Prediction of Epileptic Seizures using Digital Signal Processing and Support Vector Machine

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A thesis submitted to the Department of Computer Science and Engineering
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Declaration

It is hereby declared that

1. The thesis submitted is my/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.

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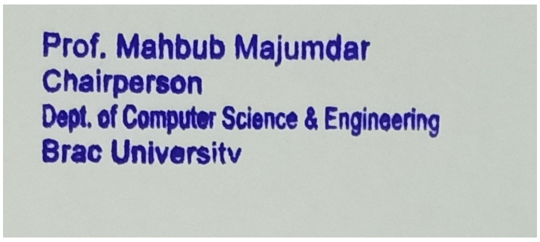

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Abstract

Epilepsy is a neurological disorder that causes abnormal behavior and recurrent seizures due to unusual brain activity. Our study has attempted to predict seizures in epileptic patients through the process of feature extraction from EEG signals during preictal and ictal periods, classification and regularization. EEG signals from various parts of the brain from 10 epileptic patients were collected. The signals were converted into its frequency components using a method called fast Fourier transform or FFT. It was then used to determine the three features- the phase angle, the amplitude and the power spectral density of the signals. In order to classify the signals, these features were then used. Regularization was then used to make better predictions i.e. increase the prediction accuracy and decrease the rate of false alarm rate. Through this study, we hope to contribute to the development of better and advanced seizure predicting devices in the medical field. .

Keywords: epilepsy, seizure, phase angle, power spectral density, support vector machine

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Nomenclature

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

$CHBMIT$ Children's Hospital Boston - Massachusetts Institute of Technology

EEG The Electroencephalogram

FFT Fast Fourier Transform

$iEEG$ Intracranial EEG

$sEEG$ Scalp EEG

$STFT$ Short-Time Fourier Transform

SVM Support Vector Machine

Chapter 1

Introduction

Epilepsy is a very common neurological disease around the globe, it affects about one percent of the world population. Epilepsy causes recurring seizures which are a sudden and unusual electrical activity in the brain. These seizures result in serious symptoms in patients such as staring or rapid blinking, muscle stiffness, loss of consciousness, etc. People without epilepsy can also experience seizures due to heavy drinking, low blood sugar, etc. However, after the repeated incidence of seizure, doctors usually diagnose the patient as an epileptic patient. Epilepsy affects people of all ages but it is more common in children and elderly people [12]. A patient can develop epilepsy due to many reasons. It can be due to genetics, previous trauma, head injury, strokes, etc. 70 percent of epileptic cases can be avoided with proper medication [11]. Surgery is another solution to permanently cure epilepsy but it is costly and not widely available. Epilepsy causes patients to suffer from unexpected injury and even death due to its unpredictable nature. These unexpected injuries and sudden death can be avoided by the early prediction of oncoming seizures.

1.1 Motivation

Seizures occur due to electrical activities in the brain that are atypical or unusual. In other words, when neurons fail to communicate with each other due to a disruption. Effects of seizures range from uncontrollable shaking to loss of awareness or consciousness. Epilepsy causes these sudden seizures in patients and makes their day to day life miserable. Around 50 million people are suffering from this disease making epilepsy as one of the most common neurological disorders [16]. Epileptic seizures are very difficult to treat. Over long time usage of anti-epileptic drugs, patients may become resistant to anti-epileptic drugs and their seizures may continue to appear [9]. More than 30 percent of patients continue to experience seizures despite taking the anti-epileptic medication regularly [31]. Another alternative treatment is surgery where doctors remove parts of the brain that cause seizures. However, surgery is expensive and bear lots of risks. Seizures can affect the entire body since it stems from the central nervous system. Patients may lose consciousness during this time and may not be aware of their surroundings. The unpredictable nature of seizures can lead to numerous life-threatening situations for the patient. The loss of consciousness causes the patients to suffer from accidental physical injury and sometimes even accidental deaths. Many epileptic patients die suddenly every year due to this unpredictable nature of epilepsy [16]. A large proportion of them are young and their death is completely disastrous and unexpected to their family. Predicting epilepsy beforehand can greatly help to avoid this tragic situation as the patient will become more careful in advance and avoid any life-threatening situations. Moreover, People with epilepsy also suffer from great emotional stress which is often overlooked. About one-third of epileptic patients suffer from depression and anxiety-related issues [30]. Thus, the prediction of on-coming seizures can vastly improve the quality of life for epileptic patients. Hazardous life-threatening situations can be completely avoided with a seizure predicting tool. EEG (electroencephalogram) helps to assess electrical activities in the brain and is crucial for studying seizures. Wave patterns are tracked by an EEG through numerous electrodes placed on the scalp.

1.2 Major Contribution

In this research paper, we tried to build a model for predicting on-coming seizures in patients by closely analyzing their EEG data. Several features were extracted from EEG data and we run two algorithms namely SVM and logistic regression to build our model. We found SVM as a better algorithm to build our model for predicting on-coming seizures as it gave very high accuracy and low false-positive compared to logistic regression.

1.3 Thesis Orientation

The following sections of this paper has been ordered in the way described below.Chapter 2 is Literature Review which is a description of the related works and various methods and techniques similar to our proposed methodology.Chapter 3 consists of the background study of our thesis which includes the anatomy of the brain structure, information regarding Epilepsy and EEG signals,signal processing and various machine learning algorithms.It also contains a brief description of our data set.Chapter 4 describes our proposed plan for predicting epileptic seizures.Chapter 5 comprises of the results we obtained and the relevant discussions concerning these results. The entire paper is concluded and summarized in Chapter 6.

Chapter 2

Literature Review

2.1 Literature Review

Electroencephalography (EEG) is a technique of tracking and detecting brain activity. Wave patterns are tracked by an EEG through numerous electrodes placed on the scalp. All the papers mentioned have used EEG signals to conduct their research as it is a vital part of seizure detection and prediction. EEG signals provide important information by measuring the difference in changes in voltage between the electrodes. A notable amount of research and study has been done in the area of detecting and predicting seizures. A lot of impressive work has been done on seizure detection. Our approach aimed for a seizure prediction model, a field that is still lacking significant research. This is also due to the shortage of open, continuous recordings of EEG data. In this section, we will discuss work that has been done in various papers in this area, using various different techniques and algorithms.

Most of the research done on epilepsy and seizure focused rigorously on seizure detection using EEG signals. In a study conducted by Shoeb et al. [22] proposed a machine learning approach to detect epileptic seizures using Support Vector Machine (SVM) with a non-invasive procedure of electrical activity in the brain . The support vector machine (SVM) classified features in two parts representing seizure and non-seizure activity. This detection technique involved a thorough analysis of EEG signals from epileptic pediatric patients using the same CHB-MIT database as us. They opted for pediatric patients over adult patients because of the greater variance. This paper tried to overcome the problem of overlapping of signals from seizure and non-seizure states by creating a patient-specific detector. They mentioned steps required to make such a machine learning algorithm included recognizing and separating signals from numerous other brain activities and carefully avoiding methods with over-optimistic results. The dataset consisted of various types of seizures with 916 hours. This experiment resulted in a 96% accuracy from 173 test seizures using 23 pediatric patients and has 4 false-alarms per 24 hours.

Unsupervised seizure detection based on rhythmical activity and spike detection in EEG signals was proposed by Tsiouris et al. [53]. This paper also used the same CHB-MIT database. The goal was to single out segments of EEG seizure in an automated manner without the need for enough details or human interference. The study tried to decrease the need for prolonged continuous EEG recordings for more practical uses. This method took more characteristics of ictal period behavior such as rhythmical activity into consideration to improve the sensitivity and to decrease the false detection rate. EEG channel localization analysis is done on selected EEG seizure segments to study patterns and provide the information and assessment to the clinician. The rhythmical activity is determined with the assistance of STFT (Short-Time Fourier Transform) by transforming the EEG signals to the time-frequency domain. This technique achieved 81.15% to 91.35% accuracy with an average false detection rate which was in the range 5.33-12.15.

A study by Alotaiby et al. [36] also used a patient-specific model to predict seizure using the CHB-MIT database . Like us, they also went with a feature-extraction, a classification technique and then a testing phase. They applied a leave-one-out cross-validation methodology. This paper aimed to make an effective seizure prediction model using scalp EEG (sEEG) instead of intracranial EEG (iEEG) as it has been proven to be more suitable for clinical application. Electric signals are obtained in iEEG by placing electrodes directly on the exposed part after partial removal of the skull while in sEEG, which is carried out by positioning electrodes on the scalp following certain guidelines. This method used LDA (linear discriminant analysis) classifier with features obtained from common spatial pattern (CSP). This paper helps to identify a fundamental concept of seizure prediction which is the importance of the preictal period which is a transition state that exists between the interictal and ictal period. CSP was used to decrease the complexity and size of data and to extract the best-suited features. Then a linear classifier classified these extracted features into a preictal or interictal segment. They then compared the result of the predictor with Poisson predictors and other prediction methods that are based on sEEG. This study was successful in achieving a mean accuracy of 89% and 0.39 as the mean false detection rate.

Time-frequency distribution has been proven to be helpful in the decomposition of signal analysis of seizures. Numerous decomposition methods have been used in studies by researchers. However, an automatic epileptic seizure onset and event detection model proposed by Ahammed et al.[28] used statistical features and wavelet-based features without wavelet decomposition . For detecting seizure events, Bonn University data was decomposed whereas the CHB-MIT database was used for the detection of seizure onset. For the detection of seizure onsets, the goal was to detect the start of a seizure with the least amount of delay. The goal for the seizure event detection was to detect seizures with the highest accuracy. The seizure event detection technique involved 3 types of EEG signals and then was classified using a linear classifier. Features were extracted using discrete wavelet transform. This methodology acquired a classification accuracy of 84.2% using a simpler classifier than other similar studies using more complex classifiers. For seizure onset detection, the extracted features were interquartile range (IQR), wavelet-based features and mean absolute deviation without wavelet. A linear classifier segmented the EEG signals into epileptic and non-epileptic signals. A classification accuracy of 98.5% was achieved by this study.

Williamson et al.[24] proposed a seizure prediction algorithm that used multiple EEG features from 19 patients in conjunction with patient-specific machine learning . Here, the features were classified using a support vector machine (SVM) into either preictal or interictal states . A mean of the outputs was calculated to produce the final result. This study used data from Freiburg EEG dataset of 21 patients with three or more seizures and the algorithm was applied to 19 of them. It successfully predicted 71 out of 83 seizures and had a total of 15 false predictions. They used high-dimensional feature vectors to enhance the results. Similar to a previous study this also uses a feature-extraction and a classification technique using machine learning. The features were normalized and the dimensions were reduced and then were fed to a support vector machine for training. Cross-validation was used to evaluate machine learning due to the lack of data. A lot of importance was given to achieve results with high sensitivity and specificity.

Chapter 3

Background

3.1 Brain Anatomy

The brain is the central organ for any living being, whether it is humans or animals. It is responsible for all the processing and coordinating the information of the body. It also acts as a control center that is responsible for our understanding of speech, movement of limbs, and other organs of our body [46]. The brain's ability to perform all these actions is due to the never-ending stream of information as electrical pulses from the neurons of our sense organs such as eyes, nose, tongue, etc. It is also a part of the central nervous system alongside the spinal cord. The three major segments of the brain are the following - cerebrum, cerebellum, and the brain stem as shown in the Figure 3.1

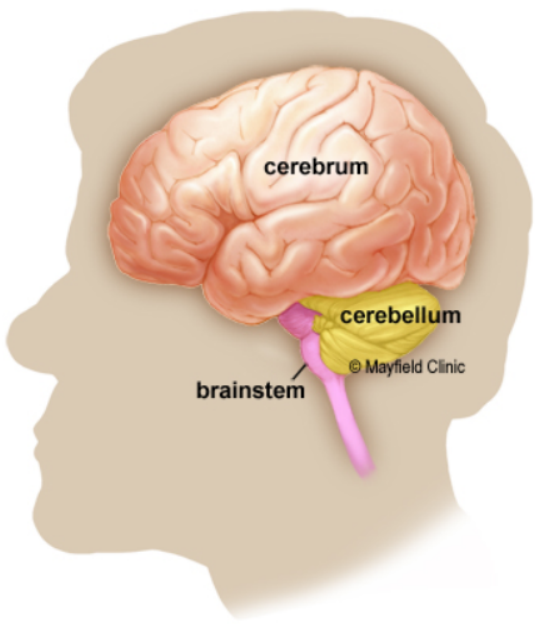

Figure 3.1: Human Brain [44]

3.1.1 The Cerebral Cortex

The cerebral cortex is the external layer of the cerebrum, residing in the uppermost region of the brain. It is liable for our conscious sensations, complex thought processing, reasoning, planning, as well as other fundamental rational processes. It is sometimes referred to as the gray matter of the brain from its color, which contrasts with the white matter in the layer below [46]. The cortex can be divided into four segments called lobes as shown in the Figure 3.2

3.1.2 The Cerebral Lobes

The cerebral cortex can be divided length ways into two cerebral hemispheres, which remain connected by the corpus callosum. There are four sections in each region called lobes [40] as shown in figure 3.2. The four portions are the frontal lobe, parietal lobe, temporal lobe, and occipital lobe, where each of the lobe's functionality is distinct [40].

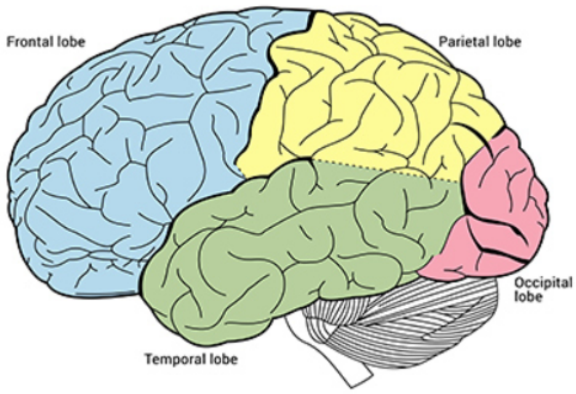

Figure 3.2: Different lobes of the cerebral cortex [65]

- **Frontal Lobe**: The frontal lobe, located at the front of the cerebral cortex, is separated from the parietal and temporal lobe by the central sulcus and temporal sulcus, respectively. The primary responsibility is to gather inputs from all other areas to produce complex cognition such as thoughts, judgments, and long term plans [46]. Furthermore, functions such as planning, reasoning, and emotional regulations take place here [40].

- **Parietal Lobe**: Behind the frontal lobe and separated by the central sulcus lies the parietal lobe. Inputs from visual, auditory and emotional areas arrive here to integrate sensory information such as pain, pressure, touch, taste, etc. to produce an understanding of the current environment [46][40]. A major part of the somatosensory cortex resides in this lobe which is vital and crucial for processing the senses of the body.

- **Temporal Lobe**: It is located in the bottom section of the brain, being separated from the frontal lobe by the lateral fissure. It contains sections whose purpose is to perform visual processing - faces and scenes. Furthermore, there are also parts where auditory information processing takes place to make sense of what we hear. Last but not the least, creating memories [40]. The temporal lobe does so by putting together perceptual information to give a complete understanding of the occurrence at any moment [46].

- **Occipital Lobe**:The occipital lobe is situated in the back section of the brain. It processes and interprets everything we see. The major visual processing takes place in this lobe, where it receives information from the eyes. It is then transferred to secondary visual processing areas that interpret distance, depth, location, etc. This particular lobe is also responsible for analyzing shapes, colors and making conclusions to what we observe [40] [51].

3.1.3 The Cerebellum

The cerebellum is situated back of the cerebrum [46]. Although, it occupies one-tenth of the brain's total volume it contains over 50% of the total neurons. This is why it is sometimes called the 'little brain'. The major functions of the cerebellum are the control of balance, posture and voluntary movements. Furthermore, it plays a major role in fine-tuning motor plans to execute precise and accurate movements through a series of trial and error [52].

3.1.4 The Brain Stem

The brain stem is the middle part of the brain. It plays an important role to regulate the cardiac and respiratory function of the central nervous system. Furthermore, it controls the movement of the eyes and mouth, maintaining involuntary muscle movements, consciousness and regulating the sleep cycle properly. It consists of three parts – the midbrain, pons and the medulla [63] [33] shown in Figure 3.3.

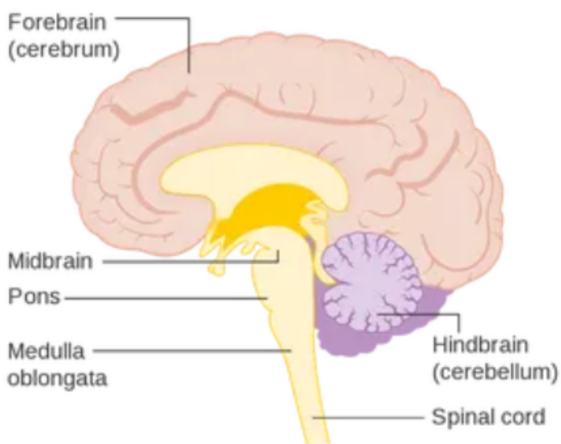

Figure 3.3: Brain Stem Anatomy [49]

- **The Midbrain**: The midbrain occupies a small portion of the brainstem, positioned above the pons underneath the cerebellum. It plays an important role in the central nervous system (CNS) as it controls many functions such as visual and auditory systems via inferior and superior colliculi, as well as the movement of the eyes [33] [52]

- **The Medulla**:The medulla is situated in the lowest part [63].It is an important part of the brain, as it contains vital control centers that are responsible for crucial functions such as blood pressure (BP), heart rate and breathing [33].
- **The Pons**: In the brainstem the pons are located in the upper part, which is responsible to connect the medulla with the cerebral cortex shown in figure 3.3. It controls a wide range of functions such as - communication between different parts of the brain, breathing and sensations like pain, taste, balance etc. Furthermore, sleep cycles and other important functions are controlled and monitored by the pons [33].

3.2 EEG

An electroencephalogram (EEG) is a measurement of the activity of the electrical impulses generated by the brain. Brain cells communicate with one another via electrical impulses. These impulses are active eternally, even when we are asleep. If this activity is displayed through an EEG machine it will display waveforms of different frequency, wavelength and amplitude. EEG is one of the most common diagnostic tests for epilepsy, but can also be used to diagnose a variety of other brain disorders such as sleeping disorders, brain tumors etc. The signal frequencies of the EEG waves are delta, theta, beta, gamma and alpha. The types of brain waves are shown in Figure 3.4

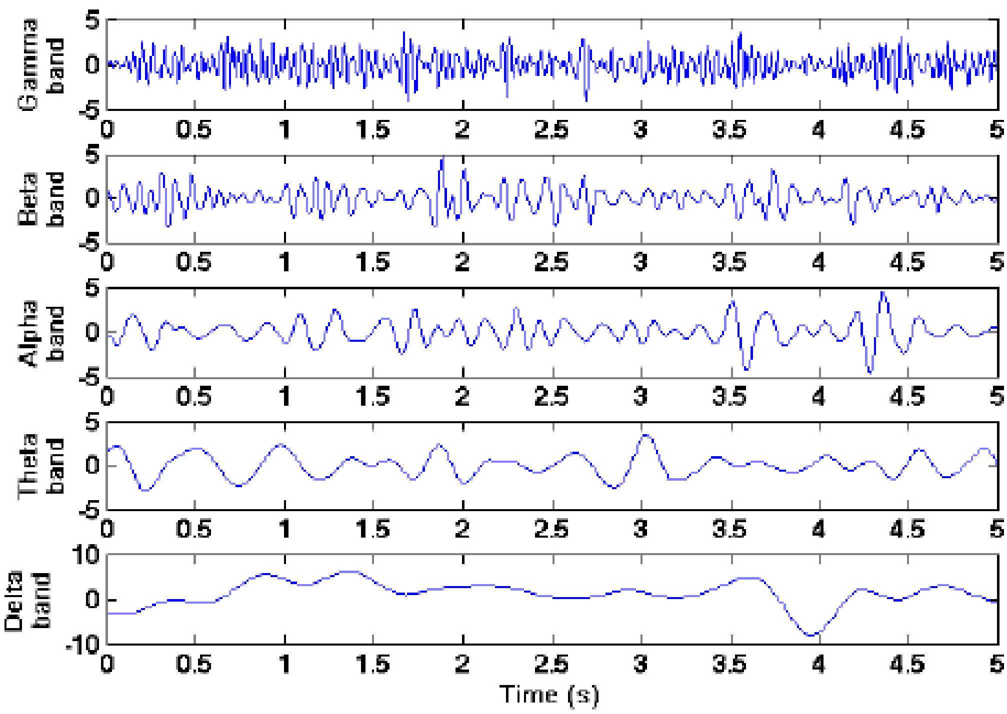

Figure 3.4: Different brainwaves of the EEG [32]

- **Alpha**:Alpha brainwaves have a frequency in the range of 7.5 Hz to 13.5 Hz. It is best found in the rear areas of the head on each side being higher in amplitude on the controlling side. The alpha brainwave spikes when someone closes their eyes and is in a relaxed state. However, the signal fades if the eyes are opened or the subject is diverted to thinking or calculating [58]

- **Beta**:Beta brainwaves have a frequency of 14 Hz and above. The activity of beta brainwaves is also called "fast activity". Usually it is observed on both the sides in symmetrical distribution but most frequent in the front part [58]. The beta band gives a reading when we are aware or doing any cognitive task like problem solving. This type of brainwaves can also be further divided into three categories (bands) – Lo-Beta, Beta and High-Beta [68].

- **Gamma**:Gamma brainwaves have a frequency of about 38 Hz to 42 Hz. Since they are the fastest of the brainwaves they pass information rapidly and quietly [68]. Gamma brainwave activity is involved in working memory, awareness and long-term memory processes. Furthermore, it is also involved in psychiatric disorders like epilepsy, schizophrenia and Alzheimer's disease [38].

- **Theta**:Theta brainwaves have a frequency ranging from 3.5 Hz to 7.5 Hz. Unlike beta brainwaves, it is a "slow" activity [58]. This type of brainwaves occur frequently during sleep but can also happen when someone is meditating deeply. It is our gateway to memory, learning and our instincts. Theta brainwaves are generated momentarily when we wake up to being fully conscious or when we are just about to sleep [68].

- **Delta**:The delta brainwaves consist of a frequency of 3 Hz or below. Unlike the Gamma brainwave, it is the slowest of all the brainwaves with the highest amplitude. It is the dominant rhythm in babies of age one or below in stages 3 and 4 of their sleep [58]. Furthermore, delta waves can be found when someone is meditating deeply like theta, and also when one is not dreaming in their sleep. Moreover, regeneration and healing of our body take place in this state [68].

3.3 Epileptic Seizures

Epilepsy or epileptic seizures is a neurological disorder that is a result of a sudden surge in the electrical impulse of the brain. Over fifty million people all over the world are affected. These seizures mostly occur abruptly without any warnings i.e., there are no prior symptoms or signs before the occurrence of the seizure [25]. Epileptic seizures can cause people to lose awareness and consciousness, leading to death. The fact that it is very random and can occur without any signs can be fatal for human beings [54]. Epileptic patients are typically treated using medications and surgeries. However, over a third of the total number of epileptic patients worldwide have uncontrolled seizures i.e., the seizures they experience are very frequent and random. Thus, these patients need to be continuously observed and examined [54]. Therefore, in this paper, as mentioned earlier, a particular technique is proposed to foretell the event of an epileptic seizure before the occurrence. This will act as a warning for the patient and will also enable doctors and the patients to take precautionary measures.

Seizures disrupt the regular activity of the brain by overflowing with excessive and abnormal electrical signals. However, how it affects the body is dependent on two major factors. Firstly, the location of the seizure and secondly the spread of the seizure to other parts of the brain. If a seizure were to spread to other parts, it might affect more parts of the body [64].There are two different types – partial seizures and generalized seizures.

3.3.1 Partial seizures

The electrical disturbance in partial seizures is limited to a particular area of one side of the brain. Partial seizures can be further divided into two types – simple partial seizures and complex partial seizures [34].

- **Simple partial seizures**:People with this type of seizure does not lose consciousness and are fully aware of their surroundings. Some people cannot move or even speak during the seizure, while in rare cases there were people who could talk with one other normally during the seizure. These seizures can hamper movement, emotions and can produce peculiar sensations such as buzzing or ringing sounds. People might also be prone to hallucinations if they have this type of seizure [34]

- **Complex partial seizures**:People with complex partial seizures tend to lose consciousness because it affects a larger portion of the brain [64]. During this type of seizure, people cannot interact with each other normally and is unable to control of their motor functions (walking, running etc.) [34] Moreover, if someone has a complex seizure, they may be fully awake but unaware of the fact that the seizure is occurring. [64] In the long run, these types of seizures may spread and evolve to become a generalized seizure where it affects the entire brain all at once [34]

3.3.2 Generalized seizures

Unlike, partial seizures these seizures affect the whole brain all at once. [64] The following are the most common types of generalized seizures -

- **Absence seizures**:It involves a short lapse of awareness. Symptoms before a seizure are: abnormal eye blinking, continuous staring and smacking of lips.

- **Tonic-clonic seizures**:This type of seizure is widely known, where the person would lose his/her consciousness and fall. Here, the body hardens with an involuntary contraction of muscles – legs and arms twitching periodically.

- **Myoclonic seizures**:They cause short jerking movements that affects both part of the body.

- **Atonic seizures**:In this seizure, people will lose all their motor reflexes and control, falling over on the ground.

3.4 EEG mechanism

Inside the brain, billions of cells communicate with one another via electrical signals. Such cells inside the brain are called neurons.These signals in the brain cause the formation of patterns known as brain waves [67]. The firing of a single neuron is very difficult to detect as it produces a minimal electrical field. However, when many of these neurons fire at the same time to communicate with each other, enough electrical field is generated to be detected from the scalp [69]. During an EEG, electrodes are placed in the scalp to detect electrical signals/waves. These signals/waves are then amplified by the EEG machine and converted to EEG signals. The electrodes are placed in the scalp according to the 10-20 international system, which is an international standardized system for placing electrodes on the scalp. There are 21 electrodes in this system shown in Figure 3.5 and each of these electrodes are placed in such a way that they are either 10% or 20% (of the total front-back/right-left distance of the skull) away from each other, and hence the name "10-20 international system" [4].

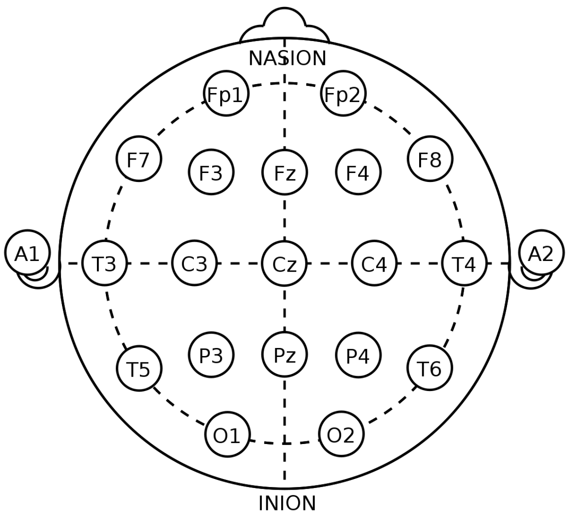

Figure 3.5: The 10-20 international system [60]

The naming of the electrode also follows a pattern. The letters indicate the position of the electrodes according to the lobes of the brain. There are four lobes of the brain: frontal (F), parietal(P), temporal(T), and occipital lobes(0). There is nothing called the central lobe, so the letter 'C' is just for identification. The number in electrode names indicates the position of the electrodes according to the hemisphere of the brains. The even numbers: 2, 4, and 8 indicate the electrodes placed on the right hemisphere. The odd numbers: 1, 3, 7 indicate the electrodes placed on the left hemisphere, and zero('z') refers to electrodes placed on the midline.

3.5 Signal Processing

3.5.1 What is signal processing?

Digital signal processing (DSP) is the mechanism whereby a signal is analyzed and modified to maximize its efficiency or performance.Basically digital signal processing

consists of methods and algorithms which enhance the quality of digital communication and makes it more effective. DSP transforms an analogue signal to a digital signal. It helps identify errors in signals by filtering out noise from a signal. Noise is nothing but random unwanted information in a signal which makes it difficult to analyze the useful bits in a signal. For example when signal processing is applied to an audio signal, it decreases the amount of noise in the signal and makes it less distorted. The main purpose of signal processing is to convert the original signal into a better,more useful signal which can be easily and more effectively analyzed.
In the previous few years, brain computer interface(BCI) and the signal processing have had a major impact in the medical research world [26] [27]. Many disorders of the nervous system like epilepsy,alzheimer,dementia can now be diagnosed by the the analysis of EEG signals [18][6][5]. As indicated previously , we have analyzed hours of EEG signals to come up with the prediction of the onset of an epileptic seizure, which will inturn be used to cure epilepsy.
EEG records the wave pattern that is generated due to the electrical activity of the brain.So how are EEG readings measured? Small metal discs are attached to different locations on the scalp of the subject with electrodes.These electrodes are nothing but conductors through which electric current enters or leaves. These electrodes are connected to a computer which keeps the records of these eeg readings.The standard arrangement of these electrodes is shown in the Figure 3.5 [10][14][1]. So how does this entire process work? An overview of the entire process is explained in the next paragraph as discussed by Al-Fahoum et al. [29].
All raw EEG signals that are recorded contain some level of noise. Noise causes disturbance in the signal which makes it very challenging to analyze and interpret the EEG data. This can make it very hard to retrieve the useful features from the original signal. Noise also known as artifacts can occur due to several reasons like muscle movements such as eye blinking that occurs during data acquisition.It can also come from external sources such as power line electrical noise [17]. A significant portion of the noise can be avoided by creating a suitable environment during recording by carefully planning these recording sessions. Certain functions and algorithms can also be applied on these signals to filter out or remove the noise and inturn have a better noise signal ratio [21]. So basically, in this entire procedure of analyzing the signal the first step is pre processing which includes signal retrieval , deletion of artifacts, averaging signal, output threshold , improvement of the signal, and finally detection. Next comes feature extraction. Feature extraction is the transformation of the original data to a data with a reduced number of data so that the data can be more easily and efficiently analyzed. A feature is a distinctive metric, structural factor derived from a segment of a pattern [15]. The next step in the procedure is classification. Classification is done by applying certain methods such as linear analysis, nonlinear analysis, adaptive algorithms, clustering, and neural networks [29].

3.5.2 Methods of Signal Processing

Features can be extracted from the signals using various techniques. Among these techniques are time frequency distributions (TFD), fast fourier transform (FFT), eigenvector methods (EM), wavelet transform (WT), and auto regressive method (ARM) [29] Fast Fourier Transform is discussed below.

- **Fast Fourier Transform**: Fast Fourier Transform (FFT) is a method that calculates the Discrete Fourier Transform (DFT) or the inverse of the discrete fourier transform of a signal [56]. Fourier Analysis transforms a signal from its initial domain i.e. a signal graph with respect to time to a representation of the graph with respect to frequency and vice versa [56]. It is displayed in Figure 3.6. DFT is acquired by the decomposition of a series of values into components of different frequencies [2]. DFT has several uses but the computation of DFT is very slow i.e. has a very high time complexity. An FFT makes quick calculations by factorizing the DFT matrix into a product of factors that mostly consist of zero values [3]. Using Fast Fourier Transform, the time complexity of computing DFT is reduced from $O(R^2)$ to $O(R \log 2R)$, where R is the size of the sample [13]. This can be of great importance when the size of R is huge and applying it will be more efficient rather than using DFT directly.The structure of an FFT algorithm is shown in Fig 3.7
  DFT is defined by the formula shown in 3.1[56]

$$x[k] = \sum_{n=0}^{N-1} x[n] e^{\frac{-j2\pi kn}{N}} \tag{3.1}$$

  where k = 0 ,........N-1
  where $e^{i2\pi/N}$ is a primitive Nth root of 1.

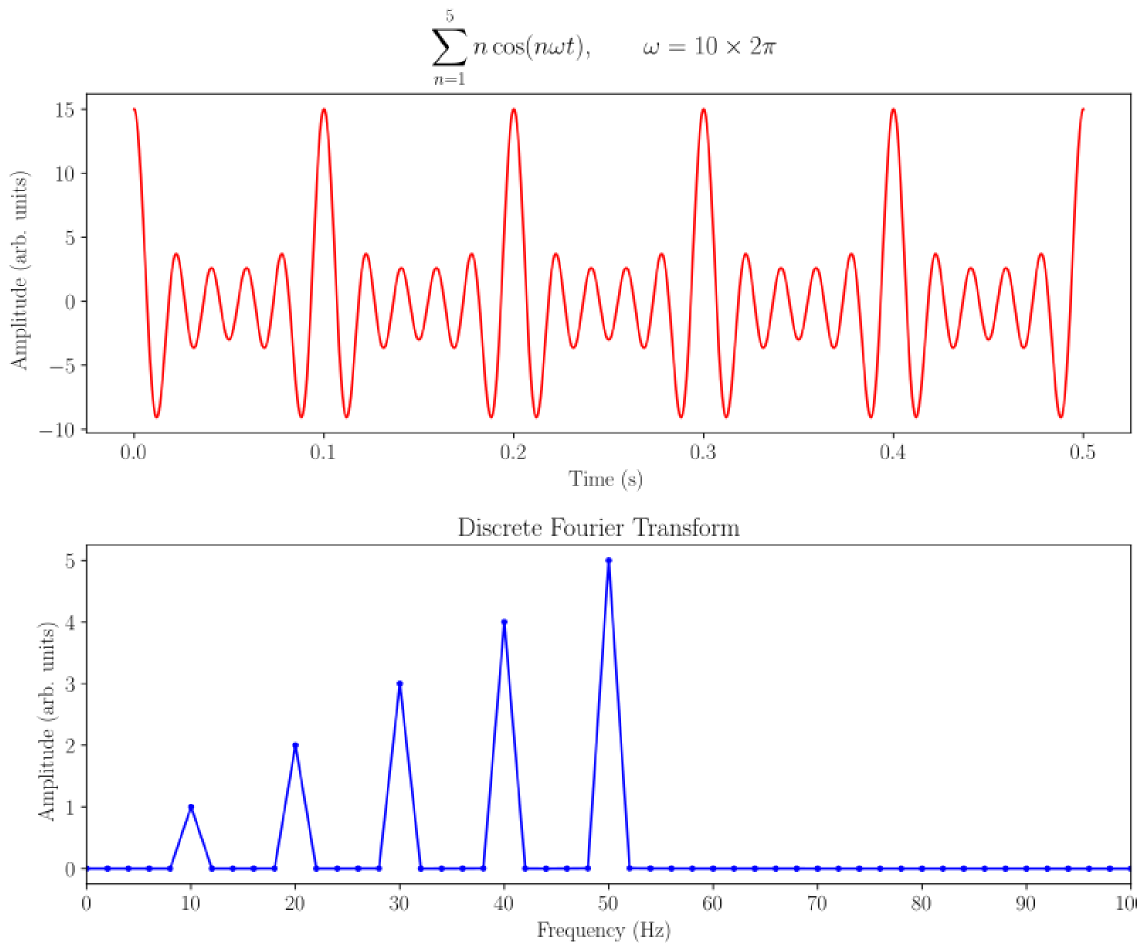

Figure 3.6: A discrete Fourier Analysis of a sum of cosine waves [61].

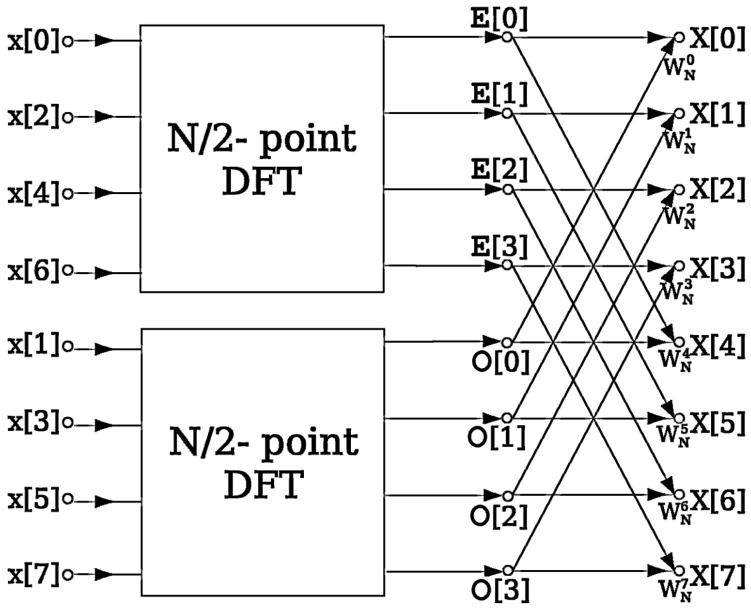

Figure 3.7: FFT algorithm structure [62].

3.6 Machine Learning

3.6.1 What is machine learning?

Machine learning is a field of technology that involves machines training themselves from given data and then making predictions or decisions based on the training it takes. It has been around for a quite a while but lately the world is starting to benefit from the effects of it. This is because machines today have access to an incredible amount of data, greater computational power of machines and better machine learning algorithms.As a result machine learning can be seen all around us. It has many applications such as its use in search engines to make recommendations according to what the users search over a period of time, spam filters in email, detection of potential fraudulent bank transactions, voice recognition in phones, etc. It has a significant impact in the field of medical science today. For instance it can be used to analyze EEG signals which in turn will help with the diagnosis of certain neurological diseases. So how does machine learning work? The whole process starts with feeding data or instructions to the machine.The machine then studies certain features in the data and makes predictions or decisions in the future based on the information that is provided to the machine. The more the number of decisions the machine makes, the more experience the machine gains and is likely to make better decisions. The main objective of machine learning is to create a model that allows the machine to learn automatically without any assistance from human beings and make changes or adjustments accordingly.So what is classification in machine learning? It is a process of categorizing the input data to different groups or classes.For instance with detecting spam emails, the main aim of machine learning is to train the model enough so that it can predict whether a certain new input i.e. email will belong to the ‘spam’ or the ‘not spam’ class.

3.6.2 Types of Machine Learning Algorithms

Machine learning algorithms are mainly of four types: Supervised ,Unsupervised,semi supervised and reinforcement learning.

- **Supervised Learning**:Supervised machine learning algorithms are those where the information used to train the machine is labelled.The algorithm uses the training labelled data to generate a function using which it can make predictions about the future outputs.After a certain amount of training, the algorithm can make output predictions for the corresponding input that is provided. Comparison can be made between the predicted output data and the output data in the data set to find out the accuracy of the model. Supervised learning has a very high computational complexity and normally produces very accurate results.Some supervised machine learning algorithms include Decision Trees,Naive Bayes, Logistic Regression,Support Vector Machines, K-nearest Neighbors(KNN), Artificial Neural Networks(ANN).Data is randomly split for testing and training and then the model is evaluated using various accuracy tests.A representation of this process of data splitting and evaluating is shown in Figure 3.8

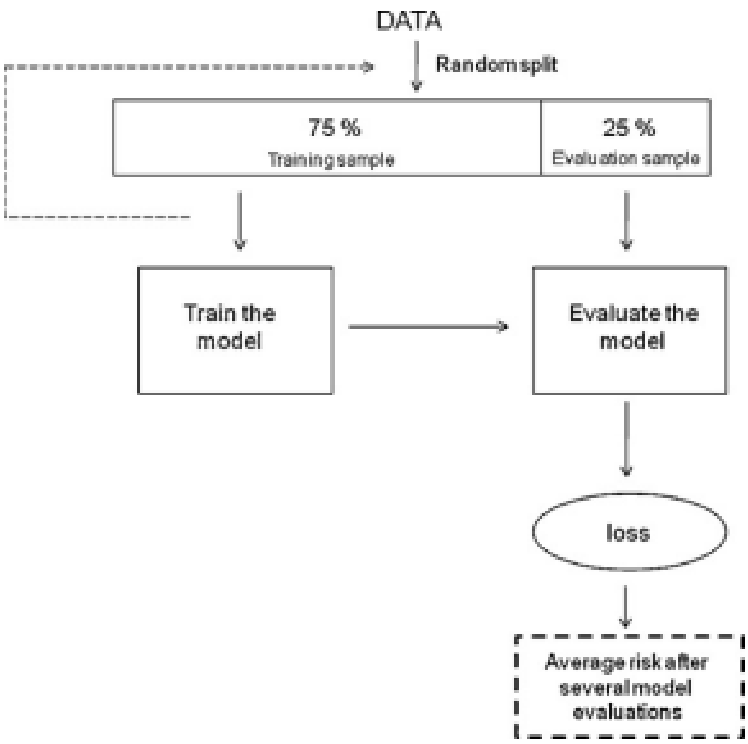

Figure 3.8: Random data splits for model training and evaluation for Supervised Learning [23]

- **Unsupervised Learning**:Unsupervised Learning operates using data that is neither labelled nor classified. The key goal of unsupervised learning algorithms is to find out the invisible patterns or structure in the given data. It does not predict an output for a corresponding input. It rather aims at finding a hidden pattern that might exist in the data.Unsupervised Learning has a low computational complexity but produces moderately accurate results. Unsupervised Learning can further be categorized into clustering and association. Clustering refers to finding clusters i.e. underlying grouping within the data. Association refers to a set of certain rules that define a large portion of the data.

- **Semi-Supervised Learning**:As the name suggests, this falls somewhere between supervised and unsupervised learning. Generally, this operates using a tiny portion of labelled data and a huge percentage of unlabelled data. Semi-supervised learning is usually preferred when the given labelled data requires additional attributes to train the model. The systems that use this technique are able to increase accuracy of predictions

- **Reinforcement Learning**: Figure 3.9 tells us how reinforcement learning works.It includes different components such as agents, actions, environment, rewards, state, policy. This is a method using which the agent performs an action in an environment and based on the actions performed the agent is given some delayed reward. This reward enables the agent to evaluate the action that it had just performed.This method enables the agent to determine its optimal behaviour in a specific environment or context. In other words, it helps the software agent choose the best action.In order to produce an effective agent, reinforcement learning undergoes these following steps:

  - :The agent analyzes the input states
  - :The agent executes the action based on the decision making function
  - :Rewards are awarded based on the action performed
  - :The state action pair information regarding the reward is noted down

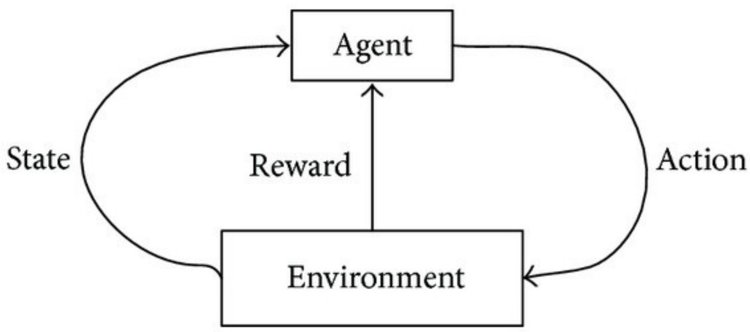

Figure 3.9: Block diagram representing how reinforcement learning works [37]

3.6.3 Different Algorithms

Support Vector Machine

SVM is a supervised machine learning algorithm which categorizes or data by drawing a line of separation between the two sets of data.

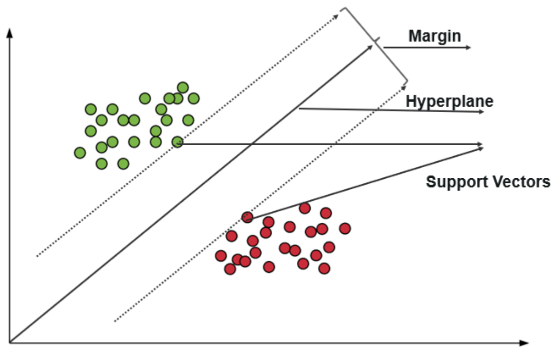

Figure 3.10: Simple representation of Support Vector Machines [50]

Figure 3.10 shows how SVM works. The training data points are represented using points in the graph.These training data points are referred to as the support vectors. These points are categorized or classified into a group by drawing a line of separation between the two sets of points. This line of separation is referred to as the hyperplane.The hyperplane has to be drawn in such a way so that the gap between the two groups is as wide as possible.This gap is known as the margin.

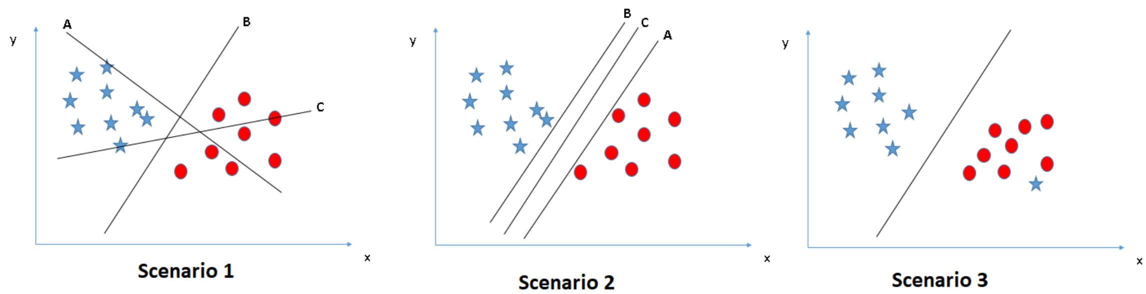

Figure 3.11: Different scenarios of picking the correct hyperplane [39]

Figure 3.11 shows us various scenarios where different lines are selected to be the hyperplanes.
In scenario 1 B is the hyperplane since B is the only line that separates the blue stars and the red circles completely. The first criteria for a line to be a hyperplane is that the line has to be drawn in such a way that all the points of one category have to be on one end of the line and vice versa.
In scenario 2 all the three lines- B,C and A completely separate the two sets of points.However, C here is the hyperplane since C is drawn in such a position where the gap between the two sets of points is the maximum. Another criteria for a line

to be a hyperplane is that the line has to ensure that it is placed in such a location where the distance between the two groups of data is the maximum.
The SVM algorithm has the capability to ignore anomalies or irregularities in the data. Here in scenario 3 , the one red circle among the blue stars is an outlier of the circle group. SVM has the ability to ignore these outliers and find a suitable hyperplane with the greatest margin as shown in scenario 3.
At times the data might be such that it is not possible to find a linear hyperplane that separates the two groups of data. So how do SVM classify such data? SVM makes use of a technique called the kernel trick. Using this, SVM transforms the input data of low dimensions to a data that has higher dimensions, thus making the inseparable data separable.

Logistic Regression

Logistic regression is a supervised algorithm for classification and is not used to model regression problems. This analysis helps to predict the probability of an output based on the data fed into the model using a nonlinear function. It is optimal for binary classification of linearly separable data. Unlike linear regression, logistic regression forms an S-shaped curve called a logistic function or logit function with 0 and 1 as asymptotes. This sigmoid function takes any real value and maps it between 0 and 1. This range on the curve indicates the probability of the dependent variable depending on the variable that is that independent. The dependent variable having two possibilities is called binary logistic regression and is called multinomial logistic regression if it has more than two.

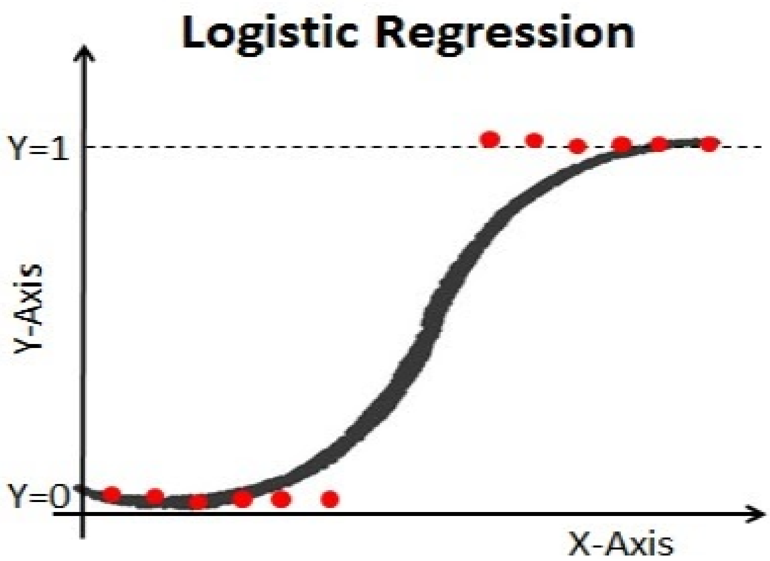

Figure 3.12: Logistic Regression S curve [45]

The logistic function or sigmoid function is as follows:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{3.2}$$

In the Figure 3.12 , the vertical X-axis indicates the predictor values and the horizontal Y-axis indicates the estimated probability of an event. The input data is initially transformed using the sigmoid function. The probability distribution is a Bernoulli distribution. The probability of an output with a value of more than 0.5 would be classified as 1 and less than 0.5 would be classified as 0. This model joins the input values by using coefficients or weights. The coefficients or parameters are determined with the training set using maximum-likelihood. This is estimated using stochastic gradient descent and the model is then used to make predictions. Logistic regression is a fast algorithm that is less likely to over-fit and has relatively low variance and is ideal for data where the dependent variable is dichotomous based on one or multiple independent variables.

Naive Bayes Classifier

Naive Bayes classifier is a group of classification algorithms with the Bayes' theorem as the underlying principle. The Bayes' theorem estimates the probability of a class or event based on other events or classes. Naive Bayes is used as a way to build classifiers and is not one unique algorithm.
Naive Bayes makes an assumption that all input values or predictors are conditionally independent of any other value or feature. In other words, each feature contributes equally and independently to the result. This is called class conditional independence. As a result, P(Q&R&S|T) can be replaced by P(Q|T) x P(R|T) x P(S|T). This makes it easier to generate the given probability which was difficult to determine before.

$$\underbrace{P(c \mid x)}_{\text{Posterior Probability}} = \frac{\overbrace{P(x \mid c)}^{\text{Likelihood}}\,\overbrace{P(c)}^{\text{Class Prior Probability}}}{\underbrace{P(x)}_{\text{Predictor Prior Probability}}}$$

$$P(c \mid X) = P(x_1 \mid c) \times P(x_2 \mid c) \times \cdots \times P(x_n \mid c) \times P(c)$$

Figure 3.13: The Bayes formula [66]

From the formula in Figure 3.13, predictor prior probability is the normalising constant and posterior probability is the output we want which is the probability of a class given the attribute is true. Likelihood estimates how ably the model forecasts the data and prior probability indicates how much the model can correctly describe actuality based on known or previous information.
This model is simple to construct and does not require any complex parameter estimation and as a result, it is ideal for big data sets. It is also suitable for data sets with multiple classes [59].

Decision Tree

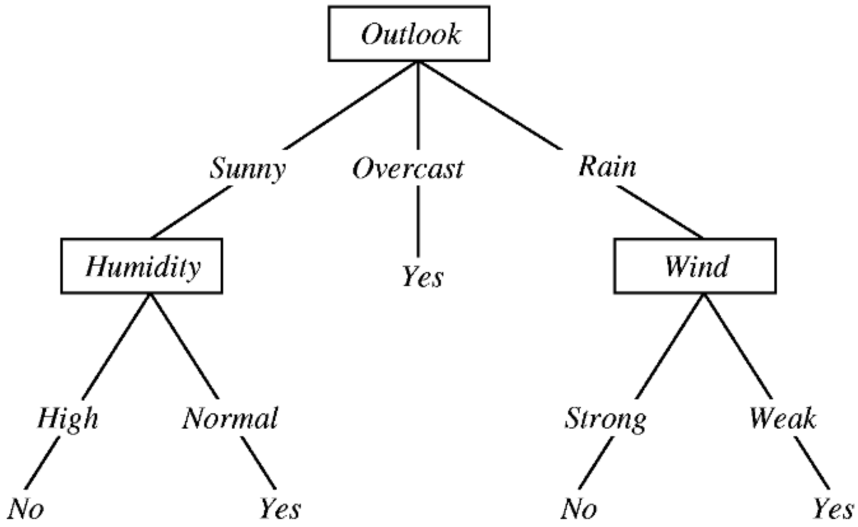

Figure 3.14: Decision tree drawn upside down with its root at the top [43]

Decision tree is a supervised machine learning algorithm that builds a model which has a tree like structure as shown in the Figure 3.14. Here in this example, the main aim of the model is to predict or come to a decision whether a certain guy on a certain day will go out to play tennis or not. The three features-Outlook,Humidity and Wind of a certain day will be taken into account to determine or predict whether the output will be a 'yes' meaning the guy will go out to play or a 'no' meaning he will not go out to play.
So how do decision trees work? To know which feature will form the root of the tree a metric called information gain is calculated.The attribute or property with the greatest information gain is the feature that is selected.The main aim is to keep the tree as small and as simple as possible. The idea is to break down the data into smaller and smaller subdivisions while the related decision tree is simultaneously constructed. The tree is built in a top-down recursive divide and conquer approach [47]. A node might have two or more branches and the leaf represents the class. The feature that is the most optimal predictor normally forms the root node. Decision trees can be used for both qualitative and quantitative data.

Artificial Neural Network

Artificial Neural Networks can also be used in the classification of data. It also is a part of the supervised machine learning algorithms. ANN has played a significant role in the sector of machine learning and deep learning. Convolutional Neural Network (CNN) is very useful in analyzing photos whereas Recurrent Neural Networks(RNN) is helpful when it comes to natural language processing(NLP) and speech recognition.

Typically there are three layers that make up a neural network - the input layer, the hidden layers and the output layer as shown in Figure 3.15. Each of these layers consists of nodes.Initially the data is fed to the input layers.The input layers pass

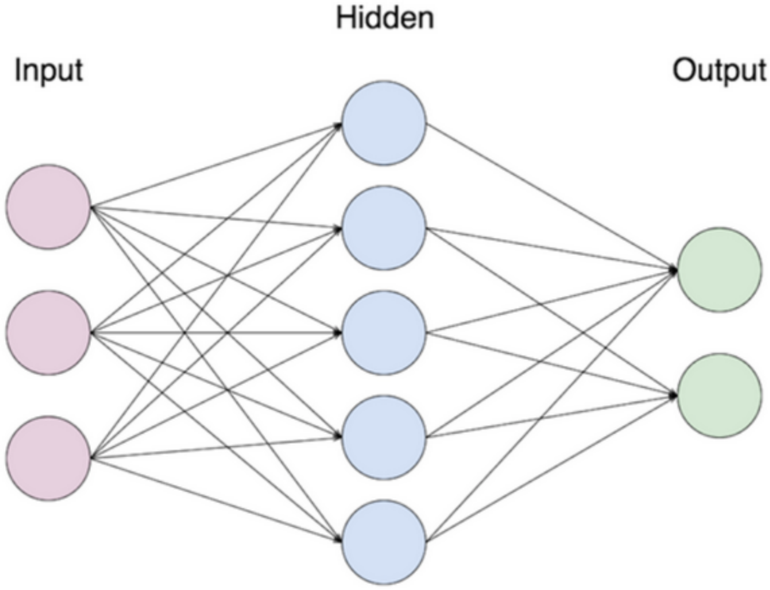

Figure 3.15: Schematic for a neural network [48]

this data onto the hidden layer.There can be more than one hidden layer in the network.The purpose of this layer is to perform certain calculations with the input data.These layers are also called the perceptron layers [57]. A weight is assigned to each input randomly from the linkage lines between the input layer and the hidden layer using which a bias is generated for each input. Inside the hidden layers certain activation functions are applied to the input data.Some of these activation functions include the linear function,the logistic function and the rectified linear unit function.The numerical inputs, the bias and the band of weights are integrated together to produce a single output which is produced by the output layer.The weights are then altered and back propagation is done to reduce errors

K-means Clustering

Clustering is a type of unsupervised learning method which separates data in order to create distinctive groups or clusters of similar items. K-means algorithm is a simple and uncomplicated unsupervised machine learning algorithm whose main goal is to group together a certain number of objects based on features into K number of groups. Therefore, K represents the number of clusters. This algorithm progresses iteratively and is ideally used for unlabeled data.

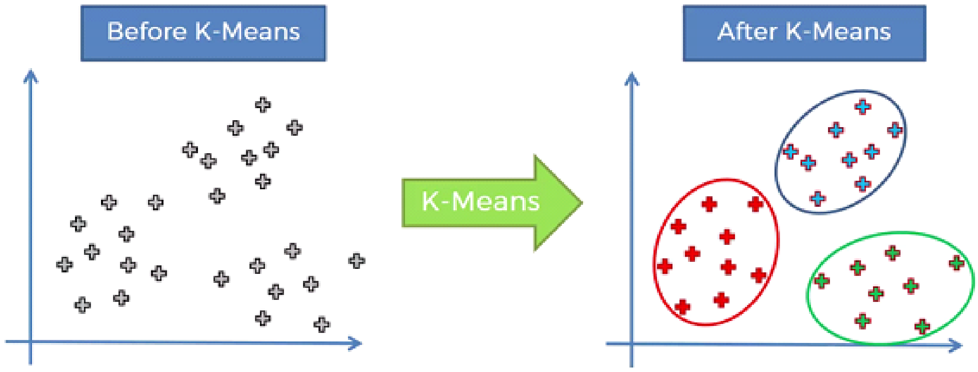

Figure 3.16: Simple representation of K-means clustering [42]

Figure 3.16 has three clusters which means that the value of K is 3. K is decided initially which establishes the number of clusters to identify. The algorithm then iteratively selects K points. The first K points (centroids) are selected randomly for each cluster which categorizes or separates the data into K number of clusters. Then the minimum length or separation of each data point from the centroids is estimated by calculating Euclidean distance or Manhattan distance. Grouping is done based on these distances and data points are assigned to clusters with minimum distance from the centroids. New centroids are then determined by calculating the mean of all the points of each group. This process repeats iteratively until the data points are no longer assigned to any new groups and permanent clusters have formed [41].

3.7 Database Description

In this research, CHBMIT open database was used [20]. This database consists of EEG recordings of 22 subjects collected from Children's Hospital Boston. Out of 22 subjects, five of them are males and seventeen of them are females. All the subjects are very young, their ages range from 1.5 to 22 years. In most of these subjects, continuous 23 EEG signals were recorded from different channels. With a 16-bit resolution, these signals have a sampling rate of 256 samples per second. To record these EEG signals, the international 10-20 system was used. The database was grouped into 23 cases. Each case has EEG recordings of a single subject except for two cases that contain EEG recordings of a single subject whose EEG data was recorded twice in one and a half year gap. Each case has 9 to 43 edf extension files of continuous EEG recordings. Most of the edf extension files contain EEG recordings of one hour except some edf files which contain EEG recordings of two to four hours. If one or more seizures had taken place during EEG recordings, those .edf files are labeled as seizure files. In this research, we only used the seizure files to build our model for predicting on-coming seizures.

Chapter 4

Proposed Model

The principal objective of this paper is to predict the event of an epileptic seizure successfully with a high accuracy and a low False Alarm Rate (FAR) in an automatic mode. A generic flowchart of the entire process is given in Figure 4.1. In general, pre-processing is used to eliminate all the undesirable components from a signal. However, our proposed plan allows a certain level of artifact tolerance with no filtering techniques being used. The attributes of the signal such as the phase, the amplitude and power spectral density are the features that will be used to classify whether the signals belong to the preictal or the interictal period. The classifier that is being used is the Support Vector Machine (SVM). Furthermore, regularization i.e. a windowing technique is then used to make the final prediction.

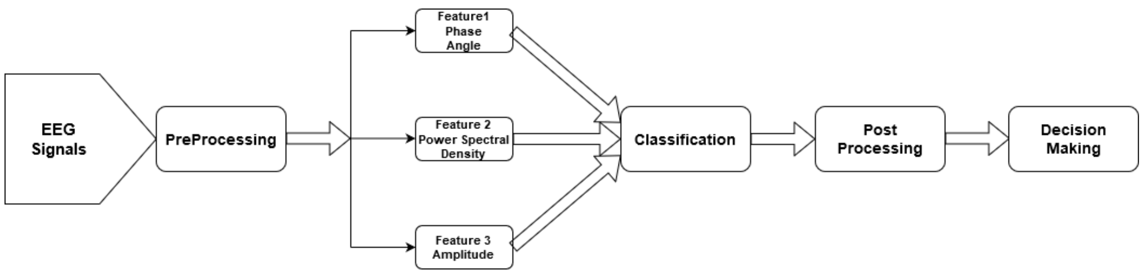

Figure 4.1: Proposed Plan Flowchart

4.1 Data Construction

The dataset that is being used is collected from the Children's Hospital Boston. The dataset is open to the public which can be found on the internet. This is a cited resource in many studies of detecting and predicting epilepsy [7]. It consists of EEG readings from patients under the age of 18 with uncontrolled epilepsy. We worked with the 10 patients among which 6 are females and 4 males. It is to be noted that each patient had readings from 23 different channels. The channels are -
FP1-F7, F7-T7, T7-P7, P7-01, FP1-F3, F3-C3, C3-P3, P3-01, FP2-F4, F4-C4, C4-P4, P4-02, FP2-F8, F8-T8, T8-P8, P8-02, FZ-CZ, CZ-PZ, P7-T7, T7-FT9, FT9-

FT10, FT10-T8, T8-P8
All signals were converted from the continuous time to discrete time at 16-bit resolution, at a rate of 256 samples per second. There were several files of EEG readings for all the patients, where each file contained hours of data, but for our research we have used only the ones where seizures had taken place. For each seizure that had occured, 90 minutes of readings prior to the end of the seizure was noted. The first 60 minutes were classified as the pre ictal period and the remaining 30 minutes as the inter ictal period, where it was given a class value of 0 and 1 respectively.It is to be noted that in a period of 90 minutes we are considering only one seizure, meaning that if there were two or more seizures in a period of 90 minutes, it was not be considered.

4.2 Feature Extraction

After obtaining the dataset the eeg signals consists of two phases, preictal and interictal periods, where each seizure file is divided into epochs of 10s.Thus each 90 min seizure file will contain 540 rows of data. Fast Fourier Transform (FFT) is then used which converts the time series signal data to a graph with the signals frequency as the domain.FFT is basically an enhanced version of Discrete Fourier Transform (DFT). It transforms the signal into its individual spectral components and provides the signal frequency information. Fast Fourier Transform shift (FFTshift) function is then used which rearranges a Fourier transform by shifting the contents with zero frequency to the middle of the spectrum [61]. Corresponding F and T signals are found after applying the following equations.

$$F = \gamma(r) \tag{4.1}$$

$$T = \delta(F) \tag{4.2}$$

Where γ is the FFT function and δ is the FFTshift function and represents each 1/256 s of the signal.

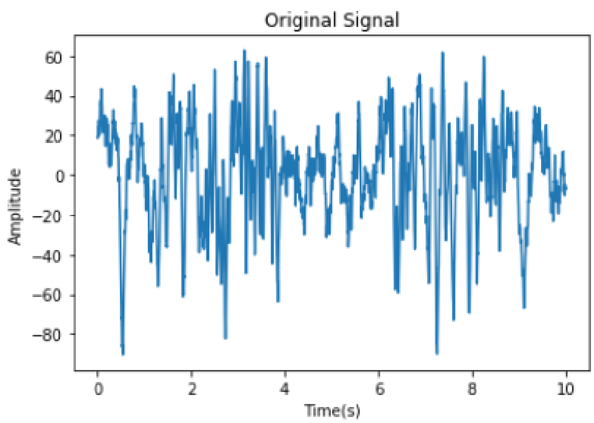

Figure 4.2: Snippet of Original Signal

Fig 4.2 is a snippet of the original signal. This image was extracted from the jupyter notebook of our code files. Fig 4.3 which also is extracted from the code files is a representation of what happens to the signals after Fast Fourier Transform is applied

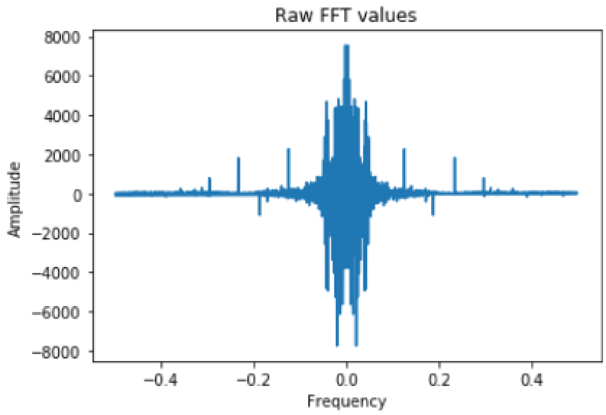

Figure 4.3: Snippet of signal after applying FFT

to it.In fig 4.2 the graph was in the time domain and FFT transformed this same graph to the frequency domain in Fig 4.3.
The three features to be used are the phase angle of the signal,the amplitude and the power spectral density of the signal. Phase refers to the position of a specific point in a particular instant on a waveform cycle [8]. Phase angle refers to the phase difference.Using python's numpy library, the phase angle for the signal is then calculated using the T signal and numpy's angle function. A = numpy.angle(T) , where A is the phase angle The average of all the phase angle values, 2560 values for every 10s, is calculated and each 10s epoch is assigned the single corresponding mean phase angle value.
In physics, amplitude of a wave is the maximum displacement of a point from its mean position of rest [55]. The amplitude of a signal measures the value of the signal at any point in time. The EEG signal amplitude is the frequency of the pattern in terms of electric energy microvolts. There are four common EEG frequency patterns: Beta (13-30 Hz), Alpha (7-12 Hz), Theta (4-7 Hz), and Delta (0.5-3 Hz), respectively. As the frequency increases the amplitude of the eeg decreases. The amplitude of the signal at a point in time is calculated using the formula below.

$$X = \left(\frac{2}{n * F}\right) \tag{4.3}$$

The average of all the amplitudes ,2560 values for every 10s, is calculated and each 10s epoch is assigned the single corresponding mean amplitude value. For a given signal, the power spectrum explains how power is transmitted into the frequency components that form the signal. The signal's Power Spectral Density (PSD) represents the strength of the variations(energy) in terms of frequency. The power spectral density of the signal at a point is calculated using the formula below .

$$P = 2\left(|\frac{f}{n}|\right)^2 \tag{4.4}$$

Where P is the power spectral density and n is the epoch size.
The average of all the power spectral densities,2560 values for every 10s is calculated and each 10s epoch is assigned the single corresponding mean power spectral density value. For each of the seizures we have considered, these three features are extracted for each of the 23 channels, producing a total of 23 x 3 features for each of the 540

rows of data.Figure 4.4 shows a snippet of the power spectral density of the signal shown in Figure 4.2

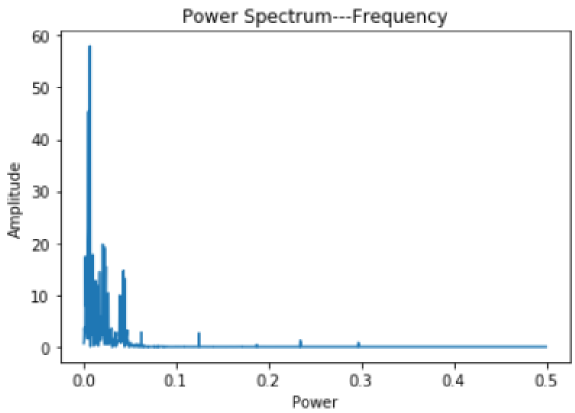

Figure 4.4: Power Spectral Density of the signal

4.3 Classification

After extracting the three features - phase angle, power spectral density and the amplitude from each of the 23 channels for each 10s, the dataset (540 x 70) is then randomly shuffled. To classify the preictal/interictal signals, the Support Vector Machine (SVM) [19]. classifier is being used as it is optimal for no stationary signals. A linear kernel was used. Support Vector Machines operate by drawing a line between the different clusters of data points thus separating the data into different categories i.e. points on one side of the line will belong to preictal group and the points on the other side will belong to interictal group. The dataset is then divided into 5 segments where each segment is once used as the test set while the four other segments were used as the training set to obtain the predicted values for each segment i.e. the entire dataset is cross-validated . These predicted values are then further processed to make accurate predictions.

4.4 Post-Processing

Many artifacts such as muscle movements due to eye blinking during data acquisition may lead to incorrect classification of preictal and interictal signals. Thus, further post-processing is required to make accurate predictions on the SVM classified signals. We have used regularization i.e. simple windowing technique as used by Parvez et al. [35].This is a two-step process, where x of v analysis is performed to make the predictions. It is to be noted that a window size of 5 minutes is used. The preictal period is assigned a class value of 0 and the interical period is assigned a class value of 1. In the first step, five 10s (50s) epochs are analyzed and in the second step six of these 50s windows are analyzed. The first step is a 3 of 5 analysis i.e. if three or more 10s epochs have a value of 0 the entire 50s window is considered a preictal period and is assigned a class value of 0 and if not it is considered a interictal period and is assigned a class value of 1. The second step is a 2 of 6 analysis i.e. if two or more 50s windows out of the six windows have the value 1 the entire 5-minute window is considered an interictal period and is assigned a class value of 1 and if not the 5-minute window is considered a preictal period and is assigned the value 0. This analysis made it very easy for us to calculate the false alarm i.e. the prediction of an epileptic seizure where the seizure had not occurred and also calculate when the seizure was predicted.

Chapter 5

Results and Discussion

The features that are being used in our proposed model are - phase angles, power spectral density and the amplitude. SVM classifier and regularization is used to accurately predict whether the signals belonged to the preictal or interictal period. Both Support Vector Machine and Logistic Regression was used to classify the 10 second periods either as preictal or interictal periods.Both of these algorithms were successful in predicting whether the 10s segments belonged to the preictal or interictal periods.

Both the tables, Table 5.1 and Table 5.2 show the calculated early time per seizure per patient using support vector machine and logistic regression respectively. Both the tables contain information such as the total number of seizures that were analyzed for each patient and how early each and every one of these seizures were predicted.Table 5.1 shows that using SVM all the 39 seizures were predicted numerous minutes before they had occurred, with a prediction accuracy of 100%. Table 5.2 shows that using the Logistic Regression Classifier, 38 of the 39 seizures were predicted, having a prediction accuracy of 97.4%.The tables also exhibit how SVM was more effective at predicting the seizures earlier compared to logistic regression. The average early prediction time using SVM was 25.38 minutes in comparison to 22.85 minutes using logistic regression.

False alarm refers to the situation where a seizure had been predicted but it had not occurred i.e. a after regularization 1s were predicted as class values where 0s should have been predicted. This would give a false indication to a patient that a seizure might occur, whereas it will not. These false alarms might have occured due to the over fitting of our model. The tables, Table 5.3 and Table 5.4 show there were a greater number of false alarms using logistic regression.Table 5.3 shows that using SVM, there were a total number of 27 false alarms with a false alarm rate of 0.46 false alarms per hour compared to a total of 30 false alarms with a false alarm rate of 0.51 per hour in Table 5.4 where logistic regression was used as the classifier. SVM therefore is considered for classification in our proposed model instead of logistic regression since it has a better prediction accuracy,a lower false alarm rate and also could predict the seizures earlier i.e. have a greater average early prediction time value.

Table 5.1: CALCULATED EARLY PREDICTION TIME PER SEIZURE PER PATIENT USING SVM

PN	TS	S1	S2	S3	S4	S5	S6	S7	S8	S9	Average
01	5	30	30	30	25	30	-	-	-	-	29
02	2	30	20	-	-	-	-	-	-	-	25
03	1	30	-	-	-	-	-	-	-	-	30
04	2	10	10	-	-	-	-	-	-	-	10
05	4	25	25	20	30	-	-	-	-	-	25
06	9	30	30	30	30	30	15	15	10	30	24.4
07	3	30	30	30	-	-	-	-	-	-	30
08	4	30	30	25	30	-	-	-	-	-	28.75
09	3	30	5	30	-	-	-	-	-	-	21.67
10	6	30	30	30	30	30	30	-	-	-	30
Average	-	-	-	-	-	-	-	-	-	-	25.382

PN = Patient Number, TS = Total Number of Seizures, S1-S9= Seizure Number

Table 5.2: CALCULATED EARLY PREDICTION TIME PER SEIZURE PER PATIENT USING LOGISTIC REGRESSION

PN	TS	S1	S2	S3	S4	S5	S6	S7	S8	S9	Average
01	5	0	30	30	25	25	-	-	-	-	22
02	2	20	15	-	-	-	-	-	-	-	17.5
03	1	30	-	-	-	-	-	-	-	-	30
04	2	10	10	-	-	-	-	-	-	-	10
05	4	25	10	20	15	-	-	-	-	-	17.5
06	9	10	30	30	30	30	15	20	05	30	23.2
07	3	30	30	30	-	-	-	-	-	-	30
08	4	30	30	20	30	-	-	-	-	-	27.5
09	3	30	5	30	-	-	-	-	-	-	21.67
10	6	30	30	30	25	30	30	-	-	-	29.17
Average	-	-	-	-	-	-	-	-	-	-	22.85

PN = Patient Number, TS = Total Number of Seizures, S1-S9= Seizure Number

Table 5.3: TOTAL NUMBER OF FALSE ALARMS PER PATIENT AND FALSE ALARM RATE (hour) USING SVM

PN	**TS**	**Total FA**	**False Alarm / hour**
01	5	4	0.53
02	2	1	0.33
03	1	1	0.67
04	2	1	0.33
05	4	3	0.50
06	9	7	0.52
07	3	3	0.67
08	4	2	0.33
09	3	2	0.44
10	6	3	0.33
Total	39	27	0.46

PN = Patient Number, TS = Total Number of Seizures

Table 5.4: TOTAL NUMBER OF FALSE ALARMS PER PATIENT AND FALSE ALARM RATE (hour) USING LOGISTIC REGRESSION

PN	**TS**	**Total FA**	**False Alarm / hour**
01	5	5	0.67
02	2	1	0.33
03	1	1	0.67
04	2	0	0.00
05	4	3	0.50
06	9	9	0.67
07	3	5	1.11
08	4	1	0.17
09	3	2	0.44
10	6	3	0.33
Total	39	30	0.51

PN = Patient Number, TS = Total Number of Seizures

Chapter 6

Conclusion

We have proposed a seizure prediction model in this study using feature extraction, classification using Support Vector Machine (SVM) and regularization. This paper focused on predicting the event of an epileptic seizure successfully with high accuracy. EEG signals from the data were constructed to have both preictal and interictal periods during which the features were extracted. Extraction of features (phase angle, amplitude, and the power spectral density) was done using FFT and the SVM classifier was used to classify the signals. In order to refine the LS-SVM classified signals, post-processing had to be done for optimal results. We managed to produce perfect accuracy from a difficult and challenging dataset from the Children's Hospital Boston-Massachusetts Institute of Technology (CHB-MIT) database. This database provided EEG data from epileptic children with intractable epilepsy who stopped treatment 1 week prior to data acquisition. This open-source database has been commonly used by other studies mentioned earlier. Compared to other studies that had a similar approach, ours succeeded in achieving a 100%prediction accuracy. A lot of impressive work has been done on seizure detection but our approach aimed for a seizure prediction model, a field that is still lacking significant research. However, the number of observations from the CHB-MIT database was a concerning factor. We succeeded in getting a 100% prediction accuracy but faltered in achieving an extremely low FAR(False Alarm Rate). We hope to expand our research in the future by working with more patients and applying our proposed model to a dataset with increased observations.

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