Beamforming Aided Fast Fourier Transform to Detect Epileptic Seizure Onset Based on Scalp EEG Signals and Different Learning Methods

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

Epilepsy is a neurological disorder that causes serious seizure attacks. Effect of epileptic seizure is now so severe in world that it causes patients lifetime phenomenon which can be hindrance to people to get back to normal life again. Electroencephalogram (EEG) signals help to understand brain's activity more insight-fully. These EEG data recorded from normal and seizure patient to understand the brain activity. For classifying ictal and interictal period most of the classifier do not give 100 percent accuracy. In this paper, EEG signals has been used to analysis the distribution time-frequency features than calculated energy feature from it using Fourier transform methods. Beamforming methods using as noise distortion to have less noise to get more accuracy. The features are used for training data is in machine learning. Support vector machine is used as a classifier and this approach give us 89.8 percent accuracy for detecting epileptic seizures.

Keywords: EEG, Beamforming, Machine learning, seizure detection, SVM, time-frequency.

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We would like to express our deep sense of gratitude to our supervisor Dr. Mohammad Zavid Parvez for encouraging us to do research on this project. He, guided and showed us the right path that has taken us to complete a successful research project. Moreover, in these three semesters, he was always showed his keen interest, encouraged us at various stages of this long research. Thesis plays supreme role in our undergrad life which sums up our four years. He, always helped us by analyzing every subject matter deeply and wisely. Moreover, in this long period we learned how to do a research as a team which drove us toward to do a better team work, practice logical thinking, problem solving in every stage. We will always treasure these moments working as team in the guidance of Dr. Zavid. We also want to deeply thank almighty for giving us this scope as a learning process. Last but not the least, extremely grateful to our families for always having faith in us.

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Nomenclature

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

AI Artificial Intelligence

EEG Electroencephalogram

EMD Empirical Mode Decomposition

$fMRI$ Functional Magnetic resonance imaging

HHT Hilbert-Huang Transform

MEG Magnetoencephalography

PET Positron emission tomography

$SPECT$ Single-photon emission computerized tomography

SPM Statistical Parametric Mapping

SVM Support Vector Machine

WHO World Health Organization

Chapter 1

Introduction

Epilepsy is one kind of neurological disorder due to this brain activity becomes unusual such as- periods of abnormal behavior, unresponsiveness. One the other hand, a seizure is a sudden, unconstrained electrical disruption in the brain. This disruption can easily change anyone's normal behavior. A seizure can happen anytime and mostly it goes unnoticed. If they keep coming back than it is known as epilepsy or a seizure disorder. According to the World Health Organization (WHO), approximately 50 million people worldwide suffer from epilepsy, which is making it one of the most common diseases globally. Most of the people those are living with epilepsy are low and middle income. Besides, according to WHO, 70% of the people the patients can live a seizure-free life if they get proper treatment and diagnosis. To cure this disorder and prevent before it causes risk, we use an electro-cephalogram (EEG) which is a noninvasive test that can record all the electrical patterns of the brain. As we know, there are billions of nerve cells in our brain that can produce very small signals. With these signals, we can from brain waves. EEG signals detect these brain waves through electrodes which amplify signals by the EEG machines. Then it records them in a wave pattern to detect the seizures attack and understand patterns of it.

1.0.1 Motivation

When the world started to work with technology and medical science, researchers started to work and study on the nervous system to understand our basic biology and body function. So that they can help when problems occur. Researchers are still now trying to find out ways to prevent diseases. The use of EEG in the central part of the human brain. EEG has been using for these kinds of researchers for the last 80 years. Previously working with EEG was very costly, however, in more recent years It has become extremely cheap, flexible for scientific research for understanding the early-stage development of the brain. Also, its research has moved away from analog to digital recordings. Now the cost of hardware and sensors deceased for that EEG research is open to working with various data-related projects, gained deep analytical capabilities. EEG signal is working with multiple-sensor research; therefore, the next wave of discoveries will be in the field of psychology and behavioral science. Furthermore, Epileptic seizure is a vast topic through this we have learned about signal processing, machine learning, neural networks with help of python library, and a bit about neuroscience. As it is a very big platform to work with different kinds of brain signals. As a team, we learned about knew through research, reading various papers.

1.0.2 Objectives

Purpose this research to use beamforming for noise reduction of EEG signal so that we can get more precise output for detecting epileptic seizure. We wanted to compare our output with the methodologies that did not add beamformers to reduce noise of the EEG and MEG signals. Moreover, we used many classifiers to understand how much beamforming helped us in the process of detecting epilepsy. This research answers following questions,
I) Can epileptic seizure be detected?
II) Does beamforming aided feature extraction generate more efficient detection accuracy?
This thesis paper consists of six chapter. In the first chapter we described the introduction where motivation and objective off this paper is stated. Second chapter states the literature review of this paper. In the third chapter we discussed the background history of epileptic seizure. In this chapter we have explained the anatomy of brain, EEG signal and classification of EEG signal, beamforming, Machine learning, Fourier transform and the dataset. In the fourth chapter, we emphasize on the system that we have propose to detect epileptic seizures. In this chapter, we explained the workflow of our work, the pre-processing part of signal with beamforming, use of FFT and use of SVM as a classifier. In the fifth chapter we analyzed the result and discussed it step by step. Finally, in the six chapter we concluded our research by conclusion and future work.

Chapter 2

Literature Review

Epilepsy is a persistent disorder that causes distortion in the central nervous system [8]. Epilepsy has a long-term effect in brain for this patient may have recurrent seizure attacks. Repetitive seizures produce disrupted physical symptoms for example- hallucination, less attentive, blinking eyes, deprived of sleep, restless etc. Approximately, 1 out of 3 people are endured by epilepsy [27]. Patients who suffer from epilepsy, electroencephalography (EEG) used to observe the brain activity, to analyze all EEG recordings, an expert is needed for this [25]. From the study of the electroencephalographic (EEG) recordings we gain the information, valuable knowledge and improved understanding of the process that are causing epileptic seizures [3]. epileptic seizures usually identified by the poly spike activities [3]. Also, Variety of frequencies rhythmic waves and for amplitudes spike-and-wave complexes are used to understand this disease. Several features extracted in each segment with the help of time frequency distribution for the detection of epilepsy [3]. For training the data they choose neural network[4]. The comparison between the result with short time Fourier transform that give 89%-100% accuracy [3]. Detection of ictal and interictal methods are still changing and there are multiple methods to decompose these signals. For proving classification accuracy, sensitivity, and specificity with greater consistence least square support vector machine is used as a classifier. Different brain locations large size benchmark dataset is used [1]. Machine learning algorithm detects onset seizures analyze brain's activity comparing with various physiological signals [8]. This algorithm detects 93% of 163 test seizures from 23 patients with the help of median detection delay of 3 seconds. The Median false detection rate in this algorithm was used for 2 per 24-hour period long [27]. Nonlinear time series analysis, entropies, logistic regression, discrete wavelet transform and time frequency distributions are used to analyze the performance of traditional variance-based method [2] and in this process 100% result came out. For distinguishing ictal, preictal, and interictal segments of a seizure to detect epileptic seizure manual extraction method was used instead of. raw EEG signal based convolutional neural network (CNN). After performing the three experiments standard accuracies was 96.7, 95.4, and 92.3% were derived from the Freiburg database using comparison time and frequency signal frequency domain [37]. In the CHB-MIT database the average accuracies for detection were 95.6, 97.5, and 93% in the three experiments the average accuracies were 91.1, 83.8, and 85.1% in the three experiments when time domain signals used in the Freiburg database. On the other hand, in these three experiments the CHB-MIT database signal detection accuracies were only 59.5%, 62.3%, and 47.9%. Based on these results, all these three cases are effective to identify frequency domain signals successfully. Interference of specific electrode interference has affected the detection Electroencephalographic (EEG) that can be lowered by different method, namely, beamforming, proposed in this journal [5].Without performing precisely by selecting higher-order spectra, this technique allows to improve identification of epilepsy. Spatial filtering methods are developed to allow a more accurate diagnosis. For this aim techniques based on Beamforming are used for its ability to constrain the passing electrical activity from a specified location reducing the activity to others [21]. In waveform estimation, the problem was set. By using the details about amplitude and frequency the signal is extracted from measured EEG signal. If the signal originated from epileptogenic focus then, the reconstruction of the desired signal is possible. Afterwards that, it will highlight abnormalities to have an accurate diagnosis. While showing the performance of various algorithms by considering a simple geometry Simulations and the results are demonstrated. On real data these methods have been applied. For to the reconstructing of the signal of interest, it is necessary to recognize the position of the source. As per alternative, DOA estimation methods have been studied for estimating the position of the sources. A problem is faced on the resolution issue of sources when they are very close together in a preliminary way [16]. Brain Computer interface effectively classify Electroencephalogram (EEG) [20]. Different feature extraction methods such as wavelet transform, Independent component analysis, Principal component analysis, Autoregressive model and Empirical mode decomposition mainly focus on feature extraction technique [26] and all these are used for comparison so that we can get more accuracy.These Feature represented to distinguish property and significant measurement and these are obtained from different patterns [8]. EEG signal has the ability to identify brain stimulation effectively for this brain computer interfaces are widely used.

Chapter 3

Background Analysis

Epilepsy is a vast topic in medical science and there are various reasons connect to it. Before explaining our detection methods and results, some knowledge from major aspects of this disease must be initiated. Notably, the researches were on the brain, epilepsy, and its history, causes, different signals, methods of classifiers to detect signals. All these researches helped us to find our techniques for the outcome. Here we will demonstrate the essence of our learning.

3.1 Anatomy of Brain

The brain consists of a large mass of nerve tissue that's protected within the skull. It controls every process that controls our body. The brain can process every sensory information to the body, regulates body pressure and breathing, releases hormones. Some functions such as- control our understanding of any specific situation, speech, functioning our limbs, and embodies the essence of the mind and soul. The brain has the cerebrum, cerebellum, and brain stem (Fig: 3.1).

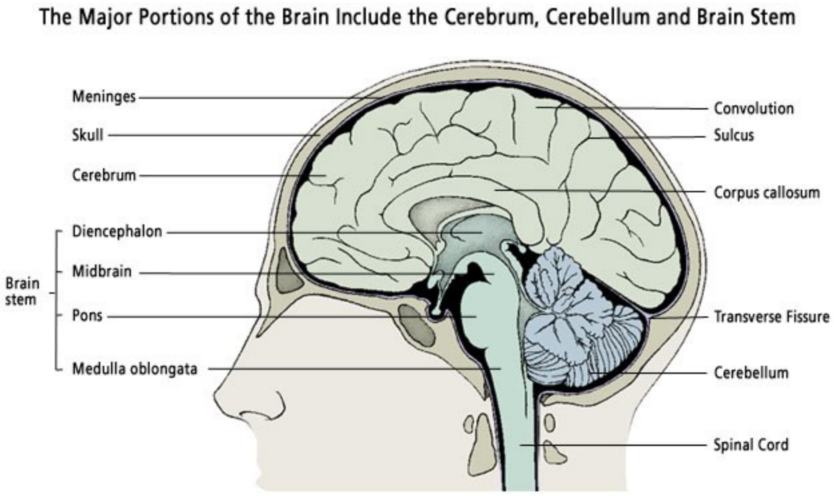

Figure 3.1: Brain Anatomy.

The brain receives information from sight, touch, taste, smell, and hearing, these are our five senses. It gathers all messages in such a way that it is meaningful to us that we can store such information in our memory. Brain and the spinal cord together composed as The Central Nervous System (CNS). Spinal nerves come from the spinal cord and cranial nerves this is known as The Peripheral Nervous System (PNS).

3.1.1 Anatomy and Function

1. **Cerebrum Cortex:**The cerebrum is the front part of the brain which is the largest part of the brain (Fig: 3.2). It is composed of the right and left hemispheres and these are connected by the corpus callosum. Two hemispheres are divided by interhemispheric fissure which is also known as longitudinal fissure [28][38]. Every hemisphere is separated into a wide zone known as lobes. Every lobe has different functionalities.
I. **Frontal Lobes:** Frontal Lobes are the largest among all the lobes. It is distinguished from the parietal lobe through space. This gap is known as the central sulcus and it is positioned from the temporal lobe through lateral sulcus. They are located in the front part of the brain. These lobes help the brain to coordinate high-level behaviors such as- controlling emotional, organizing, logical thinking, solving problems and issues. It also coordinates body responses, speaking, writing.
II. **Parietal Lobes:** Parietal lobes are in the back of frontal lobes and separated through the central sulcus. These lobes are in charge of harmonizing sensory information such as- touch, temperature, pressure, pain. Also, it can interpret words, languages, different signals through eyes, ears, motor, and memory [28].

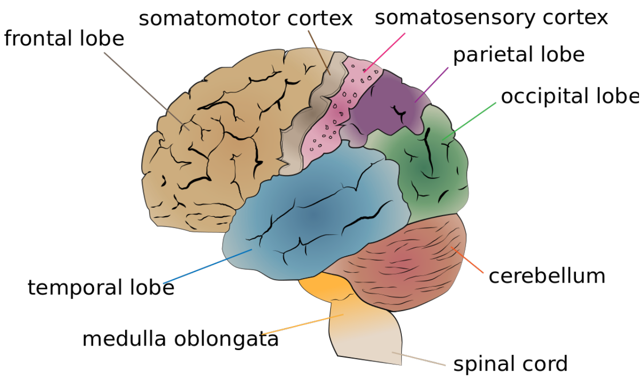

Figure 3.2: Cerebrum Cortex.

III.**Temporal Lobes:** Temporary lobes are at the same level as the ears and located on the side of the head. These lobes synchronize signals from hearing, memory, do sequences, and help us to understand a different language. It contains the hippocampus which is too important to memorize, learn, and understanding emotions.
IV. **Occipital lobes:** The primary visual cortex gets visual details from the eyes which are relayed to several visual representation areas that can elucidate details

from seen objects, distance, depth, and so on. As the occipital lobe is one of the main visual processing centers in the brain. It is located in the back of the brain [38].

2. **Cerebellum:** In Latin, the cerebellum is known as 'little brain' and it is a major structure of the hindbrain [38]. It is about ten percent of the total weight of the brain but it holds all neurons, esoteric cells that can transfer information through various electrical signals. The cerebellum is located beside the brainstem and in the back portion of the skull. Also, it is found bellow the hemispheres of the cerebral cortex. The cerebellum is containing with wrapped by white matter by cortex and it is also separated into two hemispheres exactly like the cerebral cortex. Moreover, this part of the brain is responsible for every kind of voluntary movement, motor skills for example- maintaining balance, coordinating movement, speech, vision, and other functions[38][30]. It has two parts which are described below.
I.**Cerebellar cortex:** In this part brain contains tissues that are folded with most of the cerebellum's neurons.
II. **Cerebellar nuclei:** It is one of the most innermost parts of the cerebellum that contains nerve cells. Nerve cells are capable of transmitting all kinds of communication information.

3.**Brainstem:** The brain stem adjoins the brain with the spinal cord and it is known as the smallest part of the brain[29]. The brain stem is located between the cerebrum and the spinal cords. It is consisting of the midbrain, pons, and medulla oblongata (Fig: 3.3). All of these regions are about an inch in length. The brain stem regulates blood pressure, heart rate, breathing, gives rise to cranial nerves that deliver main motor and sensory innervation. Brain stem helps us express automatic behaviors that are necessary for survival. Thus, the brain stem is the medium that can help the brain to communicate with the peripheral nervous system with the main motor and sensory system. Besides, it provides constant regulation to both the cardiac and raspatory system [29].

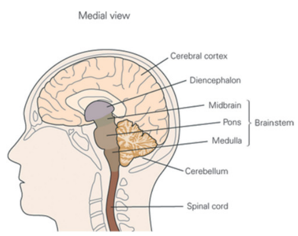

Figure 3.3: Brain Stem.

4. **Medulla Oblongata:** The medulla oblongata which is also known as myelencephalon is stated in the lower half of the brain stem. Its upper part is connected with the pons. It regulates heart rate, pressure, breathing as it consists of the cardiac, respiratory, vomiting, vasomotor centers [29].
I.**The Midbrain:** Mid brain is connected with pons, cerebrum with the forebrain. It is not more than 2cm in length. It contains the quadrigeminal plate and this

plate consists of superior and inferior colliculi, cerebral peduncles and this separated through cerebral and tegmentum. The mid brain is also known as mesencephalon and it associates such as- vision, hearing, controlling motors, sleeping cycles, temperature regulations.
II. **Pons:** In Latin pons is known as “bridge” and it is above the medulla below the midbrain and Infront of the cerebellum. Pons conducts signals and carries the sensory signal because of the white matter inside it. It is about 2.5 cm in length and consists of two stalks named cerebellar peduncles. It regulates signals from the forebrain to the cerebellum such as- expressions, taste, movements, hearing.

3.1.2 Other Internal Structure

The brain has different pathways named white matter tracts that connect the cortex to each part of the brain. Messages and signals travel to different lobs, gyrus, one side another, and also all other internal structures of the brain (Fig: 3.4).
1.**The Thalamus:**The thalamus means in Greek is “inner chamber” is the largest structure from the embryonic diencephalon. It has midline symmetrical within the brain, located between the cerebral cortex and midbrain. It is divided into four haves the hypothalamus,epithalamus, ventral thalamus, and the dorsal thalamus. Every half is 3cm long, 2,5 cm wide and 2 cm in high generally. It acts as a transfer center for both motor and sensory parts of the body and these signals send to the cerebral cortex. It regulates things like sleep, alertness, consciousness.
2.**The Hypothalamus:** The hypothalamus is named in Greek which means “under chamber” and It plays the role as an entryway between the nervous system and the endocrine system. The most important purpose of the hypothalamus is to associate the nervous system and endocrine system over the pituitary gland. It can control the autonomic systems of the brain and plays a massive role in control behaviors like thirst, hunger, intake of food and water, sleep, and defensive behavior.

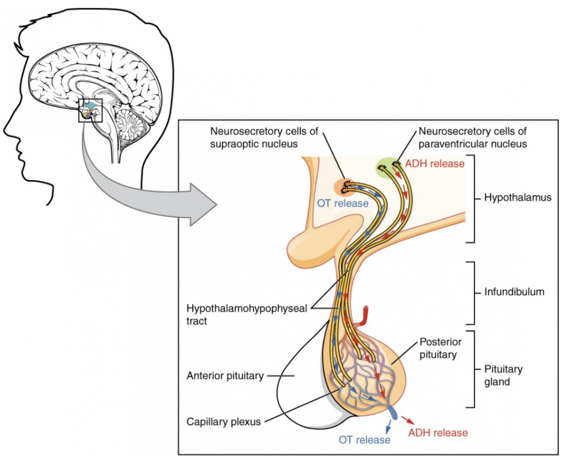

Figure 3.4: Internal Structures of Brain.

3.**The Pituitary Gland:** The pituitary gland is known as the “master gland” of hormones and it looks a pea-sized gland. It consists of three lobes named anterior,

intermediate, and posterior It is responsible for so many processes, senses the body's needs then send those signals to those organs so that they can regulate their function. It helps the body to promote bone, muscle growth, respond to stress by secreting hormones.
4. **The Pineal Gland:** In the back of the third ventricle the pineal gland is placed. It is responsible for producing melanin that helps modulate the internal clock of the body, sleep patterns, neurotraumatic production, maintenance of circadian rhythm. The Limbic system: In Latin limbus means "edge" it is responsible for activities held because of the hypothalamus and the cerebrum. The limbic system also has the meaning "circle of papez' . It has been believed as the main center of the limbic system to think about feeding, forgetting, fighting, family, fornicating. This system is separated into cortical and subcortical components.
5.**The Basal Ganglia:**The basal ganglia which are also known as basal nuclei are consists of a group of subcortical structures that can found in the white matter of the brain. It is a part of the extrapyramidal motor system that works with the pyramidal and limbic system. It sends messages to thalamus then the thalamus process and adjust the signals. It regulates movements of eyes, memory, motivation.

3.2 EEG signal

Electroencephalogram (EEG) is a process of identifying voltage alteration or oscillation on brain, which carries the graphical record of electrical activity by placing electrodes in different locations on scalp [19]. In this particular context the main prognosis is to pinpoint the brain signals which have abnormalities and can be identified as seizure. Our brain shapes how we see our environment, providing the most pertinent information; our brain captures objects based on that. Human comportment or behaviour works based in that stored information. Brain organized with a combination of one thousand millions of cells, where half of those are neurons and half of those expedites the deportment of neurons. These neurons are severely correspondent via synapses. Synapses work as entrance of inhibitory or excitatory activity. In terms of neurophysiology; neuronal event such as oscillation or response arouse by sensory invigoration is basically the relative contribution of excitatory and restraint synaptic inputs [22]. An adroit electrical incitement generated by any synaptic activity is considered as a postsynaptic potential. Eruption of a single neurone is difficult to delete without direct contact with it. An electrical field is generated wherever thousands of neurons coincide which is strong enough to spread through bones, tissues and skull. Eventually in brain surface this variation can be measured. For instance; considering a reverberation of earthquake, a single rupture might be small to notice however, a couple of persistent rhythm in the same location at the same time can create a noticeable impact even hundreds of kilometres away.

3.2.1 Brain Waves

The brain controls every emotion, behavior, and communicate with other neurons. Brain waves are the result of different kinds of synchronized electrical pulses and these are detected by placing a sensor on the scalp. These brain waves are divided

into six parts according to their bandwidths, functions, continuous spectrum of consciousness (Fig: 3.5). Brainwaves show us the refection of the different incidents, different locations. Moreover, brain waves change according to daily feelings such as- tried, slow, high, low, excited, angry, shock, hyper show different waves in a different frequency. EEG signals detect the frequencies of the delta, theta, alpha, beta waves only.
1.**Infra-low Waves:** Slow cortical potentials is another name of Infra-low brainwaves. These waves underlie higher brain functions and for measurement, it is very difficult to detect it accurately. These waves are less than 0.5 Hz. Moreover, plays a big role in brain timing and network function [17][21].
2. **Delta Waves:** The Delta wave frequency is .5 to 3 Hz and they are very slow loud brainwaves. We can find them in deepest meditations, dreamless sleep, as a source of empathy, healing, regeneration [17]. Delta waves are often found mostly in infants, young children as these waves are associated with relaxation, restoration, healing sleep. Prominently delta waves can be seen during brain injuries, while learning different problems, unable to think, ADHD. Delta waves are suppressed when we have poor sleep, revitalizing the brain. If, however, our immune system, the natural healing process, deep sleep is being regular that means there is sufficient production of delta waves [17][21].

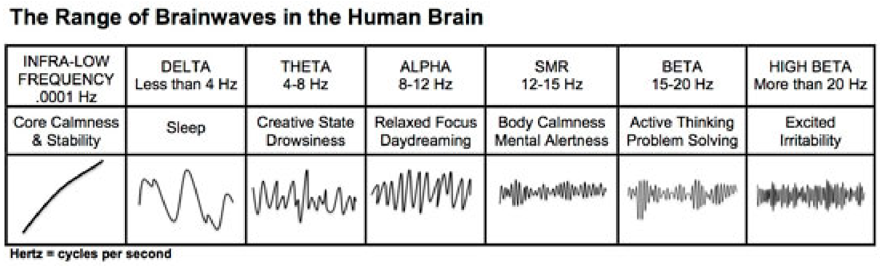

Figure 3.5: Brain Waves.

3. **Gamma Waves:** Gamma waves are produced for the fastest activities in the brain. It has a 38 -42 Hz frequency. It passes signals simultaneously and rapidly for this to give access to gamma mind has to be completely quiet. Besides, less production of gamma waves leads to hyperactivity disorder, depression, and learning disorder. Adequate production of gamma waves helps the brain with attention, focus, consciousness, senses such as- smell, sight, hearing, taste [17][21].
4. **Alpha Waves:** Alpha brainwaves work when there are quite flowing thoughts, meditate state. Alpha works in the present moment, which is also known as "the power of now". Alpha waves are responsible for a mental condition, calmness, alertness, learning, mindfulness. It helps the brain to go to a relaxed state [17][21].
5. **Beta Waves:** The awaken state which has a high frequency, low amplitude waves are beta waves. These waves work in awareness, helps to think logically, and have a stimulating effect. When we have the proper amount of beta wave, then we can focus or concentrate. "Beta wave has three ranges, low beta waves have a range between 12hz-15Hz, mid-range beta waves have a range between 15hz to 20Hz, High beta waves have a range between 18hz to 40 HZ [16]."

6. **Theta Waves:** Theta waves are placed at the time of deep meditation, daydreaming, and sleep. It is from 3 to 8 Hz [21]. If theta wave is increased more than usual then it results in hyperactivity, impulsivity, inattentiveness and if these are decreased than usual, it results in stress, poor emotional awareness, anxiety. Creativity, emotional feelings, relaxation, intuition all these are the results of theta waves [17][21].

3.2.2 The 10-20 System

The standardization for EEG electrode placement is approved by the International Federation of Clinical Neurophysiology (http://www.ifcn.info/) named the 10–20 electrode placement protocol (Fig: 3.6). 10-20 protocol standardized that there will be physical placements and designations of 21 electrodes on the scalp. [8]. All these 21 electrodes are placed on the scalp by using reference points on the skull. Reference points are nasion, preauricular points and inion. In this method, electrodes need to provide appropriate coverage to all the brain regions for this head is partitioned into proportional positions. Each electrode's name is consisting of a letter and a number. Here, the letter indicates the areas of the brain where the electrode is placed. It is divided into five parts these are F: frontal, C: central, T: temporal, P: posterior, and O: occipital [36]. On the other hand, the number indicates the cerebral hemisphere of the brain. Numbers are organized in a way that even numbers indicate in the right hemisphere and odd numbers indicate the left side of the skull. In 1985 a system was proposed, to extend the numbers of electrodes from 21 to 74 [36]. (Chatrian et al.,1988; American Electroencephalographic Society, 1994; Nuweret al., 1998; Klem et al., 1999). However, 10-20 system is mainly considered for clinical purpose, and whereas10-10 is considered for research purpose [36][9].

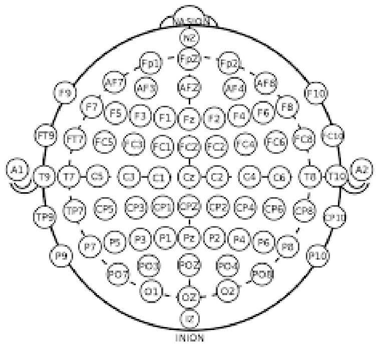

Figure 3.6: International 10-20 System.

Full land marks of skull include nasion, inion, left pre-auricular point and right pre-auricular point. Nasion means point between the forehead and head and Inion means bumps at the back of skull.Z electrodes are made between these points at the intervals of 10percentage, 20percentage, 20percentage, 20percentage, 2percentage and 10percentage along the midline of the skull. At the intervals of 10percentage, 20percentage, 20percentage, 20percentage, 20percentage and 10percentage, electrodes are measured and placed top of the head named T3, C3, Cz, C4, and T4. T3 and T4 are measured at Skull circumference just above the ears. At intervals of 5percentage, 10percentage, 10percentage, 10percentage, 10percentage, and 5percentage, Fp2, F8, T4, T6, and O2 electrodes are placed. However, Measurement methods for electrode placement always differ for the F3, F4, P3, and P4 points. Fp1-F3-C3-P3-O1 and Fp2-F4-C4-P4-O2 montages are for front-to-back measurement of head. Also, from the front and back points they can be 25% "up" (Fp1, Fp2, O1, and O2). F7-F3-Fz-F4-F8 and T5-P3-Pz-P4-T6 montages are used for the measurement of side-to-side and from the side points they can be 25% "up" (F7, F8, T5, and T6). These measurement methods vary because of different nominal electrode placements [9].

3.2.3 Artifacts

EEG record signals as artifacts are signals. Artifacts don't generate they just record. There is some artifact may imitate accurate epileptiform abnormalities or seizures. For distinguishing artifact from brain waves, it is important to have logical awareness in field of distribution for true EEG abnormality [26]. There various causes of artifacts such as causes of electrical artifacts on ECGs are manifold. Moreover, line current causes both external and internal artifacts . Line current has a frequency of 50 Hz or 60 Hz. It is applied for several reasons such as- tremors, muscle shivering, hiccups or, as in the present case, different medical devices [22].

3.3 Epileptic Seizure

Epilepsy is basically a chronic disorder which causes unproven, repeated seizures. A sudden rush of electrical activity in the brain is known as a seizure. This disorder affected 65 million people around the world which describes that it is a fairly common disease. It is a serious brain disorder. A seizure is a temporary abnormality occurs in the brain, which produces irregular physical symptoms such as- unresponsiveness, staring blankly, tingling and twitching of limbs, biting tongue, loss of consciousness[31]. At least 1 out of 3 people faces this chronic disease regardless of taking treatment through various anti-epileptic drugs. Moreover, these intractable seizures can give rise to serious health related threads which may cause both social isolation and economic hardship to any individual. 500 genes of our body can relate to epilepsy to some extent. If one parent is suffering from such kind of disease the risk of having epilepsy is 2 to 5 percent. Most of the people over 35, the main reason of epilepsy is stroke [33]. However, sudden death because of epilepsy happen to 1 percent of the population. Electroencephalographic (EEG) analyses and improved the reasons behind, causing this disorder.

3.3.1 Reasons of Epilepsy

Every year, there are 180,000 new cases of epilepsy and 30percentage of them are children[21]. This disorder most often affects children and elderly adults. However, there are no valid reasons for this disorder, some may have a genetic cause behind

it. Epilepsy may be caused because of one or more genes or some other way the genes work in the brain. Besides, if there is some structural change in an area of the brain of a child, then that can give rise to epilepsy[13]. The epileptic disorder varies from person to person. According to the statistics, 3 out of 10 children who suffer from autism spectrum disorder may also have seizures. Although, epilepsy causes mainly infections of the brain. As epilepsy patients' reasons are quite different from each other, but here are some reasons that researchers have found common in most of the patients[26].
Serious brain injury Post brain injury scars on the brain High fever or severe health conditions Strokes that may lead to epilepsy after the age of 35 Lack of oxygen to the brain during the time of birth Alzheimer disease Brain tumors or blood clot Extreme maternal drug use Genetic disorder Progressive neurological Diseases Liver and kidney dis functions Glucose level of blood

3.3.2 Different kinds of Seizures

A sudden, uncontrolled electrical disturbance in the brain is known as a seizure. There are total of six types of seizures so far (Fig: 3.7).
I. **Absence Seizures:** Before it used to know as "petit mal seizures". During this seizure, patients tend to do movements such as- lip biting or blinking repetitively. Patient lose awareness during the seizure[32].
II. **Tonic Seizure:** These cause stiffness in muscle.
III.**Atonic Seizures:** During these seizure patients lose muscle control and can fall suddenly. [33]

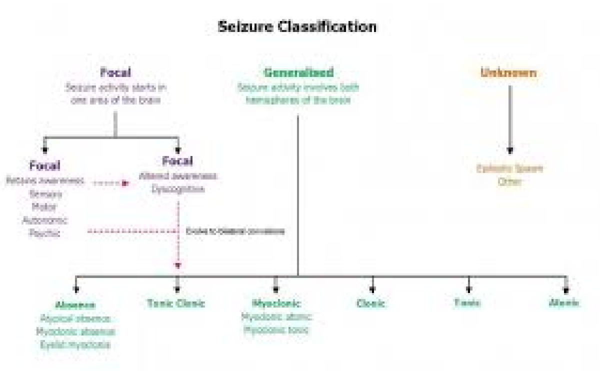

Figure 3.7: Seizure Classification.

IV. **Clonic Seizures:** Symptoms of these types of seizures are repetition, jerky muscle movement of the face, neck, arms.
V. **Myoclonic Seizures:** It causes unforced shaking of the legs and arms.
VI. **Tonic-clonic Seizures:** Before it used to know as "grand mal seizures". Shaking, certifying body, loss of bowel control, awareness, biting the tongue is the main symptoms of this seizure.

3.3.3 Classification of the epilepsy

The seizure has been classified based on the onset, a person's level of awareness, what kinds of movements happen during seizures [10]. According to the form International League Against Epilepsy, seizures have been classified into three groups[30].
I.**Generalized Onset Seizures:** Left brain and right brain both are affected at the same time during these seizures. This classification includes tonic-clonic, absence, atonic seizures.
II. **Focal Onset Seizures:** Focal means partial, it is used to have more accuracy about where the seizures begin. These seizures can cause in one area or within a group of cells. **Focal onset awareness seizures:** In this seizure patient are awake and aware of it. **Focal onset Impaired seizures:** In this seizure patient is most not aware while the seizure. **Unknown Onset Seizures:** The beginning of this seizure is not known and during this seizure, it's not observed by any other person.

3.3.4 Treatment for Epileptic Seizures

Epilepsy has multiple symptoms, according to these tests also differs from each other. In first step through medication with the help of different drugs. It is digested by stomach, then it flows through the blood stem to the brain. In this way, this medication transmits to brain and decrease the electivity. All these medications exist in the form of tablet, liquid or injectable forms. If these don't give any positive result, then doctors Diagnose the patient's condition by reviewing the symptoms and medical history. Such as- a neuroglial exam to test the patient's behavior, motor abilities, mental health or take a blood test to check the sign of epilepsy. For analyzing seizures in detail doctors use EEG, High- density EEG, CT scans, MRI, FMRI, PET, SPECT. After these tests, a doctor may combine these techniques to point out the starting point of seizures. Analysis techniques are APM, Curry analysis and MEI.

3.3.5 Beamforming

Beamforming is defined as an array of antennas can be guided to transmit a radio signal in a particular direction. Antenna arrays use beamforming in the direction of interest and transmit the signal or receive the signal stronger in the specific direction after that. Beamforming has the ability to adapt the radiation pattern from the array of antenna in any particular scenario [16] (Fig: 3.8). Beamformer does not try to explain the complete process, rather than they explain a signal from the brain position to the measure field where it is estimated. Beamforming analyzes based on the source of variance not from directly on its strength.

Beamformers methods are different such as they operate on raw data, it used to explain the signals that induce brain activity, it does not need any specification of

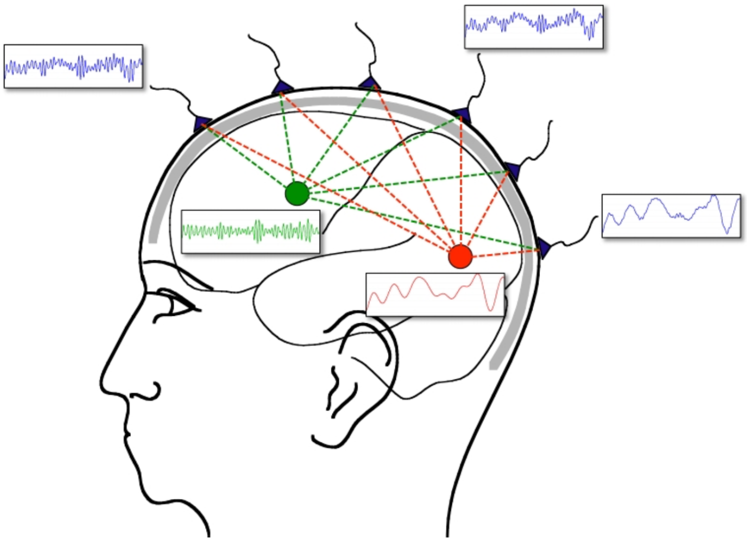

Figure 3.8: Beamforming on EEG.

the number of active sources. Beamformer try to reconnect to the contribution of one location from the measured field.
Time-varying potential differences caused by the human brain's electrical activity on the surface of the head. A measurement of these potential differences of electrodes on the scalp is done by electroencephalogram. Seizures are defined in the clinical interpretation of the analysis of the amplitudes of potentials usually reported by scalp electrodes. However, this analysis is not always adequate because the electrical activity may be obscured by noise. Noise or interference occurs due to the presence of an epileptic seizure [5]. More detailed anatomical data on irregular active regions, however, is obtained by implanting electrodes deep into various positions that are corrupted by a few artifacts compared to the scalp EEG. However, the number of implanted electrodes must be reduced because of the invasiveness of the operation and, thus, the spatial sampling of the field electrode is always inadequate. The problem is how to localize sources. A solution to this problem is use intracerebral electrodes with the Beamforming method. In the past, however, with encouraging results, the application of Beamforming techniques applied on the scalp. The EEG has been studied for solving problems with intracerebral electrodes due to their invasiveness. The use of EEG beamforming techniques was for spatial filtering. It was originally developed for radar signal processing applications such as- it allows the contribution of a single brain position to measure the range then it calculates the range and the interference and noise. After that it is separated from the desired signal to obtain accurate information when a seizure occurs [7]. Beamformers are designed to calculate a linear combination of time sequences. It was measured by different sensors and these sensors were used for electrodes detecting electrical activity in the scalp [37]. The goal is to maintain the signal components emanating from a desired direction or position, while removing interference from other locations at the same time. The behavior of a beamformer determines the choice of coefficients for linearly integrating the input signals. The signals recorded by scalp electrodes are simulated and analyzed in this work. In order to determine the output of each one in the estimation of the signal waveform, different beamforming algorithms are investigated. Following a better algorithm together with a DOA estimation method

could allow a map of neural activity to be obtained where the epileptic origins are confirmed. Basically, a Beamformer is built to allow the neuronal signal to pass through a certain position and orientation of the source, known as a pass-band [24]. In other positions or orientations, known as stop-band, it can block noise or any unwanted signal. In beamformers, there is a significant limitation that they cannot properly reconstruct two spatially separate sources but temporally associated sources; for example, when they are positioned next to each other spatially, then they cancel each other. When they are spatially distant from each other then they merge [18]. Signal beamforming in EEG or MEG falls into two groups. One is scalar beamformers, where a single output is reconstructed by the source time-course. Another is vector beamformers where the source time-course is reconstructed in 3 orthogonal directions. There is an orientation of the brain source for scalar beamformers that can be calculated in a method which is known as grid search. However, vector beamformers do not need any orientation from brain sources because they can reconstruct the time series of the source in 3 orthogonal time courses. There are two methods for implementation of vector beamformers. In the first method, the vector beamformer is a single beamformer and it have 3 orthogonal outputs [2]. In the second implementation, the vector beamformer is basically made of 3 scalar beamformers in the 3 orthogonal directions [24].

3.4 Fourier Transform

Flourier transform plays a really significant part in the study of mathematics, engineering, physical sciences. In our report, we have used Fast Fourier transform (FFT) algorithm that computes Discrete Wavelet Time Series [35]. Fourier transforms made revolutionary changes in the study of digital electronics, signal processing as it carries some major role in the field of data processing. Fourier transforms function of time, f (x) into function of frequency, F(s). There are very close similarities between Fourier series and Fourier transform [34]. Here, x and s are dimensioned where x measures the time t, and so that s, can correspond to inverse time or frequency. The equation of flourier transform is (i) and it is usually known as forward transform (ii) F(s) f (x). The third equation (iii) in the figure, describes complex exponential, which describes that a complex number has both real and imaginary sinusoids parts. Also, ei+1=0 relates five of the foremost important numbers in mathematics [34]. It's easier to govern Complex exponentials than trigonometric functions, and that they provide a succinct notation for addressing sinusoids of arbitrary phase, that from the idea of the Fourier transform.

$F(s) \equiv \int_{-\infty}^{\infty} f(x)\, e^{-2\pi isx}\, dx \ldots\ldots$ [..(1) Fourier Transform]

$f(x) \equiv \int_{-\infty}^{\infty} F(s)\, e^{2\pi isx}\, ds \ldots\ldots\ldots$ [..(2)Forward Fourier Transform]

$e^{i\emptyset} = \cos\emptyset + i\sin\emptyset \ldots\ldots\ldots\ldots$ [..(3)Euler's Formula]

3.5 Machine Learning

Machine learning is a branch of artificial intelligence (AI). This method gives the ability to automobiles to learn and improve then develop the computer programs from the experience without being programmed [3]. It can access data, learn from data to understand patterns and make decision from it. Machine can adapt new information and then process it. There are various kind of machine learning algorithm and these algorithms have the ability to complex calculations from big data repeatedly. These processes are iterative, scalable, advanced, fast. In the field of data mining, big data, computer operating system, cloud computing and so machine learning algorithms are used.

3.5.1 Support Vector Machine

Support vector machine is a machine learning algorithm which is a discriminative classifier and finds hyperplane in N-dimensional space which classify data points distinctly [36][31].

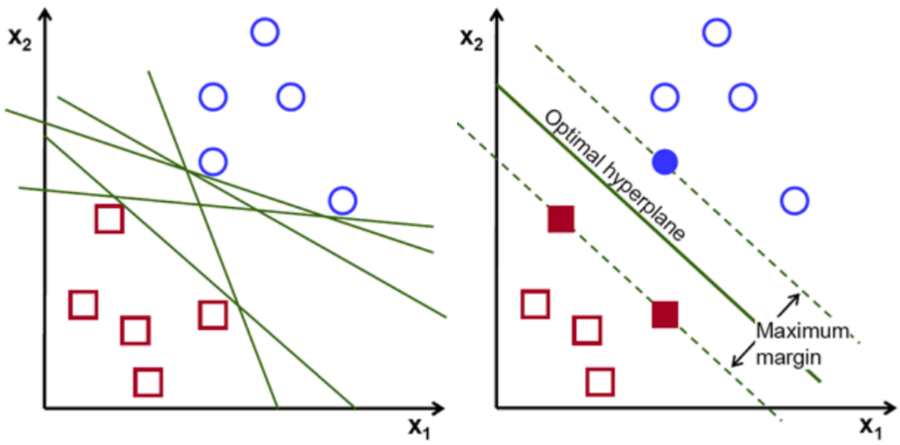

Figure 3.9: Support Vector Machine.

There are various kinds of hyperplanes to separate the two classes from a data point [31] [3.9]. We need to choose a plane with maximum margin, maximum distance between the data paths of both classes [36][31].

3.5.2 Hyperplanes and Support Vectors

Hyperplanes basically are decision boundaries. It helps to categorize data points [31] and data points which are falling on the other side of the hyperplane can be allocated into various groups. As, the hyperplane dimension has a multiple number of functions. If the input features are 2, the hyperplane is just a line (Fig: 3.10).

If the input features are 3, the hyperplane will become a dimensional plane. It becomes difficult to picture when the number of features is greater than that. [31].

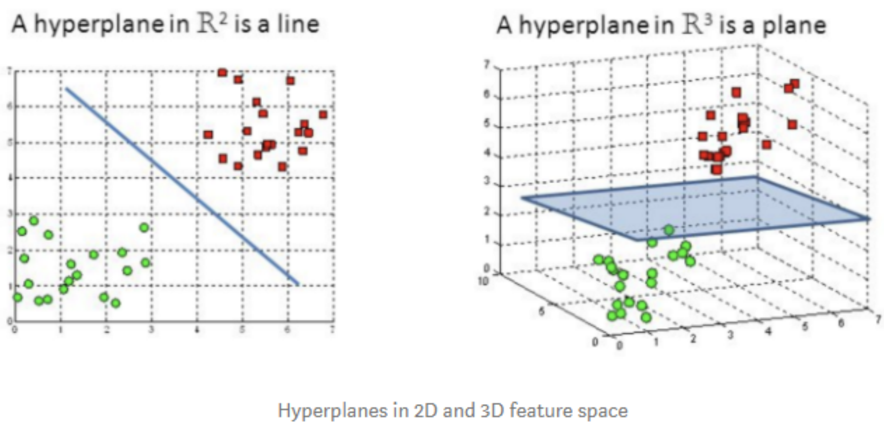

Figure 3.10: Hyperplanes in 2D and 3D features.

If the support vectors are data points closer to the hyperplane, the position and orientation of the hyperplane will be affected [10]. By using these support vectors, we can increase the range of the classifier. The location of the hyperplane will change if we remove the support vectors (Fig: 3.11). As these points allow us to construct our SVM.

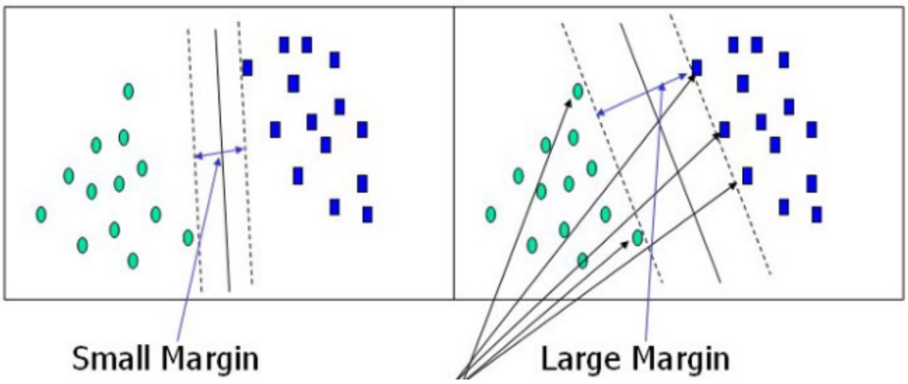

Figure 3.11: Margin classifier.

3.5.3 Large Margin Intuition

In the study of logistic regression, the linear function output is carried out to squash the value within the range of 0 to 1 by applying the sigmoid function. The squashed value assigned as label 1 only If it is greater than the threshold value (0.5). Otherwise, we assign the squashed value as label 0 [33]. We take the linear function output as in the range between 1 to -1 in SVM. So, we will mark it with one class

If the desired result is greater than 1, and if it is -1 then we will mark it as another class [19]. We're receiving this reinforcement values acts as margin if the range is ([-1,1]). [38].

3.6 Dataset

The data we have used in our research is collected from the children's hospital Boston, which consisting of different EEG recordings that are intractable with seizures. It is both created and named as Physio-Net by The Massachusetts Institute of Technology (MIT). Data grouped into 23 cases and it collected from 22 subjects. In these recordings, groups there are 5 males who are aged between 3–22; and 17 females who are aged between 1. 5–19. Here in the database only the case no chb21 was recorded 1.5 years after case no chb01, from the same female patient. In the database SUBJECT-INFO named file contains each patient's the gender and age. Each case is named such as - chb01, chb02, etc. These cases are contained from a single subject and patients age are between of 9 to 42 continuous .edf files. However, there were some gaps created because of some hardware limitations between consecutively numbered .edf files. These gaps created when the signals were not recorded. However, most cases have gaps which are not more than 10 seconds. There are some cases which may have much longer gaps. The .Edge files contain exactly one hour of EEG signals in most of the cases. In the database, chb10 which case no 10 is two hours long. There are four cases named chb04, chb06, chb07, chb09, and chb23 are four hours long. There are some, files in which seizures are recorded are shorter and these incidents or recordings happed occasionally. In the database, 256 samples are sampled into 16-bit resolution signals. The dataset contains 23 EEG signals in total. The International 10-20 system was used for these recordings which is a technique of EEG electrode positions and nomenclature. In the database there are 664 .edf files in RECORDS file and RECORDSWITH-SEIZURES file contains lists the 129 who suffered from one or more seizures . After analyzing all this information, we used various methodologies to detect the epileptic seizure. According to our result we SVM is most suitable to our research and dataset.

Chapter 4

Proposed system

4.1 Thesis Workflow

First of all, we have used the CHB-MIT scalp EEG dataset for our research. In this dataset, there are some non-linear and non-stationary signals. Non-stationary signals don't have static means, variances, covariances as these changes over time. These signals can be in trends, cycles, random walks. These need to be turned into stationary signals as it has static means, variances, covariances as these don't change over time. A non-linear signal is generated through the system that exploits superposition and scaling properties. To make the signal linear and stationary, it needs to be preprocessed. Preprocessing implicates data refining, synchronizing, artifact canceling, source reconstruction etc. With the help of python library, we have done this. Here, we cut the signals where seizure attacked according to the time series, and then in the next step, we merged signals of all seizure of every patient. After that, we have added a low and high pass filter. Band filters basically pass signals that have low frequency and high frequency within a particular brand frequency by removing extra noise or changing the input signal. After brand extraction, we used Fourier transform to convert time to frequency domain then calculated energy from it. After that we used support vector classifier to trained the data to calculate accuracy (Fig: 4.1).

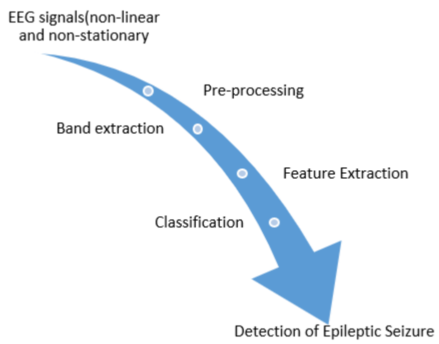

Figure 4.1: The workflow diagram of Detection of Epileptic seizure.

4.2 Pre-processing (Beamforming):

Beamforming is an array signal processing technique where by the use of signal and multiple sensor arrays; noises and intervention from others directions are repressed and amplify signals from one or multiple directions [26]. Microphones are used as sensor as audio beam forming. According to the last few decades, different areas such as: medical image identification, radar, sonar, speech processing where beam formers play a vital role. Source detection is one of the methods of this unique implementation. In this method, the path of a signal source's arrival is determined on the premise of the energy withdrawn from each direction.[23]. Moreover, noise and interference reduce by signal improvement and also restore the signals from direction of interest. Spatial filtering or temporal filtering is one of the methods to suppress interference and noise. In spatial filtering, when the frequency of the desired signal generated from a particular location lies with disturbed signals or noisy signals in same band of frequencies; it's very tough to extract desired signals from the mixture of interfering and applicable signals. However, desired signals and interfering generate from different location, the noisy signals can emit through this filtering process. The signals are processed in temporal cortex throughout the temporal refining phase, while signals are evaluated by dynamically located sensors during spatial filtering. This is the only distinction between these two filtering processes. Eventually, to obtain the anticipated filtered output, these spatially extracted signals will be combined linearly (Fig: 4.2).

The beam-former value, *y(t)* to a directionally incoming signal is expressed as[6]:

$$y\,(t) = w^H.x(t).......(4) \tag{4.1}$$

Where,
N = received input signals from the antenna array.
W = a complex weight vector $[w_1,\, w_1 \ldots\ldots\ w_N]$
$x(t)$ = function of the received signals $[x_1(t),\, x_2(t) \ldots\ldots\ x_N(t)]$

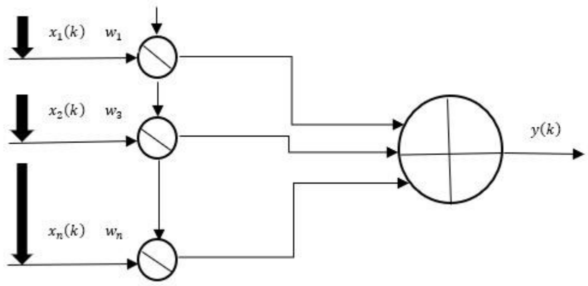

Figure 4.2: Beamforming workflow.

The main lobe is shielded in case of artifacts, value loss or array apprehension by the Linear constraints used during beamforming. The vital problem of this investigation is the array gain. It is straightforward to identify the correlation between the array gain of LCMV and LCMP. The weight w, of the LCMP is expressed as:

$w_{lcmp}^H = g^H \ [\ C^H \ S_x^{-1} \ C\ ]^{-1} \ C^H \ S_x^{-1} \ \ldots.. \ (5)$

Where,
g is the gain vector,
C is the subspace of constraints,
S is the spectral matrix.
The output power is:
$P_s = \ \sigma_s^2 \mid w^H \ v_s \mid^2 \ldots \ldots\ldots\ldots \ldots\ldots\ldots(6)$
Where,
v_s is the steering vector; The output noise power is:

$$P_n = \ \sigma_n^2 \mid w^H \ \rho_n \ w \mid^2 \ldots\ldots\ldots\ldots(7) \tag{4.2}$$

Where,
σ^2 is the variance,
ρ_n is the spatially filtered matrix and includes both the noise and interference.
Hence the gain is

$$G_0 = \frac{\mid w^H \ V_s \mid^2}{\mid w^H \ \rho_n \ w \mid} \ldots\ldots(8) \tag{4.3}$$

If the distortion restriction is used, the previous equation's numerator becomes 1.

$G_0 = \ \mid w^H \ \rho_n \ w \mid^{-1} \ \ldots..(9)$

The output signal to noise (SNR) ratio is,

$SNR_{output} = \ \frac{\sigma_s^2}{\sigma_n^2} \ \ldots\ldots\ldots.(10)$

The array gain for the LCMV beam former,

$G_{lcmv} = \ \frac{1}{g^H \ [\ C^H \ \rho_n^{-1} \ C\ ]^{-1} \ g} \ldots..(11)$

Both array gain for LCMV and LCMP are equal when the distortion-less constraint is processed and the signal is perfectly matched [6]. So,

$$G_{lcmp} = \ \frac{1}{g^H \ [\ C^H \ \rho_n^{-1} \ C\ ]^{-1} \ g} \ldots\ldots(12) \tag{4.4}$$

4.2.1 Supervision of EEG signal concentrations

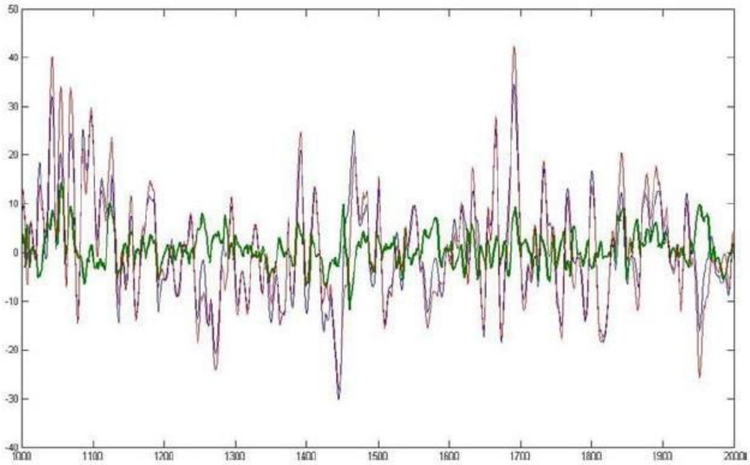

Figure 4.3: EEG signal concentrations

The signal is refined by LCMV of the first electrode. There is a green line on (Fig: 4.3) which indicates the distinction between the actual signal and the refined one. It states that an approximate classification of epilepsy can be obtained using beamforming as it allows us to take on the case. " The amplitude of 50v is known as a psychomotor, while 100v is a grand mal epilepsy."

4.3 Feature Extraction

Frequency Domain Analysis	**Time-Frequency Domain Analysis**
Estimation of spectral power where signals are stationary. (A signal is said to be stationary if its frequency & spectral content are not changing with respect of time).	Localisation of power in time & frequency.
Fast Fourier Transform.	
PSD (Power Spectrum Density)	

4.3.1 Fourier Transform

Fourier transform is a tool that breaks a waveform into an alternative representation characterised by since and cosines. Fourier transformation changes the signals from time domain to the frequency domain and back again if needed.

F(w) = $\int_{-\infty}^{\infty} f\,(t)\, e^{jwt} dt\ldots\ldots\ldots$ (13)

1. **Purpose of Fourier Transform:** The sum of sinusoidal functions, such as *cos(wt)* or *sin(wt)*, can generate complex wave masses between ± 1 [12]. 'w' is the value that represents each part of the wave. These waves (Fig. 4.4 and Fig. 4.5) can be represented as spikes in the frequency domain.

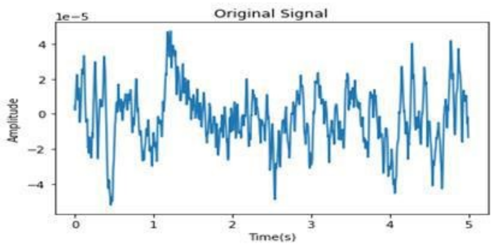

Figure 4.4: Original Signal.

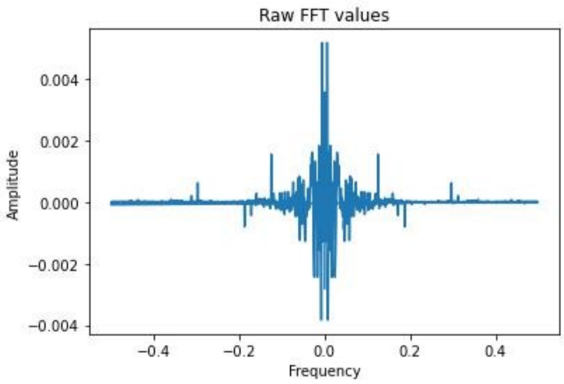

Figure 4.5: Signal after FFT.

The figure shown above (Fig: 4.4) (Fig: 4.5) actually this is what the Fourier transform does. After progressing to the transition, it seems to be much easier to grasp which fluctuations are in our waveform. The best manner to relate to this is to replace in the Euler's equation the transformation above and make the whole mechanism understandable.

$e^{2\pi i\theta}= \cos(2\pi\theta) + i\sin(2\pi\theta) \ldots\ldots\ldots(14)$

This clearly changes or redirect our function in frequency space into:

F $(k) = \int_{-\infty}^{\infty} f(t)(\cos(-2\pi tk) + isin(-2\pi tk))dt\ldots\ldots(15)$

and function in real space into:

F $(t) = \int_{-\infty}^{\infty} f(k)(\cos(2\pi tk) \ + isin(2\pi tk))dk \ldots (16)$

Sinusoidal formulas are explained clearly here, implying that a spot in interplanetary world is determined by the integral of the corresponding frequency function multiplied by a sinusoidal rotation over all space.

Discrete Fourier Transform

$X(k) = \sum_{n=0}^{N-1} X(n)(e)^{-i2\pi nk/N} \ldots (17)$

X(k) = DFT of x(n) where x(n) is the sequence & n = sum from n=0 to N-1 (Number of sample - 1).
N = Total number of samples
K = Frequency at that moment
n = Present sample number
In addition, consider 'n' as the present test number or to be a set of O→N-1 integers and make them a column. 'K' is set to be the exact thing, but only in a row. We have obtained a matrix by multiplying them simultaneously, but not purely a matrix. This is the core component of the whole transition. However, the matrix multiplication is slow and because of the reason the whole DWT process become slow. So, this is the part where we shifted from DWT to FFT with the help of recursion.
FFT which creates a revolutionary change on the terrain of computer science by making hard tasks into simpler form. This algorithm appears mainly as a general recursive application, and this is basically what it is in principle. But it is not an ordinary conversion. It makes a simple swing back and forth between hyperspace and frequency space. Besides, it is the root of many requests for physics and engineering. "FFT is the center of these scientific disciplines, starting from super-resolution imaging to superfluid vortex location." The Cooley - Tukey algorithm is the most widely used algorithms for FFT.[14].
The Cooley-Tukey algorithm is defined as:

$X(k) = \sum_{n=0}^{\left(\frac{N}{2}\right)-1} X(2n)(e)^{(-2\pi i(2n)k)/(N/2)} + \sum_{n=0}^{\left(\frac{N}{2}\right)-1} X(2n)(e)^{(-2\pi i(2n)k)/(N/2)} \ldots (18)$

$X(k) = E(k) + e^{-\frac{2\pi ik}{N}} O(k) \ldots\ldots (19)$

4.3.2 Power Spectrum Density

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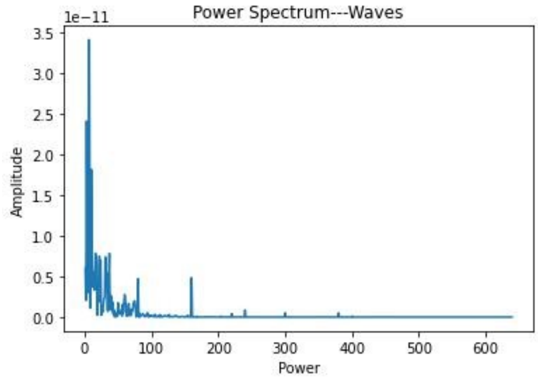
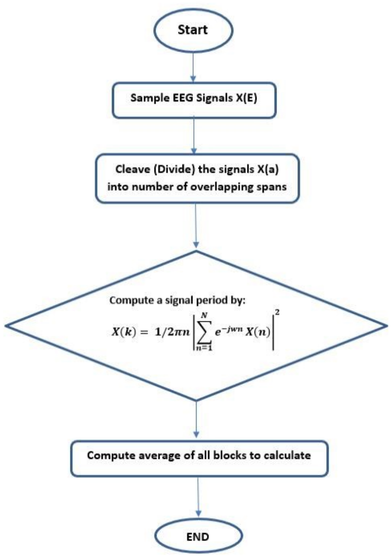


Figure 4.6: Power Spectrum Waves.

PSD choose the strength of the variations as a function of frequency.The unit of PSD is energy per frequency i.e. E/fq. The power spectrum density (PSD) is the most vastly used impertinent decomposition of signals because of the efficiency and elucidation. PSD operates based on those signals which are considered as stationary. Identify the correlate neural activity in BCI development (Unde and Shriram, 2014). PSD is the most widely used feature. PSD apprises the energy distribution of EEG (input) signals over a distinct frequency range [11] (Fig: 4.6). This particular feature apprehends overall frequency context of certain neural oscillation and expressed as Fourier transformation [15]. The PSD of input EEG signals can be computed by this following flowchart (Fig: 4.7):



[35]

Figure 4.7: Flowchart of PSD Calculation.

According to this periodogram method of PSD, the input EEG signals split up into segments constantly known as windows. A very basic implementation of PSD: First we take the length of the sequence as a sample number N= length (x) and then the FFT of the signal XDFT = FFT(x); then for obtaining energy by using PSD we use:

$X(k) = 1/2\pi n \left| \int_{n=1}^{N} e^{-jwn} X(n) \right|^2 \ldots\ldots (20)$

4.4 Classification

In our proposed method, seizure and non-seizure EEG signals are considered as classes where we implement SVM classifier to classify those by using RBF kernels. In this experiment, 75% training sets are established in the learning set and remaining 25% of training sets use to identify whether the model operates accordingly or not. After testing, the performance is judged by calculating accuracy, sensitivity and specificity. On our next chapter, the assessment result with accuracy level are explained.

RBF kernel is defined as [10]: $k(x, x_i) = e^{\frac{-|x-x_i|^2}{2\sigma^2}} \ldots\ldots (21)$

where σ controls the width of the RBF function.

$k(x, x_i) = \prod_{k=1}^{d} \cos[w_0 \frac{x_k - x_i^k}{a}] \, e^{\frac{-\left|x_i - x_i^k\right|}{2a^2}} \ldots\ldots (22)$

Where,
d = dimension
a = flexible coefficient
x_i^k = k-th component of i-th training data.

Chapter 5

Experimented Result and Discussion

We have been proposed one feature extraction technique base on Fast Fourier transform, as our main goal is to classify seizure and non-seizure EEG signals therefore, we use SVM classifier to classify them and finally detect if it is seizure or not. There are 40 patient dataset that are cropped into 3600s, where 1800s before the seizure and 1800s in interictal phase. Sometime EEG signal have noises and artifacts due to motion. Beamforming help to reduce interfering signals and noise. In this experiment we use beamforming to remove line noise. Then using our proposed technique FFT to convert time domain to frequency domain and calculate the energy. The energy is defined as

$E_x^{frequency} = \sum_{f=0}^{fs/2} |X[f]|^2$ ....(23)

After training and testing data using SVM we get result in binary. Sensitivity, specificity and accuracy are statistical measures the performance of a binary classification result. These criteria are used to verify the classification result and determine seizure and non-seizure signal. The sensitivity, specificity, and accuracy are defined as

Sensitivity $= \frac{TP}{TP+EN}$*100 ....(24)

Specificity $= \frac{TN}{TN+FP}$*100 ....(25)

Accuracy $= \frac{TP+TN}{TP+TN+FP+FN} * 100$ ....(26)

Here, respectively, TP and TN show the entire number of true positive events and true negative events observed. The FP signifies the false positive rate and the FN, false negative rate. We have applied various methods to compare and validate our overall result (Table 1 and Fig 5.1).

Table 1: Comparisons of Sensitivity, Specificity and Accuracy of different methods with proposed method

			Existing Method [19]		***Proposed Method***
Kernel	**Brain Location**	**Criteria**	**EMD**	**DCT**	**Beamforming Aided FFT**
RBF	Frontal	SEN	29.41	8.70	60.25
		SPE	80.51	79.73	98.20
		ACC	77.90 3	78.10 3	88.95
	Temporal	SEN	66.67	4.00	62.69
		SPE	80.28	98.63	94.88
		ACC	80.20 1	79.70 1	90.65
	Avg	SEN	48.04	6.35	61.47
		SPE	80.40	89.18	96.32
		ACC	79.05	78.90	89.8
Linear	Frontal	SEN	28.95	27.28	62.90
		SPE	80.35	80.61	86.39
		ACC	78.40	76.6	84.20
	Temporal	SEN	84.21	6.00	60.46
		SPE	85.28	96.13	90.75
		ACC	85.20	78.10	87.67
	Avg	SEN	56.58	16.64	61.68
		SPE	82.82	88.37	88.57
		ACC	81.80	77.35	85.94

We Conduct the experiment by comparing the specificity, sensitivity and accuracy percentages between existing methods [neuro] for instance EMD, DCT (Discrete Cosine Transform) and our proposed method beamforming-aided FFT with the classifier RBF Kernel and basic linear classification method of SVM. In terms of sensitivity, specificity and accuracy; existing methods (neuro) generates the average sensitivity of 27.2%, specificity of 84.8% and accuracy of 78.97% whereas beamforming-aided FFT generates the specificity of 96.32%, sensitivity of 61.47% and accuracy of 89.8% (on average) with RBF Kernel classifier. However, for linear classification, SVM generates average sensitivity of 36.61%, specificity of 83.59%, accuracy of 79.5% for existing method (neuro) where beamforming aided FFT generates average specificity, sensitivity and accuracy of 88.57%, 61.68% and 85.94% respectively. For seizure detection, sensitivity is more important than specificity as the cost of failure detecting the ictal is heavier than non-seizure detection (neuro). So, our proposed method outperformed the existing methods in terms of these criteria.

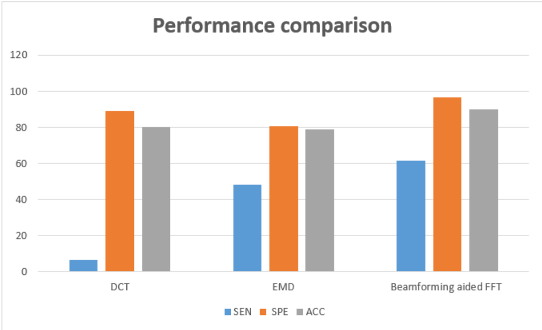


Figure 5.1: Performance comparison between existing models and proposed system.

For the FFT based energy, we get 61.4% sensitivity 94.5% specificity, and86.7% accuracy. Whereas in EMD based energy, we get 48.0% sensitivity 80.4% specificity, and 79.8 % accuracy. On the other hand, DCT based energy calculation there are 6.35% sensitivity 89.18% specificity and 78.90% accuracy.

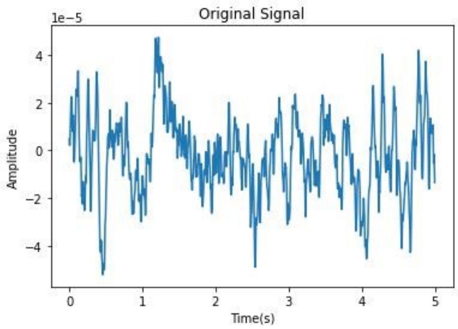


Figure 5.2: Original EEG signal with respect to time domain.

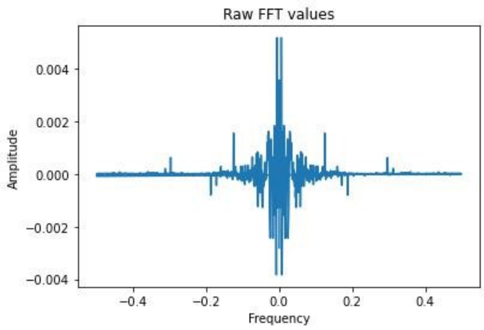


Figure 5.3: Signal after applying Fast Fourier Transformation.

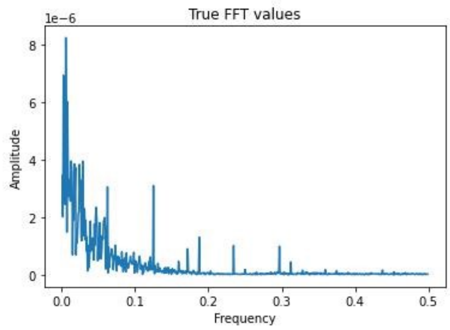


Figure 5.4: True FFT values of the signals.

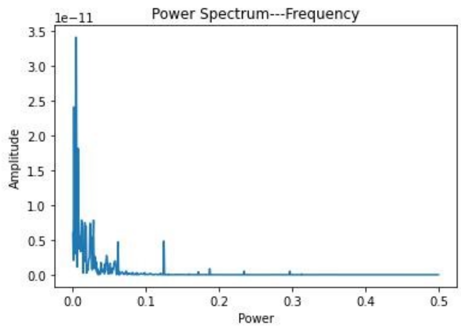


Figure 5.5: Power values calculated using FFT.

The performance of the SVM is measured by ROC plot (Fig: 5.6). A receiver operating characteristic curve, or ROC curve, is a graphical plot that shows a binary classifier system's diagnostic capacity as its threshold of discrimination is varied. The ROC plot includes sensitivity against the specificity. In other words, it puts the true positive rate (TPR) against the false positive rate (FPR) at random threshold settings. The plot also shows probability of detection in machine learning.

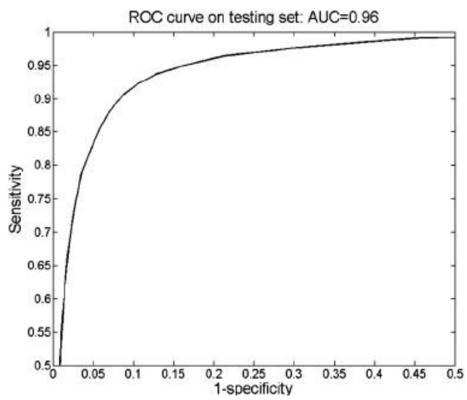


Figure 5.6: ROC on testing set.

The successful methods of detection of epileptic seizures are proposed in this chapter, which exploits EEG signals for time-frequency. The approach proposed outperforms the existing methods with respect to sensitivity, precision and accuracy consideration.

Chapter 6

Conclusion

Detecting ictal and non-ictal seizures is a challenging task due to instantaneous occurrence between these signals. This work presents an efficient method for noise reduction and feature extraction of EEG signal for CHB MIT dataset. Our proposed system uses beamformers to reducing the noise before band extraction method and that give us decent result. Moreover, signals are inconsistent due to different brain locations, patients, types of seizures and hospital environment of the patient. As we did not get our expected result from classifying data through support vector machine (SVM). For improving the accuracy, we can use beamformer to the minimum-variance and minimum-norm families of spatial filters in future. For improving accurate in feature extraction Empirical Mode Decomposition (EMV) using application of Hilbert-Huang Transform (HHT) can be used to detect time-frequency domain. Comparing EMV with SVM can give us knowledge about which feature extraction methods works best with our dataset. As our propose system give 92.46percentage accuracy comparison can be done with various existing methods using beamformers or any frequency domain method. In future we can analyze the data with the help of real time analysis than EEG signal can detect improve accuracy of signal with help of 10-20 electrode placement. In our proposed methods, one kernel used to classify the time-frequency feature if we can use more kernels as classifier that we can detect these signals more accurately.

October 17, 2020

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Appendix A.

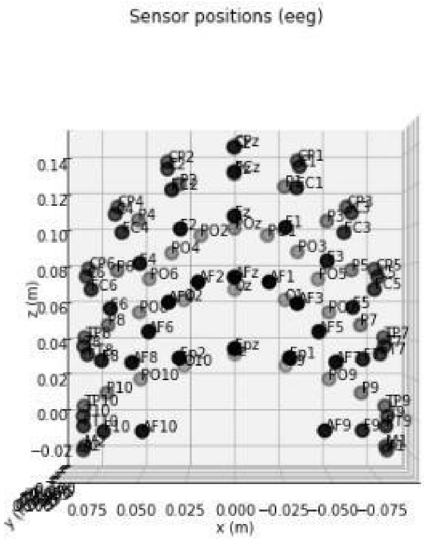

Figure 6.1: 3D Montage Plot.

```
print(raw.info)
```

```
<Info | 7 non-empty values
 bads: []
 ch_names: FP1-F7, F7-T7, T7-P7, P7-O1, FP1-F3, F3-C3, C3-P3, P3-O1, ...
 chs: 23 EEG
 custom_ref_applied: False
 highpass: 0.0 Hz
 lowpass: 128.0 Hz
 meas_date: 1976-11-06 13:43:04 UTC
 nchan: 23
 projs: []
 sfreq: 256.0 Hz
>
```

Figure 6.2: Raw Information.

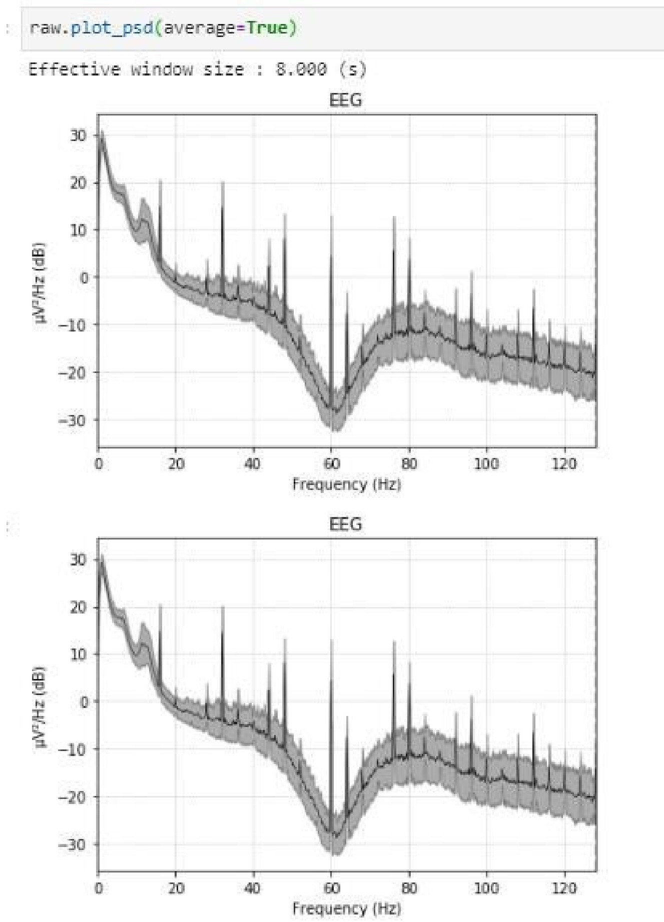

Figure 6.3: PSD Plotting.

```
     index                     C1F1                     C2F1  \
371    372  [3.3610861394744175e-12]  [1.7550092357784665e-12]
315    316  [4.8244706385732025e-12]  [2.0320032023328727e-12]
146    147  [1.4547998467412387e-12]   [1.116195634510653e-12]
499    500    [1.40182270585201e-12]   [7.330751936979043e-13]
115    116  [1.2947830896548845e-12]  [1.1326616335773844e-12]

                         C3F1                      C4F1  \
371  [3.4859033247311633e-12]  [1.4076127711658845e-12]
315   [4.080517129051927e-12]   [3.446070955228464e-12]
146   [7.990618118823247e-13]   [9.627136193070259e-13]
499   [7.359137606390354e-13]   [5.729175518552807e-13]
115  [1.4423293095454268e-12]  [1.1912488203696993e-12]

                         C5F1                      C6F1  \
371   [2.977894883572539e-12]  [4.0735623418773594e-12]
315   [7.449937831805964e-12]   [4.058363932906057e-12]
146   [2.949165201912454e-12]  [2.3649224537502925e-12]
499  [2.4958483722219983e-12]   [2.880364243001606e-12]
115  [3.0079920418748253e-12]  [3.5799584352697905e-12]

                         C7F1                      C8F1  \
371  [1.6719625172006123e-12]    [2.16583440301389e-12]
315   [4.080330773554217e-12]   [5.532407593762905e-12]
146   [9.853800384935915e-13]  [1.3317168857461898e-12]
499   [8.310437696884583e-13]  [1.3203380190559676e-12]
115  [1.0698124965524232e-12]  [1.6723795808044893e-12]

                         C9F1  ...                     C15F1  \
371   [3.792208402098512e-12]  ...  [3.9850639795694736e-12]
315   [3.954821463978973e-12]  ...    [4.381347454607527e-12]
146  [1.4104468655750707e-12]  ...  [1.0187268639649591e-12]
499   [1.507164996175985e-12]  ...    [6.484716612921741e-13]
115   [3.726349996496516e-12]  ...  [1.2188558965115742e-12]

                        C16F1                     C17F1  \
371   [4.370178051496732e-12]    [7.59580014341919e-12]
315  [6.2248069729754705e-12]   [8.509148564093619e-12]
146  [1.2909818102125793e-12]  [2.9225841991409756e-12]
499  [1.0902907294848687e-12]   [2.939158657107375e-12]
115   [1.464380010167556e-12]    [4.51828147432543e-12]

                        C18F1                     C19F1  \
371    [4.82487950253518e-12]  [3.4843431565043282e-12]
315   [1.122883933323494e-11]   [4.077599174668772e-12]
146     [2.9823998413742e-12]   [7.992798478146463e-13]
499  [2.3452038058265164e-12]   [7.341113302651765e-13]
115   [3.359958316002272e-12]  [1.4405742134679863e-12]

                        C20F1                     C21F1  \
371   [8.310896131408952e-13]  [3.7593669727369355e-12]
315  [1.3572472162215751e-12]   [2.573014084003095e-12]
146   [5.523658948567373e-13]  [1.2327490715769104e-12]
499   [4.715833955760696e-13]   [8.547876963627879e-13]
115   [4.860009750119639e-13]   [1.894575713257032e-12]

                        C22F1                     C23F1 class
371  [1.3442455658572873e-12]  [3.9850639795694736e-12]     1
315   [1.423321794200915e-12]   [4.381347454607527e-12]     0
146  [3.7410977978743546e-13]  [1.0187268639649591e-12]     0
499    [3.50662158354466e-13]   [6.484716612921741e-13]     1
115   [3.584752989514894e-13]  [1.2188558965115742e-12]     0
```

Figure 6.4: Feature Extraction values.

```
     index      C1F1      C1F2      C2F1      C2F2      C3F1      C3F2  \
53    54.0  1.093581  1.093581  1.016312  1.016312  6.440403  6.440403
657  658.0  4.112937  4.112937  7.425661  7.425661  1.649826  1.649826
564  565.0  4.317870  4.317870  4.285123  4.285123  5.840290  5.840290
274  275.0  4.285043  4.285043  2.646451  2.646451  7.573737  7.573737
350  351.0  6.288187  6.288187  4.358886  4.358886  4.352176  4.352176
..     ...       ...       ...       ...       ...       ...       ...
254  255.0  3.326796  3.326796  3.139089  3.139089  4.363461  4.363461
576  577.0  3.889814  3.889814  3.512047  3.512047  5.261544  5.261544
484  485.0  2.404527  2.404527  1.488510  1.488510  1.869520  1.869520
179  180.0  2.764062  2.764062  1.141397  1.141397  1.066121  1.066121
377  378.0  4.624245  4.624245  3.505169  3.505169  7.911076  7.911076

         C4F1      C4F2      C5F1  ...     C19F2     C20F1     C20F2  \
53   8.795572  8.795572  3.602904  ...  6.445175  5.971214  5.971214
657  4.845167  4.845167  8.768133  ...  1.647758  5.503714  5.503714
564  6.722426  6.722426  1.142385  ...  5.868080  4.113323  4.113323
274  4.615306  4.615306  4.696268  ...  7.574896  1.272251  1.272251
350  4.275504  4.275504  8.317297  ...  4.348322  3.500722  3.500722
..        ...       ...       ...  ...       ...       ...       ...
254  1.764057  1.764057  4.874337  ...  4.367741  1.735057  1.735057
576  5.289144  5.289144  1.145753  ...  5.261497  3.271816  3.271816
484  1.472331  1.472331  3.919118  ...  1.871197  9.776686  9.776686
179  1.068618  1.068618  3.012980  ...  1.063321  6.953004  6.953004
377  4.107140  4.107140  3.285610  ...  7.906819  1.551068  1.551068

        C21F1     C21F2     C22F1     C22F2     C23F1     C23F2  class
53   1.614037  1.614037  3.178395  3.178395  7.465961  7.465961    0.0
657  8.052153  8.052153  5.445329  5.445329  6.179920  6.179920    1.0
564  9.058403  9.058403  3.069473  3.069473  8.827454  8.827454    1.0
274  6.569392  6.569392  1.534242  1.534242  5.484657  5.484657    0.0
350  7.359825  7.359825  3.000017  3.000017  5.191528  5.191528    0.0
..        ...       ...       ...       ...       ...       ...    ...
254  3.202579  3.202579  1.026006  1.026006  3.753640  3.753640    0.0
576  5.785381  5.785381  2.174449  2.174449  3.914058  3.914058    1.0
484  1.395560  1.395560  4.762727  4.762727  1.931029  1.931029    1.0
179  2.518696  2.518696  4.404245  4.404245  1.457855  1.457855    0.0
377  7.261318  7.261318  2.153219  2.153219  1.171483  1.171483    1.0

[720 rows x 48 columns]
[0. 0. 1. 1. 0. 0. 1. 1. 0. 1. 0. 0. 0. 1. 1. 0. 0. 1. 1. 1. 0. 0. 0. 0.
 0. 1. 1. 1. 0. 0. 1. 1. 0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 1. 0. 0. 0. 0. 1.
 1. 1. 0. 0. 0. 1. 1. 0. 1. 0. 1. 1. 1. 1. 0. 1. 1. 1. 1. 0. 1. 1. 1. 1.
 1. 1. 1. 0. 1. 1. 1. 0. 0. 0. 0. 1. 0. 0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 0.
 0. 0. 1. 0. 0. 0. 1. 0. 1. 1. 1. 0. 1. 0. 0. 1. 0. 1. 1. 0. 1. 1. 0. 1.
 0. 1. 0. 0. 0. 0. 1. 1. 1. 0. 1. 1. 0. 0. 1. 1. 0. 0. 1. 0. 1. 1. 1. 1.]
```

Figure 6.5: Predict Value.