

Prediction of Epileptic Seizure Onset Based on EEG Signals and Learning Approaches

by

Tausif Nazim

16101037

MD. Bakhtiar Abid

16301019

Jahid Hasan Mamun

14201020

A thesis submitted to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
B.Sc. in Computer Science and Engineering

Department of Computer Science and Engineering
Brac University
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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.
4. We have acknowledged all main sources of help.

Student's Full Name & Signature:

Tausif Nazim

Tausif Nazim
16101037

Bakhtiar

MD. Bakhtiar Abid
16301019

Jahid Mamun

Jahid Hasan Mamun
14201020

Approval

The thesis titled “Prediction of Epileptic Seizure Onset Based on EEG Signals and Learning Approaches” submitted by

1. Tausif Nazim (16101037)
2. MD. Bakhtiar Abid (16301019)
3. Jahid Hasan Mamun (14201020)

Of Spring, 2020 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of B.Sc. in Computer Science on April 5, 2020.

Examining Committee:

Supervisor:
(Member)

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

Program Coordinator:
(Member)

Sadia Hamid Kazi
Deputy Head and Assistant Professor
Department of Computer Science and Engineering
Brac University

Head of Department:
(Chair)

Prof. Mahbub Majumdar
Chairperson
Dept. of Computer Science & Engineering
Brac University

Mahbubul Alam Majumdar, PhD
Professor and Chairperson(CSE), Interim Dean, School of Sciences
Department of Computer Science and Engineering
Brac University

Abstract

Epileptic seizures happen due to sudden bursts of electrical activity in the brain. This uncontrolled outburst may produce physical problems, abnormal behavior. Before the beginning of the seizure, a prediction is very useful to prevent the seizure by medication. This can be done by applying machine learning techniques and computational methods on EEG signals. However, EEG signals, in raw form, are hard to process. Feature measurement and noise cancellation can be done. Therefore, we come up with a model that presents the predictable methods of both preprocessing and feature extraction. We applied statistical methods for preprocessing and extracted time and frequency phase from the EEG signals. Our model detects the interictal state, which is the time frame between two seizures, preictal state, which is the time frame before Epileptic seizure, and ictal state, which is onset to the end of an epileptic seizure. We considered 1 hour and 30 minutes for every seizure duration to create this model. We have used the Savitzky-Golay filter for data smoothing and we used the energy of the signal, mean amplitude, skewness, and kurtosis of the signal as the features to classify seizure and non-seizure period. For classification, we have used two classifiers such as support vector machines and naive Bayes classifiers. The model is applied on the scalp EEG Children Hospital of Boston(CHB)-MIT dataset of 17 subjects and we obtained accuracy of more than 75 percent for predicting with a high true positive rate. In the proposed method, derived sensitivity is 42 percent, specificity is 80 percent, precision is 47 percent and negative predictive value is 32 percent.

Keywords: EEG, preictal; ictal; interictal; Savitzky-Golay filter; Kurtosis; SVM; Naive-Bayes; Skewness

Dedication

We dedicate this thesis to our parents who relentlessly contributed to make our life beautiful.

Acknowledgement

At first, all praise to the Almighty Allah for whom our thesis have been completed without any major problem.

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Nomenclature

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

AR Auto Regressive

BCI Brain Computer Interface

CNN Convolutional Neural Network

DCT Discrete Cosine Transformation

DNN Deep Neural Network

DWT Discrete Wavelet Transformation

EEG Electroencephalography

EMD Empirical Mode Decomposition

FFT Fast Fourier Transform

FN False Negative

FP False Positive

ROC Receiver Operating Characteristic

SVM Support Vector Machine

TN True Negative

TP True Positive

Chapter 1

Introduction

1.1 Motivation

We aimed to enhance the strategies of predicting epileptic seizures for a lot of potency because of numerous reasons brain disease has become Associate in Nursing direful issue in terms of world health. Around fifty million individuals are affected worldwide because of encephalopathy whereas nearly eightieth of patients live in low and middle financial gain countries[90]. Patients diagnosed with such neurological disorders are challenged by abnormalities in behavior and cognitive activities. Our attempt to predict seizures before half an hour will help patients to make preparations for medication and treatment. Furthermore, it'll also help the patients for the analysis of epilepsy for ensuring their medical problems as well. In this case, Electroencephalogram(EEG) signal is the way of using the arrangement and functional instruction of the brain which will help out to point the defection of neurological disorders. For the distinct varieties of symptoms there are differing types of epileptic seizures that we'd like to predict for the benefit of quality.

We observed that there are many research papers which have been published about predicting epileptic seizure in various methods. Different researches are still going to predict the seizure more efficiently. EEG signals are very helpful to understand the brain activities. So, by extracting the features of EEG signals and classifying them accordingly can make the process fast enough to work efficiently. Here we aimed for the prediction to happen before thirty minutes of a possible epileptic seizure. The EEG records will simply show these electrical discharges as a fast fluctuation in potential variations in real time. Thus neurologists invariably use graph records to research suspected seizure phenomena [27][46][34].

Traditionally this job is conducted by associate skilled medical specialists employing a visual scanning of the EEG signals that could be a time intense method and should be inaccurate. These inaccuracies are notably vital for very long time length graphical record signals[38]. The system works by remodeling the largely qualitative diagnostic criteria into an additional objective quantitative signal feature classification downside and needs to be highly sensitive so that it can determine the false seizure and discard them[48]. The aim of the proposed model does not replace the neurologist, rather to relieve him off the burden of time consuming observation by providing alarms. With this purpose we tend to develop a system which

might predict the coming seizure so the patient will get a while to require necessary preparation so he/she can avoid serious work or take medication to stay him/her purposeful.

1.2 Thesis Overview

An epileptic convulsion is designated as a duration of symptoms due to abnormal or excessive electrochemical activity in the brain; the impacts of which are uncontrolled activities, shaking, movements in either all or any specific organ with inconsistent levels of consciousness or just a subtle momentary loss of awareness[90]. In most cases, the duration of convulsion is not more than sixty seconds which is insignificant but it takes a considerable amount of time to get back to a normal and consistent phase[92]. Due to this seizure, patients can lose bladder control[90]. There are certainly some behavioral, physical and physiological activities that provoke an epileptic seizure. The mainstream reasons can be a little sleep deprivation. Main types of epilepsy are- provoked and unprovoked. Around 10 percent of people have at least one epileptic seizure in a lifetime[90]. Research derives that provoked seizures occur in about 3.5 per 10,000 people each year and 4.2 per 10,000 people each year for unprovoked seizures. After one seizure, the possibility of experiencing a second is concerning around 50-50. Studies also show that about 1 percent of the entire population gets affected by epilepsy at any given time and about 4 percent of the population at some point in time[70][49].

Moreover, almost 80 percent of those with epilepsy are inhabitants of developing countries. On the other hand, there are many diseases and factors which can cause epilepsy. Important factors like traumatic brain injuries, central systema nervosum infections, vessel malady, brain tumors, neurodegenerative diseases, organic process disabilities, perinatal insults, and familial factors are accountable for epilepsy[5]. Many treatment procedures such as vagus nerve stimulation and responsive cortical stimulation is suggested for epilepsy[17][53]. Electric signals of measurable amounts are produced by the brain in different types of band namely alpha, gamma, beta, and theta. From different characteristics of brain signals, it can be determined if the person is in the seizure phase or non-seizure phase. Brain signals are recorded as electroencephalograms(EEG) which is the movement of cerebrum measures the voltage fluidity coming about because of ionic current flow inside the neuron cells of the brain[18].

The whole process is also compared to the BCI(brain-computer interface) system. Although, the neuro-computer combination system actually has a particular motive and the field of BCI research and development has always focused mainly on neural prosthetic applications that target at recovering damaged or disabled movement[12]. EEG depicts the chronology of the neuron's electrochemical activity over an unlimited period of time by electrodes on the scalp. Different activities in the brain are visible in fluctuation of EEG signals. Thus EEG signals are necessary for predicting seizure of a patient. Specific patterns of seizure time EEG signals can help to differentiate seizure and normal phases. After considering a certain time frame of EEG signals, feature extractions and classifications are conducted.

1.3 Major Contribution

Recent multi-center clinical studies showed proof of precursory symptoms in thirty one of five hundred epileptic patients[39]. Another interview-based study found that 50 percent of 562 patients felt “auras” before seizures[7]. These clinical observations offer an advantage to look for precursory changes on Electroencephalographic (EEG) recordings from the brain. The epileptic brain consecutively transitions through completely different states of activity: from traditional interictal (far from seizures) to preictal (minutes or generally hours before the seizure) then ictic (seizure) and postictal, before returning to the interictal state [32]. Despite the present lack of an entire medical specialty understanding of the preictal brain state, that is patient and condition specific, researchers progressively hypothesise that brainwave synchronization patterns would possibly differentiate interictal, preictal and ictal states [21]. Differentiating between interictal and preictal patterns of brain activity becomes a limitation for classifying seizure and non-seizure phase[32]. Ictal and attack states are removed from the classification as a result of the task isn't to observe undergoing seizures, however to warn the patient or practitioner regarding future ones [[32].

Electroencephalograms (EEGs) are records of neural electrochemical activity. It is an essential tool for identification of neurologic diseases and brain disorders, such as epilepsy. Discrete signal conversion method is a popular and efficient tool for processing of non-linear signals, such as EEGs[54]. Relative wavelet energy (RWE) provides data concerning the relative energy related to totally different frequency bands given in electroencephalogram signals and their correlated intensity of significance[54]. The measurement of EEG-brain function relationships using measures of EEG amplitude are well known[4]. Amplitude indicates the pattern of convulsion and normal stage. However, actuarial criteria such as mean, variance, skewness and kurtosis of EEG signals can be extracted as features[78]. The sub-band frequencies of the sub-band signals obtained from the DWT have been used as a feature for classification of normal and seizure EEG signals[47]. For signal smoothing, we have used Savitzky–Golay filter. It measures the numerical significance of the least squared polynomial (or its derivative) at point $i = 0$, over the full sample set[87]. The used digital filter employs the algorithm of linear least squares for data smoothing, which helps to acquire a high proportion signal and noise also retains the original shape of the signal[87].

We are approaching features which are significant and recognizable. Thus we have selected energy of signals[54], mean amplitudes of signals, skewness and kurtosis as the main features of our approach[4][78]. Energy shows different forms of intensity of signals and different patterns of signals have different energies. However, mean, skewness and kurtosis describes fluctuation of signals from a standard reference point. We have also used discrete wavelet transform (DWT) for calculating energy from frequency domain[47]. For classification, we have used support vector machine (SVM) because it is one of the best classifiers for non-stationary signals classification[44]. Therefore, energy of signals, mean amplitude, skewness and kurtosis used as features and SVM is considered for seizure and non-seizure EEG signals classification. The proposed approach may provide an opportunity to develop a medical instrument to detect upcoming seizures.

1.4 Thesis Orientation

The subsequent sections of the thesis have been organized as follows. Chapter 2 is literature review features the related work and existing approaches based on our proposed method. Chapter 3 provides a thorough analysis of the background information related to our work along with the dataset used in this thesis. Chapter 4 contains our proposed approach for predicting seizure. Chapter 5 provides the experimental results and the related discussions. Finally, Chapter 6 concludes and summarizes the report.

Chapter 2

Literature Review

The importance of using EEG signal analysis to determine many structural brain adjustments comparable with distinct disease states. A human brain has distinct states which depend on the signals it produces. Depending upon the frequency ranges, there are five types of signals which have been labeled as delta, theta, alpha, beta, and gamma. When any changes occur during these signals that indicate the disorders such as epileptic seizures. When the pattern of signals assembled from the patients experiencing epileptic seizure this addresses a model signal of the brain with epilepsy. In recent years, EEG epileptic EEG activities have been a matter of study as epilepsy is a typical neurological disorder.

Researchers have achieved several studies about the signal analysis of epileptic seizures where the time-frequency distribution has been enormously advantageous to decompose in the signal analysis. The researchers have used several decomposition methods of which some of them are frequently used. Among the states of seizure, attack state and preictal state are excellently helpful for predicting epileptic seizures by Usman et al. [91]. The attack state can be utilized for classify seizure and non-seizure graphical record signals. The pre attack state is a helpful phase of convulsion. It begins many minutes before the attack of a convulsion, and concludes with the beginning of the attack state[91].

Many researcher[74][81][84][69][77] tried to sight the start of the preictal state by exploiting EEG signals. However, solely some have dependably detected the preictal state of brain disease. Preprocessing of the EEG signal to extend signal-to-noise proportion ratios and option extraction play a very important role in reliable prediction of epileptic seizures. The combination of multiple distinctive choices into a feature vector is accustomed to predict the preictal state of convulsion. Rasekhi et al. in [74] have planned associate degree algorithmic rule for seizure prediction with the assistance of univariate linear options. In [74], the authors used solely six graphical record channels in their planned model and extracted twenty two univariate linear properties. Thus, a 132-dimensional feature space is formed. It was assumed that preictal time starts ten to forty minutes before the ictic state with a distinction of ten minutes. Prediction of epileptic seizures is taken into account by categorizing a binary class that classifies check knowledge into either preictal state or ictic state. On average, the prediction sensitivity when applying this algorithmic rule is seventy three percent.

In [74], the authors used Support Vector Machine as a classifier to classify the preictal and attack states of EEG signals. The authors have used extracted univariate linear options exploiting the window size of seconds in their formula. Within the second step, preprocessing is finished, and finally a choice was created on encephalogram signal, following bound regularization. Three encephalogram channels are extracted by inserting electrodes on the patient's scalp that specialize in seizure, whereas the 3 electrodes are situated outside the condemned surface. The info of the non heritable encephalogram signals are born-again into segments of a non overlapping window having the dimensions of five seconds. Once changing this information to the 5-second segments, the Butterworth filter [45] was accustomed to cut back the noise impact. The authors in [74] extracted the primary four applied math moments as options. Of these four options live similarity, variance, and symmetry of consecutive samples of EEG signals. So as to alter outliers, the authors have standardized all the options, thus there'll be no outliers. Although the noise has been reduced from signals, still there was some noise within the EEG signals, because the brain may be a non stationary supply for recording the EEG signals. Smoothing is performed on the graphical record signals to remove the unnecessary noise.

It has been ascertained in literature that univariate linear options have higher sensitivity performance for encephalopathy information of graph signals. Teixeira et al. in [81] have planned a model for prediction of epileptic seizures by selecting solely six channels of graph signals and have extracted twenty two linear univariate options for every channel. The over all options pace expands to 132 dimensions. In [81], the authors have used solely six electrodes for graph information acquisition. The main reason behind this minimum conductor choice is to line free the patient from sporting an oversized range of electrodes, as patients are usually unwilling to wear such a big amount of electrodes on their scalp because of discomfort. Therefore, so as to present comfort to the mind, solely six channels are non heritable and used for prediction purposes. The authors have designated these electrodes by victimization 3 completely different approaches.

One technique is by haphazardly choosing six graph electrodes, whereas the second technique is to decide on six channels from electrodes that are placed on the scalp space from wherever seizures originate. The authors in [81] have used notch filter [43] for signal smoothing. They have conjointly tested their model for prediction by variable multiple combos of electrodes and conjointly with four completely different preictal state durations. They need to use 3 classifiers for classification and have some expected seizure. When choosing appropriate options, coaching information is fed into the Support Vector Machine for coaching the classifier, so take a look at information passed for determinative classification accuracy and sensitivity. The authors have ascertained sensitivity of seventy five percent of police investigating the seizure, that means that, out of 87, they need with success detected sixty six seizures. The authors have conjointly planned that performance will be improved by more reducing options set.

In [84], Bandarabadi et al. have planned associate formula to predict encephalopathy seizures which will extend the lifetime of epilepsy- affected patients. They have extracted spectral power options, and when appropriate choice of options, options are passed into Support Vector Machines for classification. they need ascertained sensitivity of 75.8 percent; it implies that their classifier has foreseen sixty six seizures out of total eighty seven. they need all over that, by applying these ways, when reducing planned options set will improve seizure prediction performance. In [69], the authors have used ripple methodology for prediction of seizures. They need extracted options together with ripple energy and ripple entropy. 2 or 3 channels are selected for testing functions on a dataset of six patients. Sensitivity has been reported as half of one mile with an average anticipation time of twenty-two minutes. Zandi et al. [77] have additionally planned a model for predicting seizures mistreatment scalp encephalogram signals on the idea of zero crossings. The authors in [55] have computed the bar chart of all intervals in an exceedingly moving average window and have elect values from specific bins for observations. Once the full method is completed, last five seconds of observations are compared with totally different reference sets of points, containing preictal and interictal states. They have measured a similarity index on the idea of variational theorem Gaussian mixture [8] model of encephalogram information.

Researchers over the past twenty years engaged on signal process ways and conjointly attempting to categorise the convulsion. They knew completely different signal characteristics from graph signals and conjointly to classify the signal segments supported the measured options [71]. Therefore, numerous automatic epileptic spike detection ways are developed. actual supply localization of epileptic space could be an obligatory condition for self-made surgery and its description from functionally applicable regions. The physiological aspects of seizure generation and therefore the treatment and observation of a seizure are necessary problems that require to be thought of. Electroencephalography (EEG), magnetolectric machine roentgenography (MEG) and purposeful magnetic resonance imaging (fMRI) are the most neuroimaging modalities used for sleuthing seizures. EEG/ERP shows the neural activity at the scalp [71][63].

The daring (blood-oxygenation- level-dependent) areas within the purposeful magnetic resonance imaging of the os clearly show the epileptic zone. The self-report personality inventory is generally used for this type of observations and information recordings [55]. The fMRI facility is prescribed to the main hospitals and is expensive. Hence, it's not possible to use functional magnetic resonance imaging for all the epileptic patients [64]. million has a similar drawback that it's solely put in in massive and main hospitals. Finally, the electroencephalogram provides the answer to those problems in terms of value and quality for the study of encephalopathy. The epileptic seizures are controlled through medications if it's detected before time. Therefore, it becomes necessary to sight the conditions resulting in encephalopathy.

Hence, a true time prediction system is terribly useful for the clinicians moreover because the patients. The system is going to be ready to predict or sight partial encephalopathy attacks in order that preventive measures are taken by the patients

or caretakers. Different strategies are used for prediction and detection of seizures in literature which incorporates linear and nonlinear strategies. The quick Fourier remodel was used because of the ancient technique to require graphical record time domain signal in frequency domain. FFT is a non-parametric technique for analyzing graphical record spectrum. The non-linear pattern of graphical record signals, direct application of FFT is inappropriate[42]. However, for brief segments of At times, graphical record signals are often thought-about as stationary signals. The riffle remodel up to some extent overcomes the constraints of Fourier remodel by mouldering signal into completely different resolutions and scale levels [19]. Univariate Linear strategies used to this point for seizure declaration are automobile regressive moving average, accumulated energy[29], spectral band power and applied math movements. a graphical record signal is taken into account nonlinear in nature. nonlinear strategies used to this point are correlation dimensions, correlation entropy, energising similarity index and largest Lypanouv exponents[31].

To classify the signals, there are varied techniques. Machine learning technique is one amongst them. There are such a big amount of approaches to machine learning. Among them most typically used among them are SVM(Support vector machine) and ANNs(Artificial neural networks). ANNs have widely been applied to classify graph and graph signals over the last 20 years. a spread of various ANN primarily based approaches were according to the literature for convulsion detection[25]. Neural network place along methodologies are basically supported building models of epileptic and normal graphs and then utilizing these models to rearrange graphs as either epileptic or typical. Models are assembled hooked into options extracted from a preparation informational assortment. options area unit chosen with the goal that they capture the contrasts between the epileptic and normal graph.

Feature extraction method assumes an essential job on the classification execution of the ANN models[56]. SVM classifier as a general classifier is introduced in some approach that has demonstrated nice outcomes in characterizing seizure and non-seizure graph signals hooked into the data transfer capability parameters[62]. Specially, linear svm may be a methodology that's utilised in an assortment of applications. This isolates categories by a hyperplane and makes plots of varied isolated classes. The partition by hyperplane may be thought of either 2D or 3D hooked into the knowledge. Beside these two, Gaussian mixture model classifier is employed by Rajendra et. al[67] wherever the probability density capability of every category is predicted to comprise a combination of three-dimensional Gaussian distributions. A Gaussian mixture model expects and treats all of the knowledge focused are created from a combination of a restricted variety of Gaussian distributions with obscure parameters.

Chapter 3

Background Analysis

For Analysis of our work, there are some background learnings which are very much important for our research work. Also, we have found a lot of resources which will help us to work on our desired topic. By studying those different techniques and applying our approaches which will lead us to acquire the outcome more efficiently and well organized. Here is the analysis of our learning.

3.1 Brain Cytology

In our human body, the most important part which commands the nervous structure is the human brain. For the neurological organs and instructing the muscles, the human brain is the way to receive the signals and make decisions by sending instructions to the rest of the body[23]. The human brain controls most of the operations of the body, for example, processing, integrating and regulating the information which it obtains from the sense organs[26]. The brain is also responsible for all functions of the body, demonstrating the abstract of the mind and soul. The brain consists of three major parts including cerebrum, cerebellum, and brain stem. Details of brain's part shown in Figure 3.1

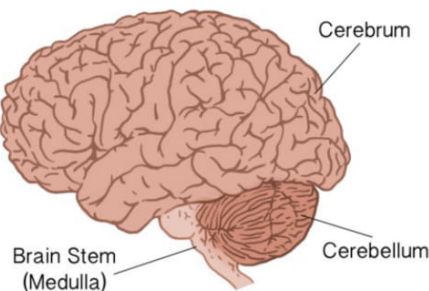


Figure 3.1: Cytology of Human Brain[26]

3.2 The Cerebrum

The cerebrum is the biggest part of the human brain and it is referred to in intellectual functions for example memory, attention, awareness, thought, language and

consciousness. These are the things that essentially make all of our perception of senses and it dictates and commands and it tells our muscles to move. The cerebrum processes sensory information and motor information. In humans, there are five distributions of the brain where the cerebrum is most enormous and best-developed among them[11].

3.3 Left And Right Hemispheres

The cerebrum contains two hemispheres: the left and right hemispheres. The number of fibers which is named as the corpus callosum is responsible for transmitting messages from one side to another side[33]. The left side of the brain commands movements and controls the right side of the body. The left hemisphere is responsible for controlling the academic and logical side of the brain[41]. For math and science computational problems it plays an important role in the brain. Also, the left side of the brain manipulates many of the duties of speaking and pulls facts from memory. On the other hand, the right side of the brain commands movements on the left side of the mind. The right hemisphere leading person excels in creativity, intuition, emotions, feelings visualization, etc. When a stroke happens on the right side of the brain, it causes the left arm or leg to be paralyzed[61].Figure 3.2 shows the left and right hemisphere of brain.

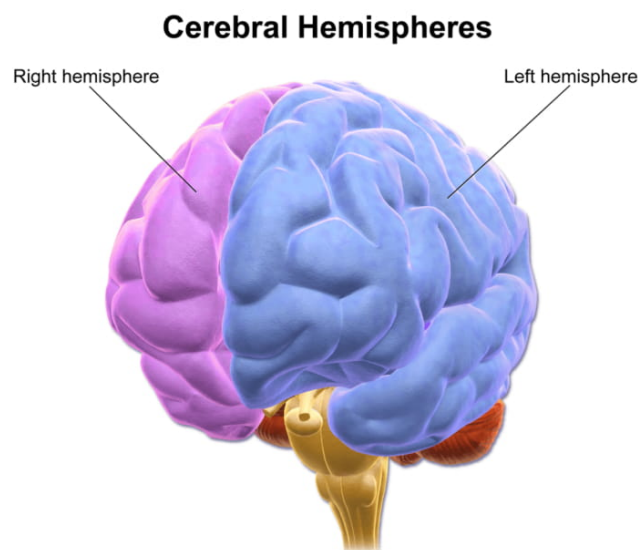


Figure 3.2: Hemisphere of Human Brain[33]

3.4 Lobes Of The Brain

Traditionally, the cerebral hemispheres have distinct into four lobes: frontal, parietal, temporal and occipital. From reasoning to auditory perception the lobes of the brain have been combined with different functions. The lobes of the brain have very complicated relationships between the left and right hemispheres [96].Different lobes of brain are shown in Figure 3.3.

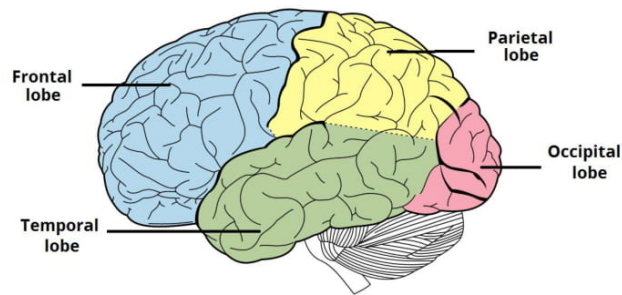


Figure 3.3: Lobes of Human Brain[96]

3.5 The Frontal Lobe

There are two major boundaries of the brain that define the frontal lobe: central sulcus and lateral (Sylvian) Sulcus[13]. The frontal lobe is the part of the brain that plays a vital role in controlling important cognitive skills in humans including emotional expression, reasoning, language, problem-solving, memory, judgment, planning, intelligence, concentration, self-awareness, and sexual behaviors[76]. It performs the control panel of our personality and maintains the capability of communication. It is a very common place where any time danger can occur which creates changes in personality, limited facial expressions, and concentrations.

3.6 The Parietal Lobe

The parietal lobe is situated above the occipital lobe of the brain and at the back of the frontal lobe. The main function of the parietal lobe is to process sensory information such as touch, temperature, and pain. The parietal lobe is considered one of four main lobes. It also deals with spatial sense and navigation. The parietal lobe performs several areas that help with language processing. Damage to the right side causes visual problems also damage to the left side damages the ability to read, write, and solve questions[28].

3.7 The Temporal Lobe

The temporal is located below the parietal lobe so it's right in a lower back portion of the brain The temporal lobe is kind of to the side of the brain. It is involved in processing auditory signals. The hearing procedure is also processed in the temporal lobe[6]. It also plays a role in speaking and understanding written and verbal material also a perception in particular of face recognition. The temporal lobe has importance with the memory in particular of the hippocampus which is actually part of the limbic system in the brain[36]. It's one of the original parts of the brain. It plays a role as a sort of timekeeper. It helps us keep track of time. So, the hippocampus plays a big role in memory and it plays with the temporal lobe. If any damages occur in the temporal lobe that causes problems with language skills, speech perception, recognizing face and memory.

3.8 The Occipital Lobe

The occipital lobe is about vision. It is the smallest of the four main lobes in the brain. It sits right at the back behind both the parietal and temporal lobes. The occipital lobe deals with visual sensory information[16]. Subsequently, partial or complete blindness may be the damage to the occipital lobe. Damage to the association area of the left occipital lobe tends to affect the right visual whereas damage to the association area of the right occipital lobe tends to affect the left visual field. The visual field is not the same as an eye. The left visual field is comprised of the left section of both eyes and the right is comprised of the right section of both eyes. The left visual field is processed by the right occipital lobe and the left occipital lobe[68].

3.9 Memory

Memory is a complex process that is distinct into three phases: encoding, storing and recalling. In order to form new memories, when the information has changed into a usable form that happens in the process which is called encoding. There are different types of encoding including visual, acoustic, and semantic encoding. For later use of memory when the information performed as successfully encoded it is stored in memory. The recalling process provides stored memories into conscious awareness[35].

3.10 Sensory memory

The sensory memory is the first stage of memory when information enters the nervous system through senses such as eyes, ears which are two most common. The sensory memory plays a vital role in filtering out the vast majority of useless information that enters our senses. It enables us to focus on the more important information during the time information enters the nervous system. It is then encoded as a neural message in the sensory memory. Affecting the sensory memory causes a serious problem such as Schizophrenia and Alzheimer's[35].

3.11 Short-term memory

Short term memory is known as working memory which occurs in the prefrontal cortex. The main function of this short-term memory is to store information that is about one minute. The capacity is limited to seven items. It keeps the information about sensory memory and long-term memory. It is the quick process and manipulating of information. It deals with the things in the current moment[35].

3.12 Long-term memory

The long-term memory working principle is activated when something that is memorized for a long time. It proceeds with the continuing storage of information. Long-term memory is known as the pre-conscious and unconscious. It refers to all

forms of memory that are more persistent than working memory. Long-term memory has no clear capacity limit. Long-term memory loss causes a serious problem such as dementia[35].

3.13 The Cerebrum

The cerebellum meaning the little brain is a structure located at the base of the brain it contains 50 percent of all the neurons in the brain and serves to coordinate other areas of the brain involved with movement allowing them to work together to perform smooth precise movements. It increases the muscles resistant to passive stretch. Damages to the cerebellum create problems such as loss of coordination of motor movement, the inability to judge distance, movement tremors, and weak muscles[58].

3.14 The Brain stem

The brain stem connects the various elements of the nervous system referring to the brain and spinal cord. It is set below the diencephalon and controls vital functions of the body. Many of the cranial nerve pairs come out of the brain stem. Due to this, it is responsible for many vital autonomic functions as well as the sensations and movements in our face and head[9]. In Figure 3.4 positioning of brain stem is shown.

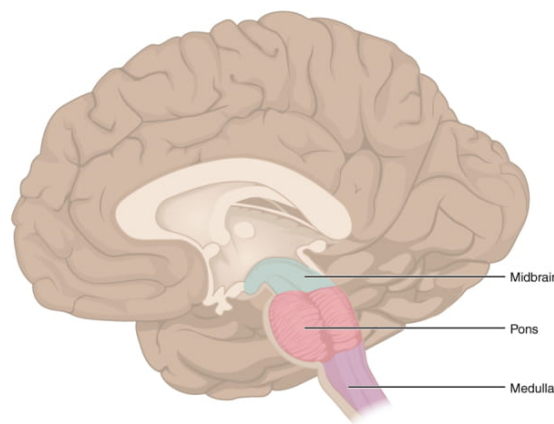


Figure 3.4: Brain Stem Cross Section[9]

3.15 The Mid brain

The upper part of the brain stem is known as the midbrain. The midbrain plays a major part in the processing of visual information, auditory information and integrating reflexes to auditory and visual stimulus. It is a part of the central nervous system which is related to hearing, motor control, vision, sleep and wake cycles, and temperature[9].

3.16 The Pons

The pons means “bridge”. The pons is located under the midbrain. Its main role is to bridge, or relay, sensory information between the cerebrum and the medulla. To facilitate this role, the pons is made up of many nerve tracts that carry information through the brain stem towards the upper portions of the brain. It also integrates with the medulla oblongata to produce normal breathing patterns[9].

3.17 The Medulla Oblongata

The lower part of the brainstem is the medulla oblongata. It refers to sending sensory information to the thalamus and the other portions of the brain stem. It is considered a major autonomic center because it regulates our visceral functions such as breathing, heart rate, and digestion[9].

3.18 Deep Structures

The coronal cross-section of the brain is specified as the deep structures of the brain. There are some pathways which are called white matter tracts related to nerve fibers that have the connection with the areas of the cortex of each other. While receiving any information towards the brainstem, this information can move from one lobe to another lobe and from one side to other deep structures in the brain[52].

3.19 The Hypothalamus

The hypothalamus is placed on the base of the brain stem controlling bodily functions including heart rate, digestion and blood vessels. The hypothalamus performs a major role in some functions such as releasing hormones, hunger, thirst, controlling appetite. Damage to the hypothalamus may cause problems in body temperature regulation, emotions, growth and sleep cycles[15].

3.20 Thalamus

Thalamus is a bilateral structure located at the upper of the brain stem. It is defined as a relay station, controlling the movement of information to the neocortex. The thalamus is variations of many distinct nuclei, and each containing thalamic relay neurons. The main purpose of the thalamus is associated with some functions by controlling touch, pain sensation, attention and motor activity[40]. Damage to the thalamus may cause problems associated with movement disorders, risk of coma and lack of movement.

3.21 Basal Ganglia

Basal ganglia are the number of collections of gray matter that lie deep within the brain. The structures about basal ganglia consist of globus pallidus, caudate and putamen in the cerebrum. There are some important features that are mostly

dedicated to motor functions that are generally part of the telencephalon. There are so many different structures including motor control and more clinical significance[22]. It is associated with some functions which control fine motions such as fingertip movements, eating and writing. Damages to the basal ganglia create problems about controlling speech, sustaining movement and posture.

3.22 Limbic System

There are some groups of brain structures found deep under the cerebral cortex above the brain is known as the limbic system. This brain function is associated with controlling our emotions and motivations including fear, hunger, anger and sexual behaviour. It is also related to higher mental functions such as learning and memory. If there's any damages occurring in the limbic system that can create problems in the hormonal system to become unbalanced[30].

3.23 Electroencephalogram(EEG)

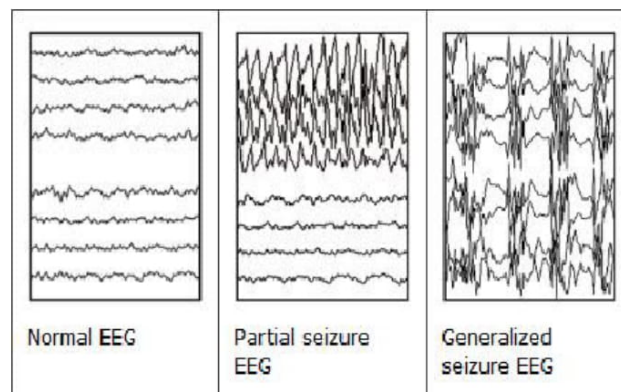


Figure 3.5: Different pattern of EEG[94]

Figure 3.5 shows the different trends of EEG due different form of seizure. EEG is that the recording of the electrical activity occurring at the periphery of the brain. This activity mensuration seems on the screen of the graph machine as waveforms of various frequency, form and amplitude. The recorded waveforms replicate the electrical form of cerebrum activity. A German medical specialist named Hans Berger [59] fancied electroencephalogram and projected the method of recording brain waves by placing electrodes on the human skull in 1929. Although his method was met with criticism at first it was later recognised later[95].Ever Since a lot of researchers engaged in this field of studying the interaction between computers and humans by observing emotional reactions[57][82].

EEG devices are called noninvasive due to the fact that it does not affect or influence the brain anyway. EEG requires electrodes to be placed on the human skull,which picks up brain waves resulting from electrochemical pulses within neurons in the brain. Electro chemical pulses are received by the EEG machine and passed on to an amplifier, in order to make them view-able on a paper or a display. Simple

mechanism and being noninvasive, EEG has emerged to become the best method of detecting brain-wave[75]. Information from the electrodes of the EEG cap [85] can be transferred in different methods such as Bio-Semi[50],B-AlertandBio-Radio150[85]. While recording brain-waves the machine pickup various noises due to eye blinking,muscle movement and also instrument noise[73].To Avoid Inconsistencies The Noise Is Removed By Usingbandpassfilters,Independent Component Analysis(ICA) can be used as accounted in [37]and[10].Noise can be reduced further by making sure that there is proper conductivity at the contact points of the scalp[85].

3.24 Brainwaves

Electrical pulses in the main cerebrum system that have repetitive cycles or patterns are what we call “Brain Waves” [50]. These neural oscillations responsible for neural transmission are measured in Hertz. [89] Pulses generate from either a neuron or due to interaction between two neurons. Information is passed onto the target muscle or destination through the nervous system in order to perform motoraction,send sensory information or just virtual information. Therefore Brain Waves differ based on what information or instruction they are communicating[80].High Frequency brain waves can be observed when a human is ecstatic, however low frequency brain waves can be observed when humans feel lazy or bored. The different brainwaves of varying frequency range can be observed through an EEG. They can be categorized in terms of their frequency range into five types [88].In Figure 3.6, various illustrations of brain waves are shown.

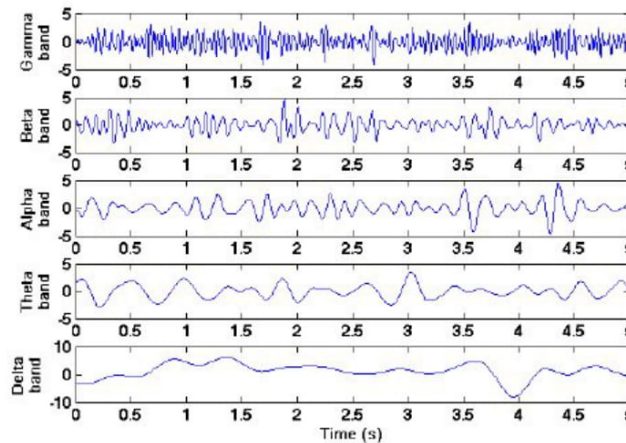


Figure 3.6: Different Brain waves[88]

3.25 Delta

Delta Brainwaves Moderate,boisterous brainwaves with a frequency dimension of 4Hz or below[16].It is really typical as the overwhelming mood in new children upto one year and furthermore in the stages 3 and 4 of rest. It might happen centrally with subcortical sores and all in all dissemination with diffuse injuries, metabolic encephalopathy hydrocephalus or profound midline lesions[2]. It is usually the foremost clear frontally in grown-ups and posteriorly in youngsters.

3.26 Theta

Theta has a frequency of 4 to 8 Hz and is delegated moderate activity[18]. It is exquisitely typical in children up to thirteen years and in rest but thought to be abnormal in wakeful elders.. It tends to be viewed as an indication of central neural structure sores. In theta, we tend to be in an exceedingly fantasy, clear symbolism, insight and information past our typical cognizant attentiveness.

3.27 Alpha

Alpha has a frequency somewhere in the range of 8 and 13 Hz[18]. It is generally best found in the back districts of the cerebrum on each side, being higher in acceptability on the prevailing side. It ordinarily generates when closing the eyes and unwinding thus, vanishes when opening the eyes or alarming by any mechanism[18]. It is the important wave found in ordinary loosened elders as this beat helps generally speaking mental coordination, peacefulness, preparedness, inner self and body combination and learning.

3.28 Beta

Beta is quick action wave having a frequency of 14 and more prominent Hz[18]. It is typically determined on the two halves in uniform provision, and is most evidently in front. At no matter purpose thought is coordinated towards subjective tasks, beta brainwaves rule our standard waking condition of cognizance which could be missing or lessened in territories of cerebral damage. It is by and large viewed as an ordinary beat and the overwhelming cadence in patients who are excessively cautioned or on edge or have their eyes open.

3.29 Gamma

Gamma brainwaves are the quickest of brain waves with most astounding frequency sufficiency and identify with concurrent handling of data from various brain territories. Gamma brainwaves pass information quickly and unobtrusively because the most obscure of the brainwave frequencies[14]. It is expected that gamma rhythms tweak observation and cognizance and a lot of distinguished closeness of gamma identifies with extended awareness and transcendental development.

3.30 What is Epilepsy

A convulsion may be a short scene of signs or manifestations because of remarkably unconscionable or synchronous neural movement within the brain. The Outward Impact will Shift From Uncontrolled jerking movement (tonic-clonic seizure) to as inconspicuous as a transient loss of awareness (absence seizure).Epileptic seizures are caused by associate unsettling influence in the electrical movement of the cerebrum. There are various kinds of convulsion. Anybody Can conceivably have a solitary epileptic seizure anytime in our lives. This isn't the comparable of having epilepsy,

which is an inclination to have seizures which begin in the brain[94]. This brain disorder may be a chronic upset within which congregation of neural cells in the cerebrum generally signal abnormally and cause seizures. Neurons unremarkably generate electrical and chemical signals that act on alternative neurons, glands, and muscles to provide human thoughts, feelings, and actions. Throughout a seizure, several neurons fireplace (signal) at constant time –as several as five hundred times a second, abundant quicker than traditional. Such abrupt electrochemical activity happening at constant time causes involuntary movements, sensations, emotions, and behaviors and conjointly the temporary disturbance of ancient somatic cell activity might cause damage in consciousness.

Brain disorder will be thought-about a spectrum disorder as a result of its completely different causes, different seizure sorts, its ability to fluctuate in intensity and impact from person to person, and its range of co-existing conditions. Some individuals could have convulsions (sudden onset of repetitive general contraction of muscles) and lose consciousness.

Others could merely stop what they're doing, have a short lapse of awareness, and stare into the house for a brief amount. Some individuals have seizures terribly occasionally, whereas others could expertise many seizures every day. There are many various varieties of brain disorder, ensuing from a spread of causes. Recent adoption of the term “the epilepsy” underscores the range of sorts and causes. While several kinds of brain disorder need womb-to-tomb treatment to manage the seizures, for some people the seizures eventually depart. the chances of changing into seizure-free are not nearly as good for adults or for youngsters with severe brain disorder syndromes, however it's doable that seizures could decrease or maybe stop over time.

This is often additionally possible if the brain disorder detected in early stage, has been treated by medication, or if the person has had operation to stop neural activity of the irregular cell production. Many of us with brain disorders lead productive lives, however some are going to be severely wedged by their brain disorder. Medical and analysis advances within the past years have resulted in a far better understanding of epilepsies and seizures. Quite twenty totally different medications and a range of dietary treatments and surgical techniques (including 2 devices) are currently offered and should give smart management of seizures. Devices will modulate brain activity to decrease seizure frequency.

Advance neuroimaging will establish brain abnormalities that lead to seizures which may be cured by surgical process. Even dietary changes will effectively treat sure varieties of brain disorder. Analysis on the underlying causes of the epilepsies, including identification of genes for a few kinds of brain disorder, has resulted in a greatly improved understanding of those disorders that will cause simpler treatments or maybe to new ways of preventing brain disorder.

3.31 Classification of Epilepsy

Neural convulsion can be categorized according to intensity, pattern and cerebral positioning.

3.32 Idiopathic epilepsy

Defined as encephalopathy of chiefly genetic or probable genetic origin and in which there's no gross neuro-anatomic or neuro-pathologic abnormality. Included here are convulsions of probable multi factor or complicated inheritance, except for that genetic elements are not included.

3.33 Symptomatic epilepsy

Defined as brain disease of associate degree non inheritable or genetic cause; related to gross anatomic or pathologic abnormalities, and/or clinical options, indicative of underlying disease or condition. We have a tendency to embrace during this class organic process and non heritable disorders wherever these are related to cerebral pathologic changes, whether genetic or non inheritable (or so cryptogenic) in origin. additionally enclosed are single factor and alternative genetic disorders during which brain disease is simply one feature of a broader phenotype with alternative cerebral or general effects.

3.34 Provoked epilepsy

Defined as brain disorder during which a particular general or environmental issue is the predominant explanation for the seizures and during which there aren't any gross motivation neuro-anatomic or neuro-pathological changes. Some "provoked epilepsy" can have a genetic basis and a few associate degree non inheritable basis, however in several no inherent cause may be identified. The reflex epilepsy is enclosed during this class (which are typically genetic) additionally because the epilepsy with a marked seizure precipitant.

3.35 Cryptogenic epilepsy

Defined as brain disorder of probable symptomatic nature during which the cause has not been known. the quantity of such cases is decreasing, however presently this is often still an important class, accounting for a minimum of four-hundredth of adult-onset cases of brain disorder.

3.36 Partial Seizures

The aspect effects of a halfway seizure may be fateful. Be that because it could, some outer aspect effects will happen and be seen by shut read by any person[21]. These manifestations won't typically happen, as each seizure and individual is completely different. Some outside changes are possible: all of an unforeseen feeling ever-changing with no reason, snickering or weeping for reasons unknown, twitch or match of a solitary piece of the body, additional usually than not a leg or arm, bother talking.

3.37 Complex Partial Epileptic Seizures

Complex partial seizure otherwise referred to as a central disabled awareness seizure[23]. This kind of seizure usually begins during a solitary zone of the brain. This territory is a lot more typical than not the transient flap of the brain. This kind of seizure has been notable to happen in people with cerebral dysfunction. These seizures are ordinarily short, and also the individuals having the seizure are going to be unconscious of their surroundings. they'll likewise finish up oblivious for an apothegmatic time frame. a fancy partial seizure will have completely different conceivable manifestations. Be that because it might, these aspect effects might happen amid one seizure and not another. advanced partial seizures frequently simply last one or two of minutes. Seizures beginning within the frontal projection region of the brain are ordinarily shorter than people who begin within the fugitive flap territory. Most extreme time indications can begin all of a fast and also the individual encountering the seizure might not be conscious they're encountering it[34].

3.38 Tonic Seizure

In generalized seizures the complete brain is influenced by the weird electrical aggravation and also the individual moves toward changing into unconscious. Sometimes, the amount once the individual is oblivious may be exceptionally summary and can be missed. Seeing a tyke or anybody having a seizure may be terribly appalling. The tyke is oblivious amid generalized seizures, in order that they do not understand what is happening. they will encounter unreasonable facet effects a epileptic seizure that may caution them to a seizure starting. On the off likelihood that this happens conceive to get them to a protected place, no matter whether or not that's alert on the ground. It's doubtless that this notice or quality is the beginning of the seizure in exactly one player within the brain, before it spreads to the complete brain.

3.39 Clonic Seizure

"Clonus" suggests quick stiffening and reposement of a muscle that happens repeatedly. In alternative words, it's perennial jerking[24]. The movements can not be stopped by restraining or positioning the arms or legs. throughout a convulsion seizure, an individual could lose management of bodily functions and start jerking in numerous elements of the body. He/she could quickly lose consciousness, followed by confusion. convulsion seizures begin in time of life. They usually seem to be a case of huge bilateral epileptic spasm, though the motor options of it's going to be less symmetrical. convulsion seizures are rare and most typically occur in babies. Most often, convulsion movements are seen as a part of a combination of tonic and clonic seizure.

3.40 Tonic-Clonic Seizures

A generalized tonic-clonic seizure, to boot referred to as a epileptic seizure, is associated with unsettling influence within the operating of the other sides of the brain. This is caused by electrical signs spreading through the brain improperly. Sooner

or later this may end in signs being sent to muscles, nerves or glands. The unfold of those signs in the brain will influence you to lose cognizance and have extraordinary muscle compression. Tonic-clonic seizures get their name from their 2 clear stages. within the tonic section of the seizure, muscles solidify, folks lose awareness, and should tumble down. The convulsion stage contains fast muscle constrictions, likewise referred to as convulsions.. Tonic- convulsion seizures typically last 13 minutes. If the seizure remains longer than 5 minutes, a restorative crisis is needed. Seizure that's not known with encephalopathy might occur at any section of your life. The seizure could be a therapeutic emergency depending upon the historical background of encephalopathy or alternative well-being conditions.

3.41 Absence Seizures

Absence seizures is otherwise referred to as epilepsy minor seizure. they're temporary, usually underneath fifteen seconds, and they have side effects that might be scarcely comprehend. Be that as it may, loss of awareness, nevertheless for such a quick time frame, will build absence seizures parlous. Absence seizures are a lot of typical in children as opposition grown-ups and might happen routinely. At the purpose once a private influenced by absence seizure lands up oblivious for a quick span. they will stop what they're doing, look clear and gaze, or their eyelids might get squint or vacillate. they'll not react to what's happening around them. On the off probability that they're strolling they will continue strolling, nevertheless won't comprehend what they're doing. Amid an everyday absence the individual lands up clear and languorous for some moments. they will begin to watch to be 'staring off into space'. The seizures might not be viewed on the grounds that they're temporary.

3.42 Atonic Seizures

It is a kind of seizure that makes sudden loss of muscle strength. These seizures are furthermore referred to as a kinetic seizures, drop ambushes or drop seizures. The sharp absence of muscle quality, or tone will create the individual tumble to the bottom. The person once unsure remains aware and will not for the foremost half tumble down. Their head could drop, their eyelids could suspend, and that they could drop something they were holding. These forms of seizures systematically begin in pre-adulthood and will last into adulthood. At times, they're related to numerous conditions, for example, Lennox-Gastaut issue.

3.43 Myoclonic Seizures

It is a temporary, stun like branch of a muscle or a gathering of muscles.. "Myo" suggests muscle and "clonus" infers quickly exchanging compression and unreeling snapping or jerking of a muscle. By and enormous they do not last over a second or 2. Amid myoclonic seizures, a burst of electrical activity within the muscle management venue of the mind causes an unexpected jerk of the muscles within the arms, legs, neck or body. Seizures oftentimes happen shortly when following waking, or once the individual is exhausted before progressing to bed[47]. there's a brief time of loss

of comprehension. The time is brief, that's the explanation. We have a tendency to don't see this. Myoclonic seizures, generally, incorporate the alternative sides of the body meantime, and therefore the individual might collapse.

3.44 Atypical-Absence Seizure

Atypical-Absence seizure is exclusive, shocking or not typical contrasted with commonplace absence seizures. they're a sort of generalized starting seizure, which suggests they start within the 2 sides of the brain. Atypical absences are epileptic seizures that chiefly happen in children with extreme learning and hurting handicaps of epileptic encephalopathies, chiefly, Lennox-Gastaut syndrome. They are clear from regular absences therein starting and finish is moderate, electrical resistance of cognizance is mellow, and that they are often connected with noteworthy tone disturbances.

A typical absence seizures were motivated in Long Evans hooded rodents by treatment with a cholesterol biogenesis substance, AY-9944 (AY), amid development. associate atypical absence seizure has less sudden starting and counterpoised loss of awareness than regular absence seizures. they're oft connected with completely different highlights, for instance, loss of tonic of the top, trunk or appendages (regularly a nonstop droop) and unpretentious myoclonic jerks. Atypical absence seizures often happen in folks with bookish incapacity. The loss of awareness could be negligible with the patient continuing with associate action, nonetheless additional step by step or with slip-ups

3.45 Infantile Spasms

Infantile spasms are a staggering epileptic brain disorder delineated by formative years spasms and later seizures. Infantile spasms (IS). It's additionally referred to as West Syndrome. It is remodelled into serious long brain disease later in life. it's one among the black youth brain disease on account of the trouble in controlling seizures and the relationship with mental retardation. Infantile Spasms unremarkably influences babies quite a pair of year sold-out.

Infantile Spasms is delineated by epileptic spasms, formative problems and a precise brain wave style on electroencephalography (EEG) testing known as hypsarrhythmia. youngsters with infantile spasms and hypsarrhythmia EEGs had sealed variations from the norm in soundness and ghastly power contrasted with typical offspring of comparable ages. Amid rest increments in delta, theta, alpha and beta coherence were seen, particularly at long between cathode separations whereas at short between anode separations cognizance were diminished within the alphabetic character and beta vary, particularly within the frontal region. With legitimate treatment, a watchful demonstrative assessment some youngsters will accomplish seizure management and to accomplish a typical early recognition.

3.46 Causes of Epilepsy

The epilepsies have several doable causes, except for up to half folks with brain disorder a cause is not known. In alternative cases, the epilepsies are clearly coupled to genetic factors, organic process brain abnormalities, infection, traumatic brain injury, stroke, brain tumors, or alternative recognisable problems. something that disturbs the traditional pattern of neural activity – from unwellness to brain damage to abnormal brain development – will cause seizures. The epilepsies could develop attributable to AN abnormality in brain wiring, AN imbalance of nerve signaling within the brain (in that some cells either over-excite or over-inhibit alternative brain cells from causing messages), or some combination of those factors. In some medical specialty conditions abnormal brain wiring causes alternative issues like intellectual impairment. In alternative persons, the brain makes an attempt to repair itself when a head injury, stroke, or alternative drawback may unknowingly generate abnormal nerve connections that cause brain disorder. Brain malformations and abnormalities in brain wiring that occur throughout brain development additionally could disturb neural activity and cause brain disorder.

Genetic mutations could contribute within the development of bound epilepsies. Many varieties of epilepsy have an effect on multiple consanguine relations, informed by a powerful genetic component. In alternative cases, cistron mutations could occur impromptu and contribute to development of encephalopathy in individuals with no case history of the disorder (called “de novo” mutations). Overall, researchers estimate that many genes may play a task within the disorders. Several forms of encephalopathy are connected to mutations in genes that offer directions for ion channels, the “gates” that manage the flow of ions in and out of cells to assist regulate neuronal signals. For instance, most infants with Dravet syndrome, a kind of encephalopathy associated with seizures that begin before the age of 1 year, carry a mutation within the SCN1A gene that causes seizures by touching atomic number 11 particle channels.

Genetic mutations even have been connected to disorders called the progressive myoclonic epilepsies, that are characterised by ultra-quick muscle contractions (myoclonus) and seizures over time. For instance, Lafora illness, a severe, progressive style of myoclonic epilepsy that begins in childhood, has been connected to a cistron that helps to interrupt down carbohydrates in brain cells. Mutations in genes that manage somatic cell migration – a vital step in brain development – will result in areas of misplaced or abnormally fashioned neurons, called cortical abnormal condition, within the brain that may cause these mis-wired neurons to misfire and result in epilepsy. alternative genetic mutations might not cause encephalopathy, however could influence the disorder in other ways. For instance, one study showed that several individuals with bound varieties of encephalopathy have associate degree abnormally active versions of a cistron that ends up in resistance to anti-seizure medicine. Genes additionally could manage an individual’s status to seizures, or seizure threshold, by touching brain development.

3.47 Treatment for epileptic seizures

Once brain disorder is diagnosed, it's vital to start treatment as before long as doable. For regarding seventy percent of those diagnosed with brain disorder, seizures may be controlled with fashionable medicines and surgical techniques. Some medications are simpler for specific styles of seizures. An individual with seizures, notably people who aren't simply controlled, might want to ascertain a neurologist specifically trained to treat brain disorder. In some youngsters, special diets could facilitate control seizures once medications are either not effective or cause serious aspect effects. While brain disorder can not be cured, for a few folks the seizures may be controlled with medication, diet, devices, and/or surgery. Most seizures don't cause brain harm, but ongoing uncontrolled seizures could cause brain harm. It's not uncommon for folks with epilepsy, particularly youngsters, to develop activity and emotional issues in conjunction with seizures. problems may additionally arise as a result of the stigma connected to having brain disorder, which can be a crystal rectifier to embarrassment and frustration or bullying, teasing, or shunning in class and different social settings. for several folks with brain disorder, the danger of seizures restricts their independence (some states refuse drivers licenses to folks with epilepsy) and recreational activities.

3.48 Epilepsy Prediction

Many prediction works are finished to this point victimization numerous signal process ways and every of them totally different from another. We are able to divide the prediction task into two parts; first off processing the encephalogram information for feature extraction, then use those options to predict seizure analyzing patients encephalogram recording. For encephalogram signal classification, parameters extracted from the encephalogram signals victimization numerous signal process ways are terribly helpful for nosology seizure related cases.

3.49 Fourier Transform

Spectral parameters supported the Fourier remodel area unit helpful for analyzing the graph signals and have shown smart results on their classification [34][46]. However, it's necessary to notice that the Fourier domain doesn't exhibit any time-domain characteristics within the signal giving the options that are suboptimal for feature extraction from some signal process eventualities[1].

3.50 Wavelet Transform

Discrete ripple transforms (DWT) analysis and approximate entropy (ApEn) of graph signals is another common technique for seizure detection and it's performed in 2 stages. Within the 1st stage, graph signals are rotated by DWT to calculate approximation and detail coefficients. While next stage, Approximation Entropy (ApEn) values of the approximation and detail coefficients are calculated. important variations are found between the ApEn values of the epileptic and also the traditional graph permitting U.S. to sight seizures with 100 percent classification

accuracy victimization artificial neural network [79]. In [72], separate ripple re-model (DWT) with the Multi-Resolution Analysis (MRA) is applied to decompose graph signal at resolution levels of the parts of the graph signal and also the Parseval's theorem are used to extract the percentage distribution of energy options of the graph signal at completely different resolution levels

3.51 Discrete Wavelet Transforms

The sub-band frequencies of the sub-band signals obtained from the DWT are used as a feature for classification of traditional and seizure graph signals. The road length feature of the sub-band decomposed signals obtained by exploitation DWT has been used for classification of healthy and convulsion graph signals. The approximate entropy in conjunction with autoregressive model features obtained from the Fourier transforms of the graph signals is employed in linear and nonlinear classifiers.

3.52 Methods for Seizure Prediction

There are many methods for seizure prediction.

3.53 Empirical mode decomposition (EMD)

Presently, new methods for the analysis of nonlinear signals have been projected that are principally supported empirical mode decomposition (EMD) [24]. The EMD could be a time-frequency based mostly methodology that decomposes signals into a variety of intrinsic mode functions (IMF) that are oscillating elements. This characteristic of EMD has impelled the researchers to use it for the analysis of encephalogram signals. In [51], The EMD breaks associate encephalogram signals into a limited set of band-base wavelet termed intrinsic mode functions (IMFs). The mean frequency (MF) for every signal has been computed using Fourier-Bessel growth. The radio frequency live of the IMFs has been used as a feature so as to spot the distinction between ictic and seizure-free intracranial encephalogram signals. It has been shown that the radio frequency feature of the IMFs has provided statistically vital distinction between ictic and seizure-free encephalogram signals.

3.54 Multivariate EMD

After applying Hilbert-Huang rework within the electroencephalogram data, it expedited the extraction of the EEG intrinsic modes yet because of the ultimate electroencephalogram frequency/energy content analysis. The analysis of the frequency and energy content of each extracted mode has been performed via Hilbert rework, that was achieved through the chase of the fast frequencies and amplitudes. David Hilbert weighted frequency has been accustomed to facilitate discriminate between healthy and seizure electroencephalogram patterns[65].

3.55 Higher Order Statistics in EMD

In [94], more efficient statistical methods like variance, skewness, and kurtosis are used for categorizing the EEG signals within the EMD for detection seizure and neural disorder. The correctness of these methods in distinctive signals is measured through an in depth analysis within the EMD range. Besides the strengths of feature extraction strategies associated with instantaneous frequencies (IF), it's vital to notice that the extraction of IF is additional meaningful once the IMFs extracted from the EEG signals are mono-component.

3.56 Phase space representation of IMFs

In this paper [3], we've planned the new options supported the space illustration (PSR) for classification of convulsion and seizure-free EEG signals. For the aim of classification of convulsion and seizure-free EEG signals, two-dimensional (2D) and three-dimensional(3D) PSRs are used. New options supporting the 2nd and 3D PSRs of IMFs are proposed for classification of convulsion and seizure-free EEG signals. These measured parameters show vital distinction between convulsion and seizure-free EEG signals. The combination of those measured parameters for various IMFs has been utilised to make the feature set for classification of convulsion EEG signals.

3.57 Hilbert Huang Transform with Bayesian Classifier

In [86], once preprocessing of intracranial encephalogram information for removing noise and acquiring information segments for window analysis, feature extraction was done using Hilbert-Huang transform. Feature choice using correlation based mostly feature choice rule, binary classification by theorem networks, and a straightforward post-processing rule to get rid of spurious detections, therefore they got higher performance for large variety of encephalogram recordings.

3.58 Machine Learning

Machine learning is an information analysis methodology that uses applied mathematics techniques that allows learning from information, operating with patterns recognition, call makings and different connected tasks without taking specific detailed instructions unlike the systematic methods. By definition, it's clear that machine learning is an associate degree approach to computer science. to spot the brain diseases like convulsion machine learning is one in every of the most effective approaches. Machine learning may be divided into four classes in line with the purpose- supervised learning, unattended learning, semi-supervised learning and reinforcement learning.

3.59 Supervised Machine Learning

Supervised learning is once somebody has each the input and output variable and decipher the way to reach to the output from the input victimization algorithms to be told acceptable mapping operates. therefore if Y may be an operation of x ; $Y=f(x)$, then the operation ought to be mapped, which means that for each new input file of x there'll be a prediction for output variable Y [20]. it's referred to as supervised learning on the grounds that the arrangement is supervised or target-hunting. To be a lot of express, there's an Associate in Nursing objective arrangement that's given. As an example, there are bats and balls unbroken during a basket. If the machine is tutored that something spherical may be a ball and not spherical one may be a bat, it'll show the results consequently for each object within the basket. As indicated by the targets supervised learning has 2 sorts-classification and regression. within the event that the target arrangement is in qualities or categories e.g. colour,it is classification. Then again, if the target house is constant e.g. weight, it's regression.

3.60 Support Vector Machine(SVM)

SVM is employed in each classification and regression model. It's outlined by a separating hyperplane to differentiate between categories or plots. The hyperplane is selected by the realm wherever it separates the categories best accurately. This rule is effective in high dimensional areas. To determine the hyperplane, there's conjointly one factor to think about that is margin. The hyperline ought to have the most distances from every category. There are scenarios where the linear hyperplane isn't attainable. During these cases, the 3D system will solve the matter. wherever this drawback arises, the z axis ought to be brought in thought.

3.61 Artificial Neural Networks (ANN)

An ANN is strategy or that procedure data or information and is trailed by the approach however natural sensory systems operate work, as an example, the brain. It's designed for a large life of big quantities of interconnected getting ready segments e.g. neurons acting at identical time to elucidate specific undertakings. it's not controlled by task specific rules. In natural frameworks, there includes changes in accordance with the holding of neurochemical between nerve cells that exist within the neurons. ANNs work that manner. primarily, ANNs accumulate data because the manner within which humans do; by model and encounter and isn't changed with any endeavor specific tenets. it's masterminded specific errands and activities, as an example, style acknowledgment or data grouping or others, by suggesting that of a way of getting ready by model or experience[93]. As an example, there exists a program that will acknowledge any image because it is aware of the characteristics.

It will indicate a cow with an image labeled as 'cow'. However this system will have identical issues with none previous information concerning cows. Instead, they mechanically manufacture indicating characteristics and options from the educational material that they method themselves. We can say, associate ANN depends on a bunch of connected units or nodes referred to as artificial vegetative cells that

additionally or less imitate the neuron in an exceedingly biological brain wherever every affiliation will broadcast signals among artificial neurons like they take signals and pass it. a synthetic somatic cell that acknowledges a sign will operate it and afterwards pass it to more alternative counterfeit neurons related to it. The associations between counterfeit neurons are referred to as 'edges'. Artificial neurons and these edges essentially contain weights that match as learning receipts. The burden alludes to the estimation of the standard of flag in associate association. Within the manner of ANN executions, the signal among the association between artificial neurons may be a real variety. To boot, the result from every artificial nerve cell is set by non-straight capability of the combination of its embedded feeds.

3.62 Unsupervised Machine Learning

Unsupervised learning is once somebody simply has the arrangement of data factors with no relating yield factors. not like supervised learning, there's no settled target. it's wherever the machine discovers the demonstrating structures of sources of information, association between data sources. At the purpose once the knowledge inputs don't seem to be distributed or marked, unattended learning involves organizing among the knowledge utilizing applicable calculation. there's no supervising for that. The machine has to separate among the knowledge itself. During this approach, in unattended learning, an appointment of knowledge is organized and characterised as per the similarities and variations between them[60]. For instance,if there are round the bend and balls in a very basket.

The machine has not been given any steerage. on these lines, what the machine will do is to require the spherical objects in a very single aspect and therefore the not cycle ones in alternative. This is often the tactic for composing the knowledge which suggests that unattended learning works. Unsupervised learning is gathered into agglomeration and association learning. agglomeration is once there area unit some certain qualities in data and as indicated by that it's characterised, as an example, gathering people as per their age. Association is once there's a number of examples to depict the knowledge and later it's sorted by that style. as an example, a gathering of people that like frozen yogurts in addition like chocolates.

3.63 K-means Clustering

K-means clustering may be a kind of unsupervised learning, that is used after you have unlabeled info. The target of this calculation is to find bunches within the info, with the amount of gatherings spoken to by the variable K. The calculation works iteratively to appoint every data to one of K bunches captivated with the highlights that are given[3]. The system pursues an easy and straightforward approach to rearrange a given informational assortment through a particular range of teams. k-means is one amongst the foremost straightforward unsupervised learning computations that pay attention to the well-known clustering issue. The principle thought is to characterize k centers, one for every bunch.

These centers have to be compelled to be placed keenly on the grounds that dis-

tinctive areas cause various outcomes. During this approach, the higher call is to place them as way as attainable from each other. The following stage is to require every direct having an area toward a given informational assortment and partner it to the highest focus. But once no point is left, the initial step is finished. Now, recalculating k new centroids as center of mass of the bunches going on attributable to the past advance is required[3]. From that time forward, another coupling should be done between similar informational assortment focuses and also the highest new focus. during a procedure of this, a circle has been made.

Chapter 4

Proposed Model

This chapter will explain how the prediction model has been done. At first, a collection of EEG signals from 17 patients were collected from a source. But those EEG signals were not ready for analyzing and processing. We had to run a signal smoothing process, in this case, savitzky-golay[66] to filter out the noises and make them extractable. After the filtering process, we tried to extract some features to differentiate between signals at different times. Specifically four feature extraction methods have been considered: mean, energy, skewness and kurtosis. We tried to distinguish the differences in properties of the signals to see the changes and predict them afterwards. At last, SVM[83] classifier has been used to train the dataset for prediction of abnormalities in signals. Figure 4.1 shows the work flow of seizure prediction.

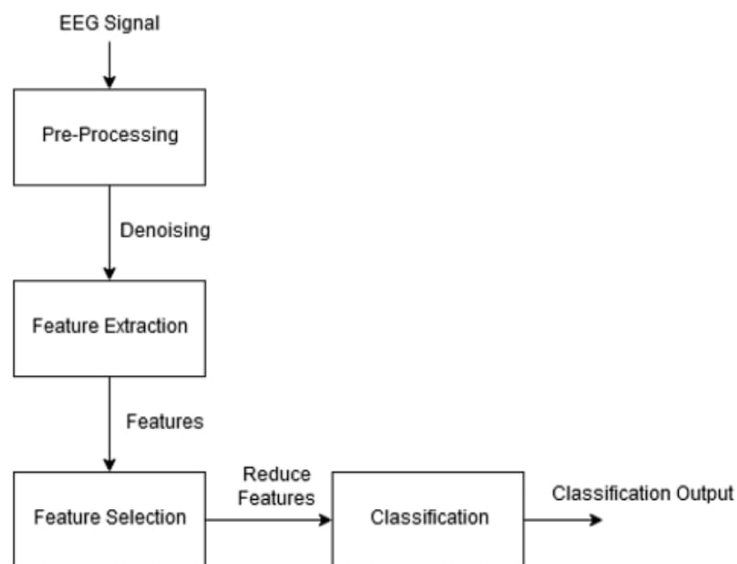


Figure 4.1: Workflow of Seizure Prediction

4.1 Dataset Description and Analysis

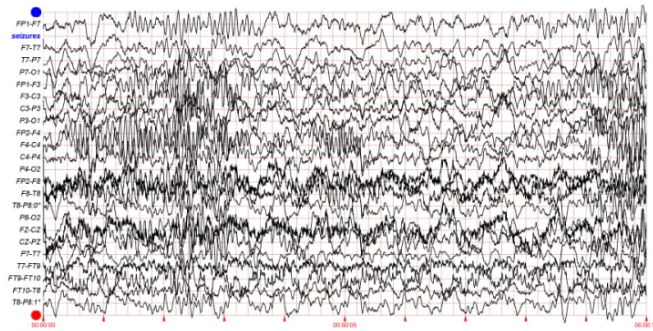


Figure 4.2: EEG signal of first 10 seconds of subject 3

Figure 4.2 consists of EEG recordings from pediatric subjects with intractable seizures. Subjects were monitored for up to several days following withdrawal of anti-seizure medication in order to characterize their seizures and assess their candidacy for surgical intervention. Example of channel number and names are given in Table 4.1.

Table 4.1: Channel name and number

Channel Number	Channel Name
Channel 1	FP1-F7
Channel 2	F7-T7
Channel 3	T7-P7
Channel 4	P7-O1
Channel 5	FP1-F3
Channel 6	F3-C3
Channel 7	C3-P3
Channel 8	P3-O1
Channel 9	FP2-F4
.	.
.	.
.	.
.	.
.	.
Channel 22	FT10-T8
Channel 23	T8-P8

EEG recordings, grouped into 23 cases, were collected from 22 subjects (5 males, ages 3–22; and 17 females, ages 1.5–19). See Table 4.2 for description.

Table 4.2: Subject Description of Dataset

Subject	Gender	Age(years)
1	Female	11
2	Male	11
3	Female	14
4	Male	22
5	Female	7
6	Female	1.5
7	Female	14.5
8	Male	3.5
9	Female	10
10	Male	3
.	.	.
.	.	.
.	.	.
22	Female	9
23	Female	6

Data representation has been done from the raw EEG signals of the dataset to minimize the calculation of important parts only. All irrelevant signals have been omitted and scattered wave of different timelines have been compiled. A dataset in a tabular form has been created for every Seizure found on every patient. The total timeline of 1 hour 30 minutes of wave signals were taken into consideration in making the compiled dataset. This timeline includes interictal, preictal and ictal stages(see Figure 4.3) of every seizure.

Time frame difference from the previous seizure	Timeframe of the pre-seizure	Timeframe of when seizure was occurred
Interictal	Preictal	Ictal

Figure 4.3: Interictal, Pre Ictal and Ictal part of Seizure

We merged necessary EEG signal files to get interictal, pre ictal and ictal part for feature extraction and classification. We built merged signal of 5400 seconds with 1382400 sampling point whereas 3600 seconds for inter ictal part and 1800 second for pre ictal and ictal combined. Table 4.3 illustrates the merging of necessary signals.

Table 4.3: Merged EEG signals of Dataset

Merged Points	FP1-F7	F7-T7	T7-P7	T8-P8
1	0.0000885	0.0000916	0.0000317	0.0000117
2	0.0000705	0.0000476	0.0000901	0.0000091
3	0.0000422	0.0000770	0.0000950	0.0000289
4	0.0000765	0.0000293	0.0000410	0.0000900
5	0.0000805	0.0000612	0.0000111	0.0000788
...
...
...
1382400	0.0000907	0.0000225	0.0000621	0.0000707

4.2 Signal Preprocessing

Savitzky-Golay can be applied to a set of data points to smooth the data without distorting the signal tendency. This method is based on a mathematical procedure which was familiarized by Abaraham Savitzky and Marcel J. E. Golay. The generalized formula of S-Golay filter is stated below.

$$y_t = (-2xt - 3 + 3xt - 2 + 6xt - 1 + 7xt + 6xt + 1 + 3xt + 2 - 2xt + 3)/21.$$

Here a moving polynomial is handled just like weighted moving average where the coefficients of the smoothing steps are constant for y values. It is defined via a least squares polynomial approximation problem. Figure 4.4 illustrates the comparison of of before and after applying signal filter.

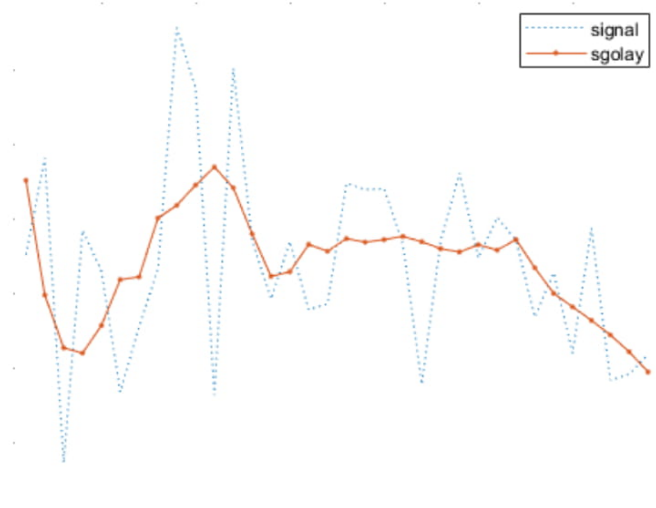


Figure 4.4: Comparison of Signal Segment before and after Smoothing

4.3 Feature Extraction

As we have selected energy as a feature, we take 10 second time frame of a signal and divide signal into 540 signal segments. Then we calculate average energy of each signal segments applying signal energy formula and dividing by the total number of signal points.

$$\text{Average Energy} = \sum_{i=1}^n x_i^2 / 2560$$

For mean amplitude, we take sum of all sampled points in signal segment and divide the result with total number of signal points.

$$\text{Mean Amplitude} = \sum_{i=1}^n x_i / 2560$$

Skewness considers the angle and direction of the values. A wave can be positively skewed (to the right) or negatively skewed (to the left). Here positively skewed will be represented by a positive value and a negatively skewed will be represented by a negatively skewed value.

$$\text{skewness} = \frac{\sum_{i=1}^N (Y_i - \bar{Y})^3 / N}{s^3}$$

Kurtosis is similar to skewness but it measures the apex of distribution and the density of the tails of points. A positive kurtosis is heavier than average or normal distribution. A negative kurtosis has tails that are lower than the normal distribution.

$$\text{kurtosis} = \frac{\sum_{i=1}^N (Y_i - \bar{Y})^4 / N}{s^4} - 3$$

Here s is the standard deviation of data.

4.4 Classification

After done with feature extraction we had to classify the data. Support Vector Machine algorithm is followed to classify these which gave different results.

Support Vector Machine

The objective of the support vector machine is to find hyperplanes in an N -dimensional space, where N is the number of features that distinctly classifies the data points. Hyperplanes are called the decision boundaries. When there are 2 features the hyperplane is just a line when there are 3 features the hyperplane becomes a plane with

2 dimensions. It gets complicated when there are more than 3 features. Support vectors are data points which are influential to the hyperplane. It means how much closer or far the features are from the hyperplane. A hyperplane with small margin the features are closer and large margin has the features far from the hyperplane. Small margin gives more accurate classification but a perfect classification defeats the purpose of classifying the features and also the complexity is not worth. There are 2 kernels of SVM: linear and RBF. Linear svm is used as a line to classify the features whereas the rbf can be used as a plane of multidimensional to classify the data. Linear svm works on a single plane. On the other hand RBF creates the polynomial dimension to create the plane in order to make a margin. Linear doesn't work well when the data points are scattered and mixed. But RBF kernels can classify them in different dimensions.

Chapter 5

Result and Discussion

5.1 Performance Evaluation Parameters:

We conducted performance test by calculating sensitivity, specificity and accuracy. As our aim is classify convulsion and non convulsion phase, all features are passed in SVM classifier to detect seizure or not. These are measures of binary classification. These are defined as following.

$$Specificity = (TN / (TN + FP)) * 100$$

Here TN signifies correctly measured negative trend and (TN+FP) implies total number of actual negative trends. A negative trend identifies a captured non seizure.

$$Sensitivity = (TP / (TP + FN)) * 100$$

Here TP signifies correctly measured positive trend and (TP+FN) implies total number of actual positive trends. A trend identifies both non seizure and seizure.

$$Accuracy = ((TP + TN) / (TP + TN + FP + FN)) * 100$$

Here (TP+TN) signifies correctly measured trend and (TP+FN+TN+FP) implies total number of trends. A positive trend identifies a captured seizure.

Sensitivity and specificity are ratio of non seizures. Here TP and TN are true positive and true negative events. FP is false positive rate whereas FN is false negative rate.

5.2 Result

We obtained the overall accuracy of 73 percent with 88 percent specificity and 46 percent sensitivity. Our obtained precision is 68 percent. We selected 23 standard channel for feature extraction. We trained the data for a considerable amount of time. We conducted the programming procedure in python programming language as it is the best language for machine learning. Table 5.1 describes the obtained results of classification. In Table 5.1 PA is prediction accuracy and FA is false alarm.

Table 5.1: Prediction Accuracy and False Alarm Rate using Proposed Model

Subject Number	Sex/Age	Total Seizures	PA(%)	FA	Specificity(%)	Sensitivity(%)
1	Female/11	7	71	4	95.7	25.09
2	Male/11	3	70	9	90.7	29.76
3	Female/14	7	69	15	84.7	27.02
4	Male/22	4	67	3	96.5	12.5
5	Female/7	5	65	17	80.7	38.29
6	Female/1.5	10	67	8	89.4	21.05
7	Female/14.5	3	67	2	97.6	14.2
8	Male/3.5	5	70	22	76.5	58.1
9	Female/10	4	71	9	89.7	31.6
10	Male/3	7	69	7	92.39	13.5
11	Male/15	3	67	8	90.4	25.4
12	Male/13	40	66	4	95.2	19.6
13	Female/17	12	74	10	89.5	40.7
14	Female/18	8	68	14	84.5	26.5
15	Female/15	20	74	2	98	20.7
16	Male/14	12	65	13	84.7	32
17	Male/17	10	66	2	97.5	9.6
18	Female/9	3	74	5	94.6	24.3
19	Female/6	6	74	19	80.8	52.7

The receiver operating characteristic(ROC) curve is included in Figure 5.1.

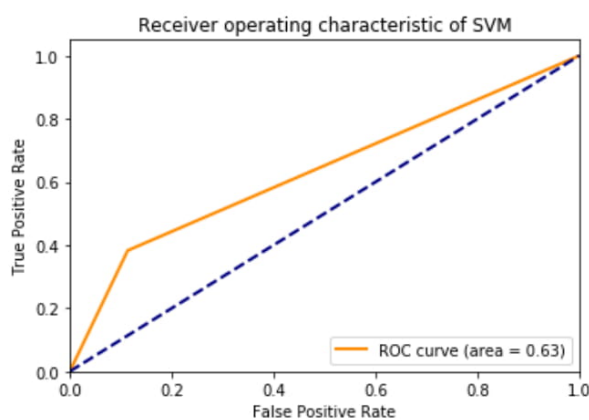


Figure 5.1: ROC Curve for Support Vector Machine

5.3 Discussion

We have considered standard 23 channels for our research. Previously EEG recording were in european data format(edf). We converted necessary EEG signal file to csv format so that we can use them in python programming easily. As the dataset is as large as 45GB so it has taken huge time converting file format. Computational duration was large due to the size of dataset. However, we find all features of EEG signal are properly associated with seizure. We observed that energy and mean amplitude are very much correlated. Seizure and non seizure phase have specific pattern of energy. Statistical features like skewness and kurtosis indicated the tailedness of signals. We also discarded many seizures as we were not able to get a total one hour and thirty minutes duration for pre ictal and inter ictal combined. We combined seizure file with necessary EEG signal file according to sample numbers. After merging we divide a signal in 540 segments and we calculate average energy and amplitude, skewness and kurtosis for each segment. While training we shuffled the dataset and keep 80 percent data for training and 20 percent data as test set. We also calculated ROC curve for support vectore machine. A receiver operating characteristic curve(i.e., ROC curve), may be a reasonably plot and by exploiting it we will illustrate the diagnostic ability of a binary classifier system as its discrimination threshold is varied. The curve includes verity positive rate (TPR) against the false positive rate (FPR) at numerous threshold settings. The true-positive rate is additionally called sensitivity and shows chance of detection in machine learning. we've got determined the roc curve supported our planned technique with DFT primarily based technique.

Chapter 6

Conclusion

Lately, characteristic convulsion has become an issue of great demand within the field of analysis and attracted the eye of researchers since it's a normally happening development. Human brain is center of any issue that involves movements, activities, thinking, awareness and dominant. it's made from signal waves of varied frequencies that have power over our activity and conduct. Changes during this signs prompts various irregular conditions and convulsion is one amongst them. Consultants utilize graph (EEG) to capture the signals and their frequencies in our brain.

Graphical record records the motions and frequency areas from the surface of our brain mistreatment the ionic current exhibited within the neurons of brain. Graphical record element has stuffed a rare want in locating convulsion. Convulsion is characterised as sharp irregular shaking, moving or comparable strange activity and behaviours which works on for a handful of minutes. Thus, the ways we have a tendency to tried to use well-tried accepted results however it's still faraway from state of the art. we've to appear at slightly totally different mechanisms making an attempt to take advantage of the statistic component of the encephalogram information. If specialists well versed during this field will be consulted and perceive their perception of the info detection of anomalies exploitation their instinct, we have a tendency to may strive some a lot of fancy neural networks and deep learning techniques to unravel this downside.

Further Research

We will apply various classification approach to develop our results such as deep neural network, random forest and relatively simple algorithms like K-nearest neighbors and logistic regression. We will try to make an electronic device in future that will give alarm of upcoming epilepsy.

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