6767 - val_loss: 0.4570 - val_accur
acy: 0.7433
Epoch 5/30
165/165 [==============================] - 125s 761ms/step - loss: 0.4647 - accuracy: 0.6978 - val_loss: 0.4530 - val_accur
acy: 0.7067
Epoch 6/30
165/165 [==============================] - 125s 758ms/step - loss: 0.4566 - accuracy: 0.7208 - val_loss: 0.4643 - val_accur
acy: 0.6683
Epoch 7/30
165/165 [==============================] - 123s 748ms/step - loss: 0.4420 - accuracy: 0.7419 - val_loss: 0.4018 - val_accur
acy: 0.8133
Epoch 8/30
165/165 [==============================] - 122s 742ms/step - loss: 0.4248 - accuracy: 0.7659 - val_loss: 0.4788 - val_accur
acy: 0.6933
Epoch 9/30
165/165 [==============================] - 122s 739ms/step - loss: 0.4004 - accuracy: 0.7916 - val_loss: 0.3628 - val_accur
acy: 0.8067
Epoch 10/30
165/165 [==============================] - 122s 741ms/step - loss: 0.3802 - accuracy: 0.8099 - val_loss: 0.3927 - val_accur
acy: 0.7633
Epoch 11/30
165/165 [==============================] - 123s 743ms/step - loss: 0.3357 - accuracy: 0.8390 - val_loss: 0.2428 - val_accur
acy: 0.9100
Epoch 12/30
165/165 [==============================] - 123s 743ms/step - loss: 0.2898 - accuracy: 0.8767 - val_loss: 0.2056 - val_accur
acy: 0.9033
Epoch 13/30
165/165 [==============================] - 122s 738ms/step - loss: 0.2541 - accuracy: 0.8964 - val_loss: 0.1704 - val_accur
acy: 0.9147
Epoch 14/30
165/165 [==============================] - 123s 745ms/step - loss: 0.2284 - accuracy: 0.9087 - val_loss: 0.1953 - val_accur
acy: 0.9083
Epoch 15/30
165/165 [==============================] - 123s 748ms/step - loss: 0.2132 - accuracy: 0.9159 - val_loss: 0.1652 - val_accur
acy: 0.9183
Epoch 16/30
165/165 [==============================] - 123s 746ms/step - loss: 0.2028 - accuracy: 0.9206 - val_loss: 0.1618 - val_accur
acy: 0.9283
Epoch 17/30
165/165 [==============================] - 123s 744ms/step - loss: 0.1922 - accuracy: 0.9235 - val_loss: 0.4231 - val_accur
acy: 0.8267
Epoch 18/30
165/165 [==============================] - 122s 740ms/step - loss: 0.1824 - accuracy: 0.9290 - val_loss: 0.1756 - val_accur
acy: 0.9250
Epoch 19/30
165/165 [==============================] - 122s 742ms/step - loss: 0.1842 - accuracy: 0.9303 - val_loss: 0.2293 - val_accur
acy: 0.8917
Epoch 20/30
165/165 [==============================] - 124s 749ms/step - loss: 0.1732 - accuracy: 0.9309 - val_loss: 0.1310 - val_accur
acy: 0.9150
Epoch 21/30
165/165 [==============================] - 123s 747ms/step - loss: 0.1648 - accuracy: 0.9344 - val_loss: 0.1958 - val_accur
acy: 0.9267
Epoch 22/30
165/165 [==============================] - 124s 751ms/step - loss: 0.1666 - accuracy: 0.9340 - val_loss: 0.1181 - val_accur
acy: 0.9017
Epoch 23/30
165/165 [==============================] - 124s 751ms/step - loss: 0.1590 - accuracy: 0.9363 - val_loss: 0.1227 - val_accur
acy: 0.9467
Epoch 24/30
165/165 [==============================] - 124s 754ms/step - loss: 0.1578 - accuracy: 0.9358 - val_loss: 0.1177 - val_accur
acy: 0.9467
Epoch 25/30
165/165 [==============================] - 125s 760ms/step - loss: 0.1555 - accuracy: 0.9378 - val_loss: 0.1405 - val_accur
acy: 0.8821
Epoch 26/30
165/165 [==============================] - 125s 758ms/step - loss: 0.1571 - accuracy: 0.9002 - val_loss: 0.1847 - val_accur
acy: 0.8723
Epoch 27/30
165/165 [==============================] - 125s 756ms/step - loss: 0.1573 - accuracy: 0.9101 - val_loss: 0.1709 - val_accur
acy: 0.8823
Epoch 28/30
165/165 [==============================] - 124s 754ms/step - loss: 0.1516 - accuracy: 0.9090 - val_loss: 0.1593 - val_accur
acy: 0.9055
Epoch 29/30
165/165 [==============================] - 126s 761ms/step - loss: 0.1431 - accuracy: 0.9232 - val_loss: 0.2098 - val_accur
acy: 0.9120
Epoch 30/30
165/165 [==============================] - 125s 760ms/step - loss: 0.1494 - accuracy: 0.9268 - val_loss: 0.1905 - val_accur
acy: 0.9202
Test loss: 0.19045889139175415
Test accuracy: 0.9202666579246521
```

Figure 5.8: Final Result

In the begging of the training (epoch 1) we got 65% accuracy and it increased gradually. At the same time the loss were 49% and the loss was too big. But by the passage, of time it started to minimize the loss and maximize the accuracy. In the end we found 14% loss and 92% accuracy.

Chapter 6

Discussion

Convolutional Neural Network(CNN) is undoubtedly the most common system for deep learning. Due to overwhelming success and efficacy of convents, the growing rise in interest in deep learning. CNN is also the go-to model for any problem dealing with images. They blast rivalry out of the water as far as precision is concerned. Recommendation programs, natural language analysis and others are also effectively used. Compared to its counterparts, the key benefit of CNN is that it instantly identifies critical characteristics without any human oversight. We also worked with CNN in our model. Basically CNN follows a specific architecture for all models. We have used CNN in our model and implemented the model with it. As shown in the figure below, all CNN models adopt a similar architecture.

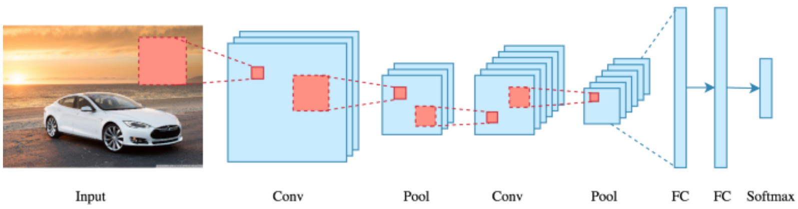
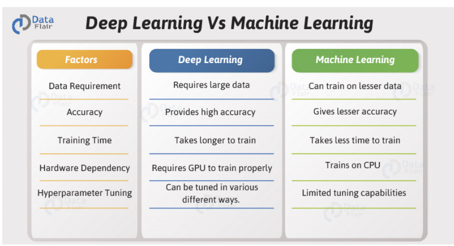


Figure 6.1: CNN architecture for all models

We can see from above model that we works on an input image and we are performing convolution as well as pooling operation and followed by a number of connected layers.Performing multi class classification our output would be softmax.All these operations are pretty essential for this architecture. We prioritized deep learning rather than machine learning in our model and the main reason is deep learning can easily handle our dataset. This is chart is given below with the differences between them:



Data Flair

Deep Learning Vs Machine Learning

Factors	Deep Learning	Machine Learning
Data Requirement	Requires large data	Can train on lesser data
Accuracy	Provides high accuracy	Gives lesser accuracy
Training Time	Takes longer to train	Takes less time to train
Hardware Dependency	Requires GPU to train properly	Trains on CPU
Hyperparameter Tuning	Can be tuned in various different ways.	Limited tuning capabilities

Figure 6.2: Deep Learning V/s Machine Learning

We know that CNN is a famous algorithm of deep learning and in our proposed model we used CNN. We could not be able to interact with those algorithms of machine learning with such a dataset of ours. We had to face some problems if we wanted to use the algorithm of machine learning. We had to work in n-dimension. We used 40GB dataset and using algorithm of machine learning if we wanted to plot them and from that if we wanted to bring the distance than we faced Problem. This type of plotting of our model could not possible at machine learning. That is the reason we used CNN here to implement for our model. At the same time machine learning cannot handle this type of signal dataset and we used deep learning here to build our model. As the batch size, number of classes and epochs number are very important to maintain..
The deep neural network will consist of three types of layers:
• The Input Layer
• The Hidden Layer
• The Output Layer

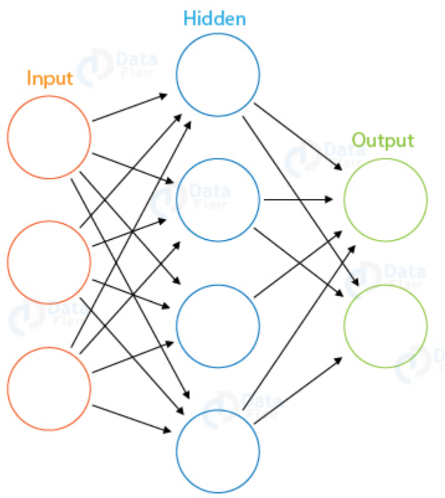


Figure 6.3: Deep neural network layer

From the above picture we can see that input layer is taking data from input.This is a secret layer which computes the input data in different directions and in the previous visualization the output layer is fully linear.In our project, we divided the dataset and sent it to deep learning and deep learning can handle the afterward works very easily. On the other hand we did not use SVM(Support Vector Machines).We know that SVM is believed to be a method of classifying machine learning that provides good results compared to other classifier types. Due to its productivity in coping with quiet small datasets we did not use it because our dataset is a big data(40GB)and in SVM we do not know from early moment how give priority to which sensor and this is not efficient and that's why we did not use SVM. We have also used some features in our model and there is a short note of each of them:

6.1 Kernel in CNN

The kernel is nothing but a filter in CNN.It is mainly used for removing the features from the images.Kernel is nothing but a matrix that passes over the input data and then it performs the dot product.After that it gets the output.On the input data, the kernel transfers the stride value. If the stride value is 2, the kernel shifts two pixel columns in the input matrix. In short, to remove high-level features like edges from the picture, the kernelis used.

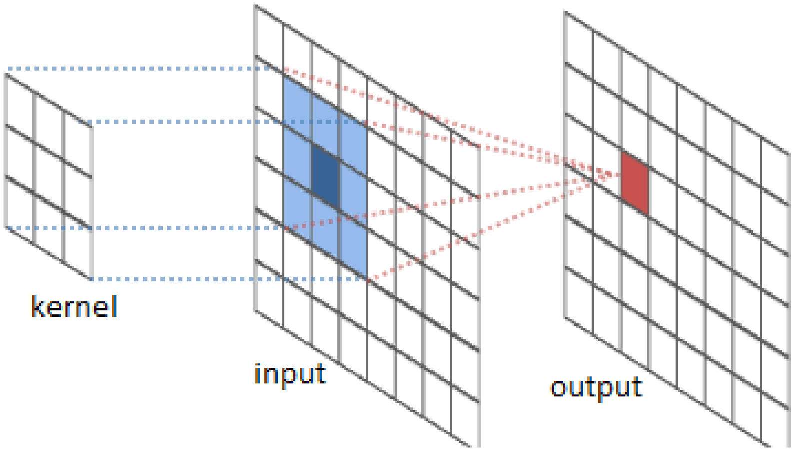


Figure 6.4: Kernel

6.2 ResNet-18

CNN is all about 18 layers deep is ResNet-18.We can easily load around one million images from the Image Net Database to a pre-trained version of the network. The pre-trained network will categorize photos into 1000 types of things, such as several animals or objects like eraser or pencil. As a result, for a wide variety of images, the network has trained rich characteristic representations.The network has a resolution of 224-by-224 image inputs. Anyone can use Classify in ResNet-18 mode to classify new images.

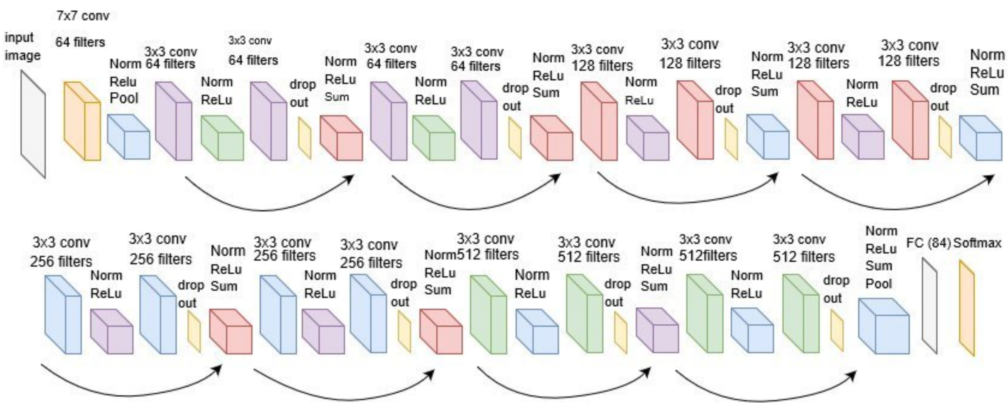


Figure 6.5: ResNet-18 Architecture

6.3 Loss Function

One of the significant components of Neural Networks is the Loss Function. The failure is nothing but a Neural Net prediction error. And the loss estimation process is called the Loss Function. The loss is used, in basic terms, to calculate the gradients. And the weights of the Neural Net are modified using gradients. This is how to prepare a Neural Net.

6.4 Optimizer Function

Basically optimizers are kind of algorithms or we can say it as methods and these are usedto change the attributes of neural Network.For example the weights and learning rate in order to reduce the losses. Algorithms or techniques for optimization are responsible for minimizing errors and producing the most detailed outcomes possible.

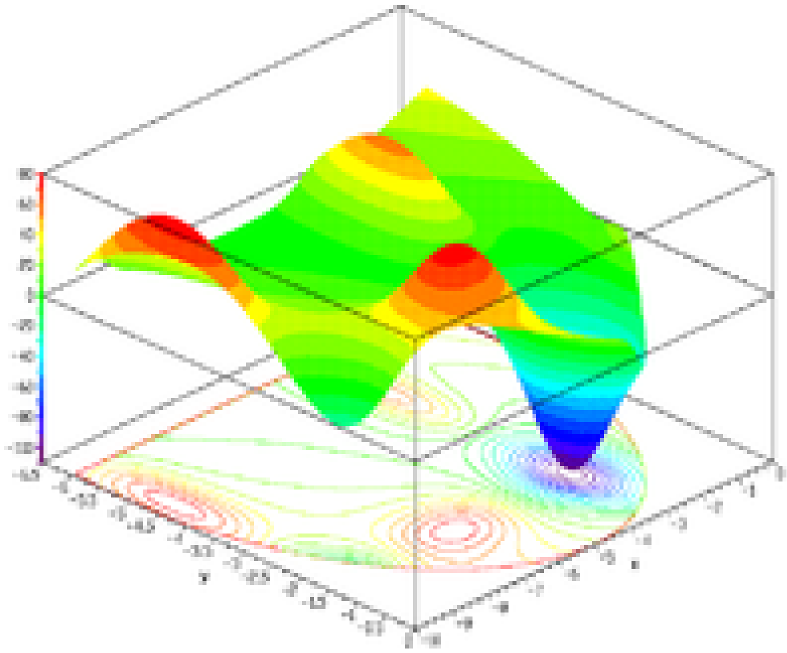


Figure 6.6: Optimizer Function

Chapter 7

Conclusion and Future Works

7.1 Conclusion

Epilepsy is one of the least known and it is the most common neurological disorder. The seizures that describe epilepsy are mostly unexplained and affect the quality of life of a sufferer, as well as raising the risk of injury and, in some circumstances, death. A large body of research has indicated that EEG recording research may identify these epileptic seizures. Our proposed model will be able to predict epileptic seizure by using deep learning methods. The main purpose of this thesis work is to predict the epileptic seizure as early as possible with high accuracy. People can secure themselves by taking precautions. It's quite hard to predict the epileptic seizure at its prior time. To execute our model we used CHB-MIT dataset. The data were found by applying electrodes in the scalp of the peoples. We used the data of brain signal of different EEG(Electroencephalogram) signal of a patient to predict the chances to have epilepsy of that particular patient. There are 24 parts of the data set. Among the 24 parts of the channel we have visualized two part of that because to deal with all 24 parts is difficult. This dataset is widely used for prediction of epileptic seizure. This can help doctors to examine the patient. We used Deep learning methods.It is a subset of machine learning and that achieves a great power.Unlike standard Machine Learning algorithms, Deep Learning includes high-end computers. Deep learning is powered by artificial neural networks, which contain several layers. Deep Neural Networks (DNNs) are those kinds of networks where dynamic operations such as representation and abstraction that make sense of images, sound, and text can be done by each layer. Deep learning, deemed the fastest-growing area of machine learning, is a genuinely transformative emerging platform which is being used to build innovative business models for more and more businesses. This accuracy is totally reliable. Different types of epileptic seizure can be predicted. With help of this model the data of the brain signal of EEG signal of a particular patient can be observed and with that observation the chances or the risks to have epilepsy can be detected.There is two picture together in the proposed model part which says about the two situations of a patient and the first picture is inter(Before having epilepsy) and the 2nd picture is ictal (After having epilepsy).There are various sensors and the changes of the values of those sensors help the doctors to help the patient who had faced a seizure and with our model the doctors will be able find a new way to serve the patients.This model will help them to take precaution to face the seizure and also our proposed model will help the patient to get enough time to take proper medication against epileptic seizure.

7.2 Future Work

The proposed model is about prediction of epileptic seizure. We predict the seizure at pre-ictal stage.While working on the project in future, we will develop our model in a better way. We will work to increase the accuracy rate. We will handle all the exceptions.Up to now we have managed about 92% accuracy of our model and in future, we will increase this accuracy level. Due to system configuration and enough time, we could not be able to increase the epoch number .We will try to increase the epoch number from 30 to 1000 gradually. By fixing up the epoch number in this way we will increase our accuracy level. As epilepsy varies from person to person, we will try to cover up all the cases. We will work on our model for more reliable accuracy.

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