

**BACHELOR OF SCIENCE IN
COMPUTER SCIENCE AND ENGINEERING**



Inspiring Excellence

**Epileptic Seizure Detection by Exploiting EEG
Signals using Different Decomposition
Techniques and Machine Learning Approaches**

AUTHORS

**Rezwanul Karim
Subah Nitol
Md.Mushfiqur Rahman**

SUPERVISOR

Dr.Md.Ashraful Alam
Assistant Professor
Department of CSE

CO-SUPERVISOR

Dr. Mohammad Zavid Parvez
Assistant Professor
Department of CSE

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We would like to thank
to Allah
our Teachers
our Parents and Siblings
and
our Friends

Without their assistance & support no achievement would be possible.

Declaration

It is hereby declared that this thesis /project report or any part of it has not been submitted elsewhere for the award of any Degree or Diploma.

Authors:

Rezwanul Karim
Student ID: 14301038

Subah Nitol
Student ID: 14301116

Md. Mushfiqur Rahman
Student ID: 14301130

Supervisor:

Dr. Md. Ashraful Alam
Assistant Professor, Department of Computer Science and Engineering
BRAC University

Co-Supervisor:

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

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The thesis titled "Epileptic Seizure Detection by Exploiting EEG Signals using Different Decomposition Techniques and Machine Learning Approaches"

Submitted by:

Rezwanul Karim Student ID: 14301038

Subah Nitol Student ID: 14301116

Md. Mushfiqur Rahman Student ID: 14301130

of Academic Year 2018 has been found as satisfactory and accepted as partial fulfillment of the requirement for the Degree of Bachelor of Science in Computer Science and Engineering

1.

Dr. Md. Ashraful Alam
Assistant Professor
Department of Computer
Science and Engineering,
BRAC University

Supervisor

2.

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

Co-Supervisor

3.

Dr. Md. Abdul Mottalib
Professor
Department of Computer
Science and Engineering,
BRAC University

Chairman

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Abstract

In recent years, detecting epileptic seizure has gained a high demand in the field of research. It is such a common and high talked brain disorder, since more than 65 million individuals worldwide are affected by this very disease. Electroencephalogram (EEG) signals is widely used for identifying brain diseases like epileptic seizure. In this thesis, two features are extracted based on short-time fourier transform(STFT) and pseudo-wigner distribution (PWD) and these features are then used to classify seizure and non-seizure EEG signals using support vector machine (SVM). Experimental results show that our proposed approach achieved high classification accuracy (i.e.,92.4%) considering five groups of people.

Key-words: EEG, Epilepsy, Seizure, SVM, STFT, PWD.

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Chapter 1

Introduction

1.1 Motivation

Our motive is to enhance the ways and contribute to the field of detecting one of the most common brain diseases known as epileptic seizure. We have gone through and analyzed several research papers related to this field and so decided to utilize our opportunity to participate in this sector of research with our own approaches. People suffering from neurological disorder such epileptic seizure have hard time dealing with abnormal behaviour, activities and sensation. It is very important to detect epileptic seizure to help the patients in diagnosis of epilepsy so that they can receive first aid and also be sure of their medical issues. Electroencephalogram(EEG) signal is useful in this case to disclose the structural and functional information of brain to help pointing out malfunctions as well as disorders in our brain. There exist different types of epileptic seizure that show several different symptoms. If it is detected sooner, first aid can be applied to ease the complexity.

From many research paper, it is clear to us that signal measurement has great efficiency to detect epilepsy or in other words, this is the only most effective way to point the the disease. Through EEG signal analysis and some other techniques followed by it such as signal feature extraction and classifying, we can successfully detect if a brain has been affected by epileptic seizure or not. Through the whole process, we can differentiate between healthy brain and epilepsy affected brain.

1.2 Thesis Overview

Epileptic seizure technically is a period of symptoms due to abnormal or excessive neuronal activity in the brain; the effects of which are uncontrolled activities, shaking, wired move-

ments in either the most parts of the body or in only part of the body with variable levels of consciousness or just a subtle momentary loss of awareness[28]. In most of the cases, these periods last less than a minute or two but it takes some time to return to normal[20]. Due to this seizure, there might occur Loss of bladder control[28]. There are certainly some activities that provokes an epileptic seizure. However, in most of the cases, it is occurred for unnoticeable or unknown facts or even just a little sleep deprivation. Epilepsy also have two types when it occurs- provoked and unprovoked. Up to 10% of people have at least one epileptic seizure in a lifetime[28]. Studies show that Provoked seizures occur in about 3.5 per 10,000 people each year while the number is about 4.2 per 10,000 people each year for unprovoked seizures. After one seizure, the chance of experiencing a second is about 50-50. Studies also show that about 1% of the entire population get affected by epilepsy at any given time and about 4% of the population at some point in time[55][6]. Moreover, almost 80% of those with epilepsy are inhabitants of developing countries. Many places even require their residents to stop driving until they have not had a seizure already for a certain period of time for the safety purpose. To help someone that has epileptic seizure, the first thing is to successfully figure out if the person contains epileptic seizure.

Our human brain produces electrical signals (i.e., EEG signals) which can be isolated into various frequency bands (e.g., gamma, alpha, so on). In the genuine situation, a man with epileptic seizure demonstrates signals unique in relation to the typical brain (see Fig. 1.1). Through viable signal examination, it can be perceived if the signs are of non-seizure or seizure influenced brain. EEG is an electrophysiological observing strategy to record electrical movement of the cerebrum. This electrical movement alludes to the signs of brain activity. It is generally electrodes that is set on the scalp. EEG estimates the voltage fluidity coming about because of ionic current inside the neurons of the brain[35]. In clinical settings, EEG refers to the chronicle of the brain's unconstrained electrical versatility over some unlimited frame reported by different electrodes put on the surface of scalp. Definite bits generally revolve either around potential outcomes related with occasion or on the captivating substance of EEG. This investigations the sort of neural motions which are known as brain waves that can be seen in EEG motions in the frequency space. Any adjustments in those brain waves or signal demonstrates malfunction. So, to detect an epilepsy, signal analysis is necessary since it points out the brain signal of a person that is similar to the epilepsy.

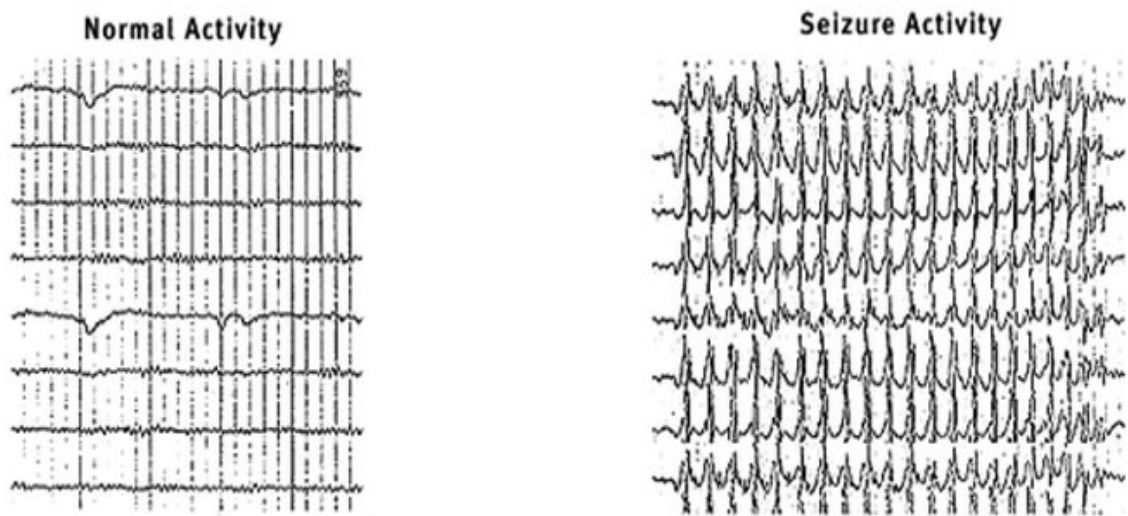


Fig. 1.1 Normal activity vs seizure activity of brain[17].

Throughout the decades, there have been many recordings of the EEG signals that occurs in a epilepsy affected patient's brain. All the recordings of these signals in EEG summarizes to a pattern. Anyone showing this pattern of signal in EEG measurement is believed to have epileptic seizure. To find out anyone who shows the pattern some applications are also needed followed by the EEG measurement. After capturing the signal, feature extraction and classification are applied. The whole process is also be compared to BCI(brain computer interface) system. Although, the Brain Computer Interface system actually has a particular motive and the field of BCI research and development has always focused mainly on neural prosthetic applications that targets at recovering damaged or disabled movement[49], the system is somewhat similar to the detection of damaged movements of brain activity. A BCI system is known to track out specific patterns in a human brain that relays to the people as they establish an action. The work is to interpret these patterns into a incidental order. After that, different EEG signal processing algorithms are driven on the commands for characterizing the patterns. There will be discussion later on about the efficient ways in detecting various patterns of human brain signals and classify them through the conduct of a classifier. Therefore, this thesis mainly focuses on following positions- the feature extraction and then feature classification. Many researchers have already discover many approaches in all the applications.

We will focus on what shows us better results or simply which ones we are most suitable to work with. The data obtained from a Bonn University dataset [53] was used in this research that includes seizure affected signals as well as the healthy ones with several subsets. There are many time-frequency decomposition techniques that work great in order to

extract feature based on discrete wavelet transformation (DWT)[29][50], Short time Fourier transformation (STFT)[2], empirical mode decomposition (EMD)[3], power spectral density (PSD)[2], Pseudo-wigner distribution (PWD)[7] and many more. Therefore, we have used time-frequency approaches in a novel way so that we can extract better features with good classification accuracy. There are many classifiers that work smooth to classify signals such as support vector machine (SVM)[16][51], artificial neural network (ANN)[33][21], Regression tree[32] and so on. We have used SVM classifier since it can handle non-stationary signals such as EEG. In this thesis, we extracted energy features using two decomposition techniques based on STFT and PWD. STFT is a Fourier-related transformation where frequency and phase content changes over time[7]. Compared to a STFT, the PWD function can furnish higher clarity in some cases. SVM is one of the best classifiers for non-stationary signals classification[19]. Therefore, STFT and PWD are used for time-frequency features extraction and SVM is considered for seizure and non-seizure EEG signals classification. The proposed method may provide an opportunity to develop a clinical device to detect forthcoming seizures in real time applications.

1.3 Thesis Orientation

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

Chapter 2

Literature Review

The ability to use EEG signal analysis to identify many structural brain changes corresponding with different disease states and the success in capability of computer based detection of many brain diseases could be of really good use for diagnosis and treatments[25]. A human brain in general has different states depending over the signals it produces. Based on the frequency ranges, these signals have been labelled as five types- delta, theta, alpha, beta and gamma[45]. Changes in these signals are indications of disorders such as epileptic seizure. From the examples of signals gathered from the patients experiencing epileptic seizure sets a model signal of brain with epilepsy. As epilepsy is a typical neurological confusion, programmed classification of epileptic EEG epileptic EEG activities has been a matter of study in recent years.

Researchers have performed several studies about the signal analysis of epileptic seizure where time-frequency distribution has been greatly useful to decompose in the signal analysis[2]. There are several decomposition methods that have been used by the researchers of which some of them are frequently used. To illustrate, Krishnaveni et. al. in [29], Abdulhamit et. al. in [50] and Hasan et. al. in [38] have conducted research papers that use discrete wavelet transform (DWT) as the decomposition method. They mentioned that using DWT as a pre-processing system has made an increase in performance than not using any. DWT is one the most used decomposition techniques in this case. Here, the decomposition of the signal guides a set of coefficients called wavelet coefficients. Thus, weighted by those wavelet coefficients, the signal can be worked as a linear combination of the wavelet capacities. For getting a correct reproduced structure of the signal, registering fitting number of coefficients is fundamental. In DWT, the energy of the wavelet is limited into a finite time interval[50]. Other commonly used techniques are Wavelet Packet Decomposition (WPD)[52], power spectral density (PSD)[2], Short time Fourier transform (STFT)[1], empirical mode decomposition (EMD)[3] etc. WPD is little bit different from previously mentioned DWT method.

For n many levels of decomposition, the WPD produces twice as n many distinct sets of coefficients. For n numerous dimensions of decomposition, the WPD creates twice as n numerous unmistakable arrangements of coefficients. From the perspective of compression, the standard wavelet transform may not deliver the best outcome, since it is constrained to wavelet bases that expansion by an intensity of two towards the low frequencies[52]. PSD which applies to signals existing over unequaled, or over a time period sufficiently expansive that it could too have been over a limitless time interval[2]. STFT is a Fourier-related transform used to decide the sinusoidal frequency and stage substance of nearby areas of a signal as it changes over time[7]. EMD depends on delivering smooth envelopes characterized by nearby maxima and minima of a grouping and ensuing subtraction of the mean of these envelopes from the underlying succession. This requires the identification of all local extrema that are further associated by cubic spline lines to deliver the upper and the lower envelopes[3].

The above mentioned methods are all good to work with as a single system. However, working with more than one time-frequency distribution methods has shown better experimental outcomes. Alexandros et. al. has shown his feature extraction by decomposing through the STFT and PSD time-frequency distribution[1]. Although, the number varies depending on number of classification, this research has disclosed that using these methods together has increased their accuracy than using them as individual. By using a single method, great results has been achieved in most cases. It depends on the researchers how they utilize them according to their methodologies. However, sometimes, together some methods can show or mostly show better outcomes. After pre-processing and feature extraction is done, the signals are required to be classified.

To classify the signals, there are various techniques. Machine learning technique is one of them. There are so many approaches of machine learning. Among them most commonly used among them are SVM(Support vector machine) and ANNs(Artificial neural networks). ANNs have widely been applied to classify EKG and EEG signals over the last two decades. A variety of different ANN based approaches were reported in the literature for epileptic seizure detection[33]. Neural network put together methodologies are essentially based on building models of epileptic and ordinary EEG and after that utilizing these models to arrange EEG as either epileptic or typical. Models are assembled dependent on features extracted from a preparation informational collection. Features are chosen with the goal that they capture the contrasts between the epileptic and ordinary EEG. Feature extraction process assumes a critical job on the classification execution of the ANN models[38]. SVM classifier as a general classifier is introduced in some test inquires about that has demonstrated great outcomes in characterizing seizure and non-seizure EEG signals dependent on the

data transfer capacity parameters[3]. Specially, linear svm is a method that is utilized in assortment of applications. This isolates classes by a hyperplane and makes plots of various isolated classes. The partition by hyperplane can be considered either 2D or 3D dependent on the information. Beside these two, gaussian mixture model classifier is utilized by Rajendra et. al[52] where the likelihood density capacity of each class is expected to comprise of a mixture of multidimensional Gaussian distributions. A Gaussian mixture model expect and treats every one of the information focuses are created from a mixture of a limited number of Gaussian distributions with obscure parameters. This classifier can be accepted as summed up k-means clustering. This classifier indeed, has preferred results over regression tree and KNN(K-nearest neighbor)[52].

Chapter 3

Background Analysis

Before we initiate our work, some background knowledge must be needed. We therefore, found the resources to gather important information about human brain, the topic we are working on and what approaches are there to adopt and finally chose our own techniques. Below is the discussion of the essence about our learning.

3.1 Brain Anatomy

The Brain is an important organ of human body that is located in the head. It is close to all the sensory organs. A human brain acts as a control center and all the functions of human body controlled by it. The brain is also has responsibility of controlling our understanding to a particular situation, speech, functioning of our limbs and many organs within our body[12]. Human brain makes the body aware of the internal and external surrounding by generating sensory signals. A brain is compiled of 3 major components; Brain Stem, Cerebrum, Cerebellum. Along with these 3 components, the descriptions of some other components are given below.

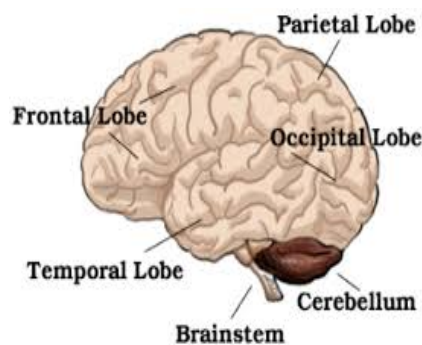


Fig. 3.1 Anatomy of Human Brain[12].

Figure 3.1 shows the brain anatomy where different parts of the brain play different roles.

3.1.1 The Cerebral Cortex

The cerebral cortex is the reason for making human being unique. It is the part of the brain which originates higher thought, language and human consciousness as well as the ability to think, reason and imagine. What we see if we look at the human brain is the cerebral cortex. It is the outermost portion of the brain. The cerebral cortex is divided into four part which are the four lobes of human brain. Gyrus is the bumps of the surface of human brain and each groove is known as a sulcus[12].

3.1.2 Cerebellum

Cerebellum is the part of brain which maintain the fine movement of the body. It is the only region of the nervous system that span the midline without any interruptions. This structure obtains the position behind the tectal plates and uses midline as a bridge. Cerebellum system is responsible mostly for movement execution, timing and multi-limb coordinates. Sometimes it is called "the little brain"[31].

3.1.3 The Four Lobes

The cerebral cortex can be divided into four sections, which are known as lobes. The frontal lobe, parietal lobe, temporal lobe, and occipital lobe. Every lobe has different functionality which is ranging from reasoning to auditory perception.

The Frontal Lobe

The frontal lobe is located at the front of the brain. It has multiple functions such as reasoning, motor skills, higher level cognition, and expressive language. Frontal lobe receives information from other lobes and utilizes these information to carry out body movements. If there are any damages in this front area, changes in sexual habits, socialization, and attention can be happened[12].

The Parietal Lobe

The parietal lobe is located in the middle section of the brain. It has several functions which are associated with processing tactile sensory information such as pressure, touch,

and pain. There is a portion of the brain named somatosensory cortex located in this lobe. Somatosensory cortex is essential to the processing of the body's senses[12].

The Temporal Lobe

The temporal lobe is located in the bottom section of the brain. The primary auditory cortex is located in this lobe. the primary auditory cortex is important for interpreting sounds and the language we hear. The temporal lobe also has the hippocampus. With the help of the hippocampus the temporal lobe is heavily associated with the formation of memories. Problems with memory, speech perception, and language skills can e happened if there is any damage in the temporal lobe[12].

The Occipital Lobe

The occipital lobe is located in the back portion of the brain. There are several functions of this lobe which are associated with interpreting visual stimuli and information. The primary visual cortex is located in the occipital lobe. Primary visual cortex receives and interprets information from the retinas of the eyes. If there is any damage in this lobe, visual problems such as difficulty recognizing objects, an inability to identify colors, and trouble recognizing words can be happened[12].

3.1.4 The Brain Stem

The brainstem also plays an important role in the regulating the cardiac and respiratory function, central nervous system. It further helps in maintaining consciousness and regulation the sleep cycle. The brainstem make the path to connect the nerve of the motor and sensory systems at the brain to the rest of the parts of the body. he basic functions of brainstem includes heart rate, breathing and sleeping.

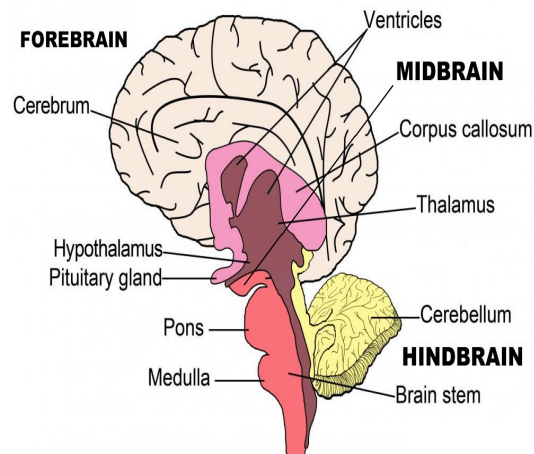


Fig. 3.2 Brain Stem Structure[26].

As the figure 3.2 [26] shows the categorization, the brain stem is comprised with three parts. the midbrain, medulla and pons.

The Midbrain

The midbrain is a small portion of the brain. It functions as a relay station for auditory and visual information. Many important functions such as the visual and auditory systems as well as eye movement are controlled by the midbrain. Again the red nucleus and the substantia nigra are the portion of the midbrain which are involved in the control of body movement[26].

The Medulla

The medulla is located in a part named spinal cord, which is in the lower part of the brain stem. The medulla controls many vital functions such as heart rate, breathing, and blood pressure[26].

The Pons

Medulla is connected with the cerebellum by the help of pons. Playing a role in several autonomic functions such as stimulating breathing and controlling sleep cycles and other important functions are served by the pons[26].

3.1.5 The Thalamus

The thalamus is located above the brain stem. Human body movements and sensory information are processed and transmitted by the thalamus. The thalamus acts as a relay station and

takes many sensory information and then passing those information to the cerebral cortex. The cerebral cortex also send information to the thalamus in order to pass it to the other elements[12].

3.1.6 The Hypothalamus

The hypothalamus is located in the base of the brain near the pituitary gland. It is a group of nuclei. The hypothalamus connects with several regions of the brain and is responsible for controlling hunger, thirst, emotions, body temperature regulation, and circadian rhythms. It controls the pituitary gland. For these reason the hypothalamus plays a great role over many body functions[12].

3.1.7 The Limbic System

There are four main regions in the limbic system. These are the amygdala, the hippocampus, regions of the limbic cortex and the septal area. These four region help the limbic system to connect with the hypothalamus, thalamus and cerebral cortex. The limbic system is called the central station for controlling the emotional response and learn[26].

3.1.8 The Basal Ganglia

The thalamas is covered with a large group of nuclei. The group of nuclei is called the basal ganglia. It is very important in control of movement. The basal ganglia is connected with the red nucleus and substantia nigra and these are the part of midbrain[26].

3.2 EEG Waves

The EEG is the recording of the electrical activity occurring at the surface of the brain. This activity measurement appears on the screen of the EEG machine as waveforms of different frequency, shape and amplitude. The recorded waveforms reflect the cortical electrical activity.

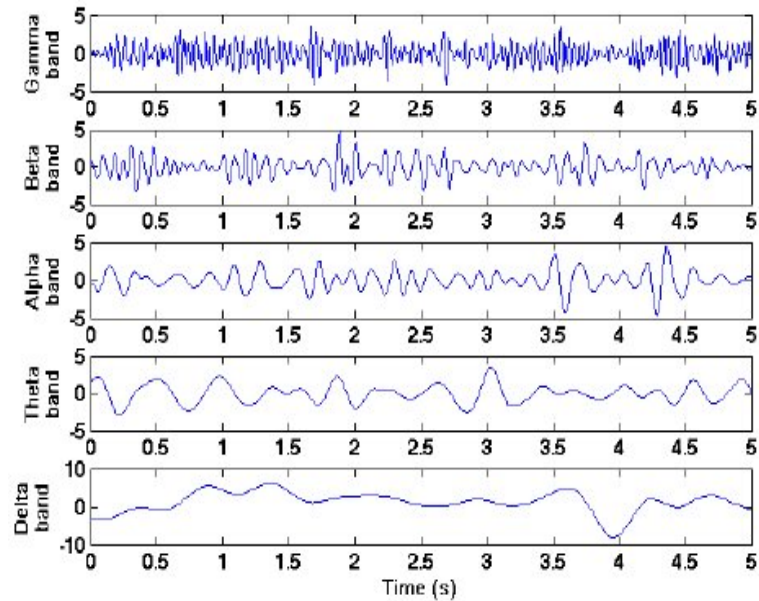


Fig. 3.3 Types of brain waves[45].

The main signal frequencies of the human EEG waves are delta, theta, alpha, beta and gamma. The types of brain waves are shown in figure 3.3.

3.2.1 Delta

Delta brainwaves are moderate, boisterous brainwaves with a frequency dimension of 4 Hz or below[35]. It is really typical as the overwhelming mood in newborn children up to one year and furthermore in the stages 3 and 4 of rest. It might happen centrally with subcortical sores and all in all dissemination with diffuse injuries, metabolic encephalopathy hydrocephalus or profound midline lesions[39]. It is generally the most unmistakable frontally in grown-ups and posteriorly in kids.

3.2.2 Theta

Theta has a frequency of 4 to 8 Hz and is delegated moderate activity[35]. It is impeccably typical in kids up to 13 years and in rest however thought to be anomalous in wakeful grown-ups. It tends to be viewed as a sign of central subcortical sores. In theta, we are in a fantasy, clear symbolism, instinct and data past our typical cognizant mindfulness. It is likewise where we hold our feelings of trepidation, beset history and bad dreams.

3.2.3 Alpha

Alpha has a frequency somewhere in the range of 8 and 13 Hz[35]. Is generally best found in the back districts of the head on each side, being higher in adequacy on the prevailing side. It ordinarily shows up when shutting the eyes and unwinding thus, vanishes when opening the eyes or alarming by any mechanism[35]. It is the significant beat found in ordinary loosened up grown-ups as this wave helps generally speaking mental coordination, tranquility, readiness, psyche and body combination and learning.

3.2.4 Beta

Beta is quick action wave having a frequency of 14 and more prominent Hz[35]. It is generally observed on the two sides in symmetrical appropriation and is most apparent frontally. At whatever point consideration is coordinated towards subjective errands, beta brainwaves rule our ordinary waking condition of cognizance which might be missing or lessened in territories of cortical harm. It is by and large viewed as an ordinary beat and the overwhelming cadence in patients who are excessively caution or on edge or have their eyes open.

3.2.5 Gamma

Gamma brainwaves are the quickest of brain waves with most astounding frequency sufficiency and identify with concurrent handling of data from various brain territories. Gamma brainwaves pass data quickly and unobtrusively as the most inconspicuous of the brainwave frequencies [18]. It is expected that gamma rhythms tweak observation and cognizance and a more prominent nearness of gamma identifies with extended awareness and otherworldly development.

3.3 Epileptic Seizure

An epileptic seizure is a short scene of signs or manifestations due to unusually exorbitant or synchronous neuronal movement in the brain. The outward impact can shift from uncontrolled jerking movement (tonic-clonic seizure) to as inconspicuous as a transient loss of awareness (absence seizure).Epileptic seizures are caused by an unsettling influence in the electrical movement of the cerebrum. There are a wide range of sorts of epileptic seizure. Anybody can conceivably have a solitary epileptic seizure anytime in our lives. This isn't the comparable of having epilepsy, which is an inclination to have seizures which begin in the brain[30].

Brain signals during seizure is shown in figure 3.4.

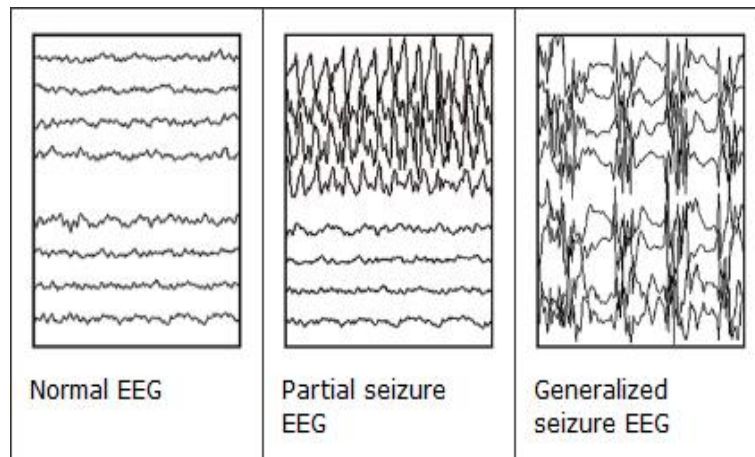


Fig. 3.4 Brain signals during seizure[37].

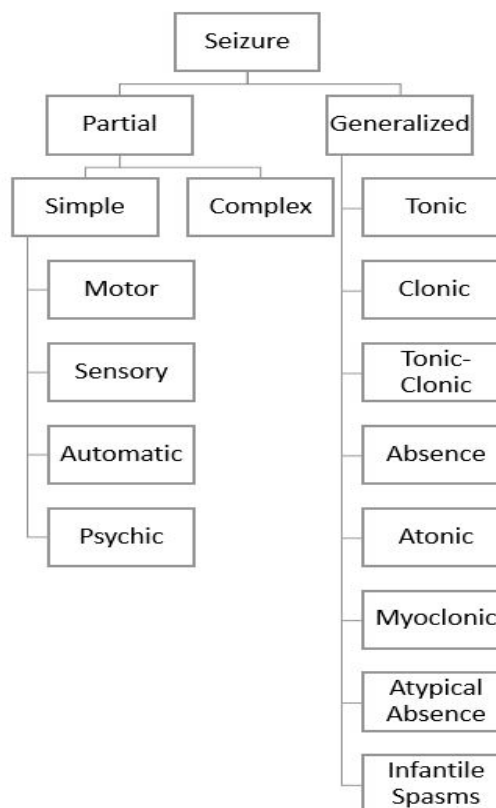


Fig. 3.5 Classification of epileptic seizure.

Figure 3.5 shows different types of epileptic seizure. Some of the types are given below.

3.3.1 Partial Seizures

The side effects of a halfway seizure can be calamitous. Be that as it may, some outer side effects can happen and be seen by close view by any person[24]. These manifestations will not generally happen, as every seizure and individual is different. Some outside changes are possibly: all of a sudden feeling changing with no reason, snickering or weeping for reasons unknown, twitch or fit of a solitary piece of the body, more often than not a leg or arm, trouble talking or talking in non-sensible ways.

Simple Partial Epileptic Seizures

Simple partial seizure influence just a single region of brain[24]. It doesn't make you lose cognizance. It is an additionally speedy, commonly enduring one moment or two.

These side effects will not generally happen, as every seizure and individual is different. Some outside change possibly : all of a sudden feeling changing with no cause, laughing or weeping for reasons unknown, twitch or fit of a solitary piece of the body, for the most part a leg or arm, difficulty talking or talking in non sensible ways[24].

Specialists grouped simple partial seizures down into four regions, in light of the area in the brain and parts of the body that affected[42]:

- **Motor:** A simple partial seizure with engine side effects will influence muscle action, causing yanking developments of the foot, face, arm, or another piece of the body. Doctors can analyze which side of the brain is influenced by seeing which side of the body encounters side effects (left brain controls right side, right brain controls left side).
- **Sensory:** A simple partial seizure with tactile indications influence the faculties: hearing issues, conceivable pipedreams and different bends.
- **Autonomic :** A simple partial seizure with autonomic side effects influences the piece of the brain in charge of automatic capacities: it might cause changes in pulse, heart beat, inside capacity and so on.
- **Psychic :** A simple partial seizure with mystic indications influences parts of the brain that trigger feelings or past encounters: it might cause sentiments of dread, tension, this feels familiar (the inclination that something has been experienced previously) etc.

Complex Partial Epileptic Seizures

Complex partial seizure otherwise called a central disabled awareness seizure[44]. This sort of seizure ordinarily begins in a solitary zone of the brain. This territory is more often than not the transient flap of the brain. This sort of seizure has been known to happen in individuals with cerebral paralysis. These seizures are normally short, and the individual having the seizure will be unconscious of their environment. They may likewise wind up oblivious for a concise time-frame.

A complex partial seizure can have different conceivable manifestations. Be that as it may, these side effects may happen amid one seizure and not another. Complex partial seizures regularly just last a couple of minutes. Seizures starting in the frontal projection region of the brain are normally shorter than those that begin in the fleeting flap territory.

Most extreme time indications will begin all of a sudden and the individual encountering the seizure may not mindful they are encountering it[56]. The individual may gaze vacantly be not able respond, wake up from rest suddenly, swallow, smack their lips or generally move their mouth repetitively, pick at things like the air, attire or furniture, say words repetitively, scream, snicker or cry, perform activities that can make potential risk themselves, such as strolling before, moving autos or evacuating all or bits of their clothing, perform developments like they are riding a bicycle, be unconscious, either partially or absolutely, of their surroundings, hallucinate, try to hurt themselves, experience perplexity when the seizure ends, be unfit to recollect the seizure[44].

3.3.2 Generalized Epileptic Seizures

In generalized seizures the entire brain is influenced by the unusual electrical aggravation and the individual moves toward becoming unconscious. Sometimes, the period when the individual is oblivious can be exceptionally concise and might be missed[13].

Seeing a tyke or anybody having a seizure can be very alarming. The tyke is oblivious amid generalized seizures, so they do not know about what's going on.

They may encounter inordinate side effects previously a generalized seizure that will caution them to a seizure beginning. On the off chance that this happens attempt to get them to a protected place, regardless of whether that is perched on the floor. It is likely that this notice or quality is the start of the seizure in only one a player in the brain, before it spreads to the entire brain.

Tonic Seizure

Tonic seizures include expanded muscle tone or solidness. Contingent upon how rapidly the seizure begins and to what extent it endures, tonic seizures might be a continuous development or a gigantic yank. A tyke might be pushed forward or in reverse and even tumble down because of the muscle hardening. They may turn blue and seem to quit breathing in light of the fact that their chest muscles have additionally solidified. Tonic seizures generally keep going for 10 to 15 seconds, yet may keep going for up to a moment. They frequently happen amid rest or soon after a tyke awakens. The tyke is mistaken for a brief span after the seizure.

The muscles of arms, legs or trunk got tense up[4]. These normally last under 20 seconds happen when individuals sleeping. In any case, in case you're standing up at the time, you can lose your equalization and fall. These are increasingly basic in individuals who have a sort of epilepsy known as Lennox-Gastaut disorder, however, individuals with different kinds can have them as well.

Clonic Seizure

"Clonus" means fast stiffening and relaxing of a muscle that happens repeatedly. In other words, it is repeated jerking[30]. The movements cannot be stopped by restraining or repositioning the arms or legs.

During a clonic seizure, a person may lose control of bodily functions and begin jerking in various parts of the body. He/she may temporarily lose consciousness, followed by confusion[9].

Clonic seizures begin in early childhood. They often appear to be a case of massive bilateral epileptic myoclonus, though the motor features of it may be less symmetrical. Clonic seizures are rare and most commonly occur in babies. Most often, clonic movements are seen as part of a tonic-clonic seizure[4].

Tonic-Clonic Seizures

A generalized tonic-clonic seizure, additionally called a grand mal seizure, is an unsettling influence in the working of the opposite sides of brain[5]. This caused by electrical signs spreading through the brain improperly. Sooner or later this will result in signs being sent to muscles, nerves or glands[5]. The spread of these signs in brain can influence you to lose cognizance and have extraordinary muscle compression.

Tonic-clonic seizures get their name from their two unmistakable stages. In the tonic phase of the seizure, muscles solidify, people lose awareness, and may tumble down. The

clonic stage comprises of quick muscle constrictions, likewise called convulsions[5]. Tonic-clonic seizures generally last 1 – 3 minutes. If the seizure remains longer than five minutes, restorative crisis is required.

Seizure that is not identified with epilepsy could occur at any phase of your life. The seizure is a therapeutic emergency depends upon the historical backdrop of epilepsy or other well-being conditions.

Absence Seizures

Absence seizures is otherwise called petit mal seizure. They are brief, generally under 15 seconds, and they have side effects that might be scarcely comprehend [48]. Be that as it may, loss of awareness, notwithstanding for such a brief timeframe, can make absence seizures perilous.

Absence seizures are more typical in kids as opposed to grown-ups and can happen habitually. At the point when an individual influenced by absence seizure ends up oblivious for a brief span. They may stop what they are doing, look clear and gaze, or their eyelids may got squint or vacillate. They will not react to what's going on around them. On the off chance that they are strolling they may continue strolling, yet will not know about what they are doing[14].

Amid a regular absence the individual winds up clear and lethargic for a couple of moments. They may begin watch to be 'staring off into space'. The seizures may not be viewed on the grounds that they are brief.

Atonic Seizures

Atonic seizures are a kind of seizure that causes sudden loss of muscle quality. These seizures are moreover called akinetic seizures, drop ambushes or drop seizures. The sudden absence of muscle quality, or tone can make the individual tumble to the ground. The person when in doubt remains aware and may not for the most part tumble down[40]. Their head may drop, their eyelids may hang, and they may drop anything they were holding. These sorts of seizures consistently begin in pre-adulthood and may last into adulthood. At times, they are associated with various conditions, for instance, Lennox-Gastaut issue.

Myoclonic Seizures

Myoclonic seizures are brief, stun like branch of a muscle or a gathering of muscles.. "Myo" suggests muscle and "clonus" infers quickly exchanging compression and unwinding snapping or jerking of a muscle. By and large they do not last over a second or two. Amid

myoclonic seizures, a burst of electrical activity in the muscle control locale of the mind causes a sudden jerk of the muscles in the arms, legs, neck or body. Seizures frequently happen not long after subsequent to waking, or when the individual is exhausted before going to bed[47]. There is a short time of loss of comprehension. The time is short that is the reason we do not see this. Myoclonic seizures, generally, incorporate the opposite sides of the body meanwhile, and the individual may fall over. They occur in various epilepsy syndromes that have different characteristics:

- **Juvenile myoclonic epilepsy:** The seizures for the most part include the neck, shoulders, and upper arms. In numerous patients the seizures regularly happen not long after subsequent to awakening. They more often than not start around adolescence or once in a while in early adulthood in individuals with a typical scope of knowledge. As a rule, these seizures can be all around controlled with medicine yet it must be proceeded all through life.
- **Lennox-Gastaut syndrome:** This is an unprecedented disorder that typically incorporates different kinds of seizures too. It starts in early youth. The myoclonic seizures ordinarily include the neck, shoulders, upper arms, and frequently the face. They might be very solid and are hard to control.
- **Progressive myoclonic epilepsy:** The rare syndromes in this classification include a blend of myoclonic seizures and tonic-clonic seizures. Treatment is normally not fruitful for long, as the patient break down after some time.

Atypical-Absence Seizure

Atypical-Absence seizure is unique, surprising or not typical contrasted with commonplace absence seizures. They are a kind of generalized beginning seizure, which implies they begin in the two sides of the brain. Atypical absences are epileptic seizures that principally happen in youngsters with extreme learning and neuralgic handicaps of epileptic encephalopathies, chiefly, Lennox-Gastaut syndrome. They are unmistakable from regular absences in that beginning and end is moderate, impedance of cognizance is mellow, and they are frequently connected with noteworthy tone disturbances[10]. Atypical absence seizures were actuated in Long Evans hooded rodents by treatment with a cholesterol biosynthesis inhibitor, AY-9944 (AY), amid development[15]. An atypical absence seizure has less sudden beginning and counterbalanced of loss of awareness than regular absence seizures. They are frequently connected with different highlights, for example, loss of muscle tone of the head, trunk or appendages (regularly a continuous droop) and unpretentious myoclonic jerks. Atypical

absence seizures regularly happen in people with scholarly disability. The loss of awareness might be negligible with the patient proceeding with an action, yet more gradually or with slip-ups[11].

Infantile Spasms

Infantile spasms are a staggering epileptic encephalopathy described by early life spasms and later seizures. Infantile spasms (IS). It is also known as West Syndrome. It transforms into serious interminable epilepsy later in life[11]. It is one of the disastrous youth epilepsy on account of the trouble in controlling seizures and the relationship with mental retardation[46].

Infantile Spasms normally influences babies more youthful than 2 years old[54]. Infantile Spasms is described by epileptic spasms, formative issues and an explicit brain wave design on electroencephalography (EEG) testing called hypsarrhythmia. Kids with infantile spasms and hypsarrhythmia EEGs had stamped variations from the norm in soundness and ghastly power contrasted with typical offspring of comparable ages. Amid rest increments in delta, theta, alpha and beta coherence were seen, especially at long between cathode separations while at short between anode separations cognizance were diminished in the theta and beta range, especially in the frontal region[8]. With legitimate treatment, a watchful demonstrative assessment a few kids can accomplish seizure control and to accomplish a typical early recognition[46].

3.3.3 Why Do Epileptic Seizures Happen?

It is hard to tell exactly why epileptic seizure occurs. Seizures may be provoked and unprovoked. Provoked seizures are results of one or more temporary events like low blood sugar level, alcohol withdrawal, low level of sodium in blood, fever, brain infection etc. In unprovoked seizures, there is no known cause such that explain of the seizures happening. Sometimes, unprovoked seizures may be due to anxiety, stress or sleep deprivation[9]. Possibilities are good that a second seizure after experiencing one seizure may occur. If it becomes a disease like where there has been at least one seizure and a risk of further seizures is called epilepsy. There are also conditions that might look like epileptic seizures but are not. These include fainting, sudden shaking or shocking and , event that is psychogenic not physical[9].

3.4 EEG Mechanism

The brain's neurons are electrically charged ions by membrane transport proteins[35]. When the wave of ions reaches the electrodes on the scalp, they can move electrons. Metal conducts the movement of electrons easily. The difference in push or pull voltages between any two electrodes can be measured by a voltmeter. Recording these voltages over time creates the EEG.

EEG activity in fact, always reflects the summation of the synchronous activity of millions of neurons. The electric potential generated by a single neuron is way too small to be captured by EEG. If the neurons do not have similar spatial orientation, they may not line up and create waves required to detect. EEG signal is mostly produced by pyramidal neurons of the cortex since they are well-arranged to sync together[35]. Activity from deep sources is harder to define whereas currents near the skull are the easier[.]

Since human brain waves have variety of frequencies, scalp EEG activity shows oscillations at various frequencies. These oscillations have frequency ranges that occurs during different states of brain activity while awake and sleep stages. The neuronal networks of brain underlying some of these oscillations are perceived, but not all of them. Researchers found the complex relationship between EEG and neuron spiking[35].

3.5 Machine Learning

Machine learning is a data analysis method that uses statistical techniques that enables learning from data, working with patterns recognition, decision makings and other related task without taking specific detailed instructions unlike the systematic methods. By definition, it is clear that machine learning is an approach of Artificial Intelligence. To identify the brain diseases like epileptic seizure machine learning is one of the best approaches. Machine learning can be divided into four categories according to the purpose- supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning. Supervised and unsupervised learning is discussed below:

3.5.1 Supervised Machine Learning

Supervised learning is when someone has both the input and output variable and figure out how to reach to the output from the input using algorithms to learn appropriate mapping function. So if Y is a function of x ; $Y=f(x)$, then the function should be mapped the way that for every new input data of, x there will be a prediction for output variable Y [16]. It is called supervised learning on the grounds that the arrangement is supervised or guided. To be more

explicit, there is an objective arrangement that is given. For example, there are bats and balls kept in a basket. If the machine is instructed that anything round is a ball and not round one is a bat, it will show the results accordingly for every objects in the basket.

As indicated by the targets supervised learning has two sorts- classification and regression. In the event that the target arrangement is in qualities or classes e.g. colour, it is classification. Then again, if the target space is constant e.g. weight, it is regression.

Here are some supervised machine learning approaches:

Support Vector Machine (SVM)

SVM can be used in both classification and regression model. It is defined by a separating hyperplane to differentiate between classes or plots. The hyperplane selected by the area where it separates the classes best accurately. This algorithm is effective in high dimensional spaces.

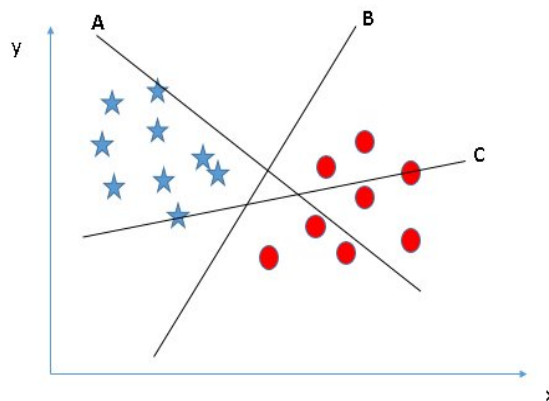


Fig. 3.6 Support Vector Machines for Classification[41].

In the figure 3.6 above, the most accurate hyperplane is B as it separates the three of the classes accurately. To determine the hyperplane, there is also one thing to consider which is margin. The hyperline should have the maximum distances from each classes. In the above figure, the hyperplane B has maintained the most distance from each classes. So, C is the most accurate one. However, in some cases, the linear hyperplane is not possible. In this cases, the 3D system can solve the problem. Where this problem arises, the z axis should brought in consideration.

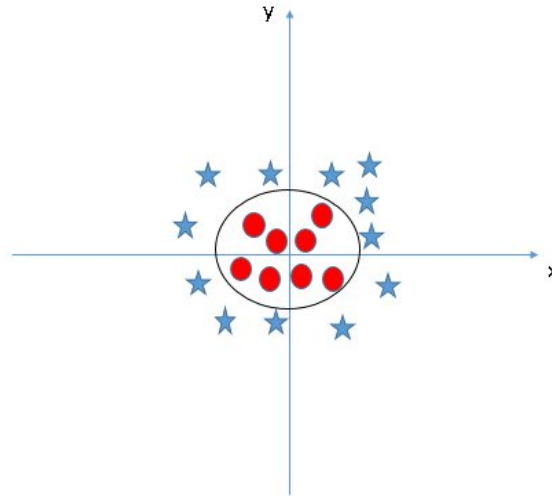


Fig. 3.7 Classifying SVM with 3D consideration [41].

In the figure 3.7, it is assumed that the the outer class in y axis is imagined as a upper class in z axis. The hyperplane is actually drawn in the z vs x axis which looks like a circle in the y vs x axis.

Decision Tree

A decision tree is a tree of the conceivable results that is produced from arrangement of related decisions to outwardly and unequivocally speak to decisions and decision making. It utilizes model of decisions which is normally utilized in information mining and also machine learning. It has impacted a wide zone of machine learning; both classification and regression. A decision tree essentially begins with a solitary node which at that point branches into conceivable results and further proceeds with like that. Consequently, every one of those results prompts extra nodes, which expand into different conceivable outcomes making it a treelike shape. Nodes are of three sorts: chance nodes, decision nodes, and end nodes. A chance node, spoken to by a circle, demonstrates the probabilities of specific outcomes. A decision node, spoken to by a square, demonstrates a decision to be made, and an end node demonstrates the ultimate result of a decision procedure. For instance, there is a decision tree that utilizes titanic information index for anticipating whether a traveler will make it to the last or not[23]. Underneath model uses 3 highlights from the informational index, which are sex, age and sibsp.

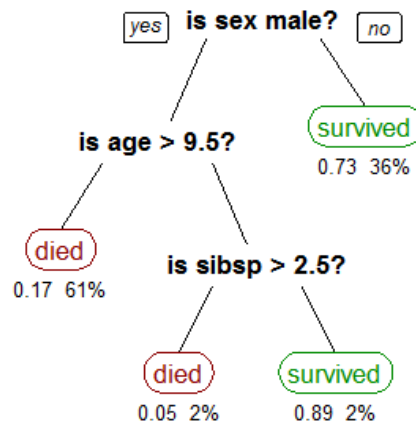


Fig. 3.8 A decision tree is drawn upside down with its root at the top[23].

In the figure 3.8, the striking content in dark speaks to a condition dependent on which the tree parts into branches. As the end of the branch does not part any longer, results in whether the traveler died or survived.

A genuine dataset will have significantly more highlights and this will simply be a branch in an a lot greater tree. Yet, the calculation is still straightforward comparatively. This tree is classification tree as the objective is to characterize traveler as lived or died. Regression trees are additionally spoken to in a similar way, simply has to predict a continuous value. The general tree making process includes choosing the highlights of decision and what conditions to apply for a part, alongside realizing when to stop. It additionally incorporates trimming or expelling a few highlights that hold less significance.

Artificial Neural Networks (ANN)

An ANN is strategy or that procedure information or data and is trailed by the way how natural sensory systems function work, for example, the brain. It is built of a huge measure of huge amount of interconnected preparing segments e.g. neurons working at the same time to explain specific undertakings. It is not controlled by task specific rules. In natural frameworks, there includes changes in accordance with the holding of neurotransmitter between nerve cells that exist in the neurons. ANNs work that way. Essentially, ANNs accumulate information as the manner in which human do; by model and encounter and isn't modified with any undertaking explicit tenets. It is masterminded explicit errands and activities, for example, design acknowledgment or information grouping or others, by means

of a technique of taking preparing by model or experience[21]. For example, there exist a program can recognize any image as it knows the characteristics. Like it can indicate a cow with a picture labeled as 'cow'. But this systems can do the same thing without any prior knowledge about cows. Instead, they automatically produce indicating characteristics and features from the learning material that they process themselves. We can say, an ANN relies on a group of connected units or nodes called artificial neurons which more or less imitate the neuron in a biological brain where each connection can broadcast signals among artificial neurons like they take signals and pass it. An artificial neuron that acknowledges a signal can operate it and afterward pass it to further other counterfeit neurons associated with it. The associations between counterfeit neurons are called 'edges'. Artificial neurons and this edges fundamentally contains weights that fits as learning receipts. The weight alludes to the estimation of the quality of flag in an association. In the way of ANN executions, the signal among the association between artificial neurons is a genuine number. Additionally, the result from each artificial neuron is determined by non-straight capacity of the aggregate of its embedded feeds.

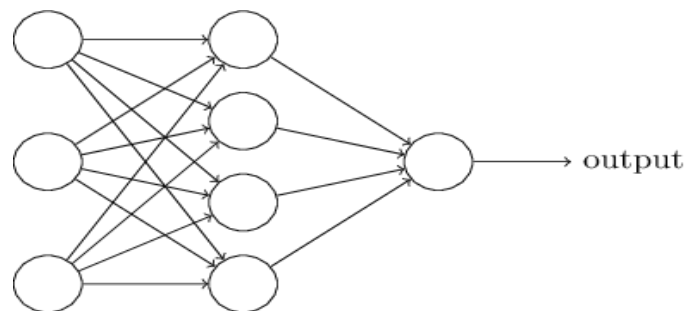


Fig. 3.9 Artificial neural networking[36].

The figure 3.9 shows how the neurons are interconnected.

3.5.2 Unsupervised Machine Learning

Unsupervised learning is when someone just has the arrangement of information factors with no relating yield factors. Unlike supervised learning, there is no settled target. It is where the machine discovers the demonstrating structures of sources of info, connection between information sources. At the point when the information inputs are not dispersed or marked, unsupervised learning comes to arrange among the information utilizing appropriate calculation. There is no supervision for that. The machine needs to separate among the information itself. In this way, in unsupervised learning, an arrangement of information is arranged and characterized as per the similarities and differences between them[51]. For

instance, if there are bats and balls in a basket. The machine has not been given any guidance. Along these lines, what the machine does is to take the round objects in a single side and the not cycle ones in other. This is the method for arranging the information and that is the means by which unsupervised learning works.

Unsupervised learning is gathered into clustering and association learning. Clustering is when there are some sure qualities in information and as indicated by that it is characterized, for example, gathering individuals as per their age. Association is when there is a few examples to depict the information and afterward it is grouped by that designs. For example, a gathering of individuals that like frozen yogurts additionally like chocolates. Here are some unsupervised machine learning approaches:

K-means Clustering

K-means clustering is a type of unsupervised learning, which is utilized when you have unlabeled information. The objective of this calculation is to discover bunches in the information, with the quantity of gatherings spoken to by the variable K. The calculation works iteratively to appoint every data point to one of K bunches dependent on the highlights that are given[22]. The system pursues a straightforward and simple approach to arrange a given informational collection through a specific number of groups.

k-means is one of the most simple unsupervised learning computations that take care of the well-known clustering issue. The principle thought is to characterize k centers, one for each bunch. These centers ought to be put keenly on the grounds that, distinctive areas causes diverse outcomes. In this way, the better decision is to put them as far as possible from one another. The subsequent stage is to take each direct having a place toward a given informational collection and partner it to the closest focus. At the point when no point is left, the initial step is finished. Now, recalculating k new centroids as barycenter of the bunches coming about because of the past advance is required[22]. From that point forward, another coupling must be done between similar informational collection focuses and the closest new focus. In a procedure of this, a circle has been produced. Because of the circle, the k centers may change their areas well ordered until the point when no more changes are required or at the end of the day, centers do not move any more.

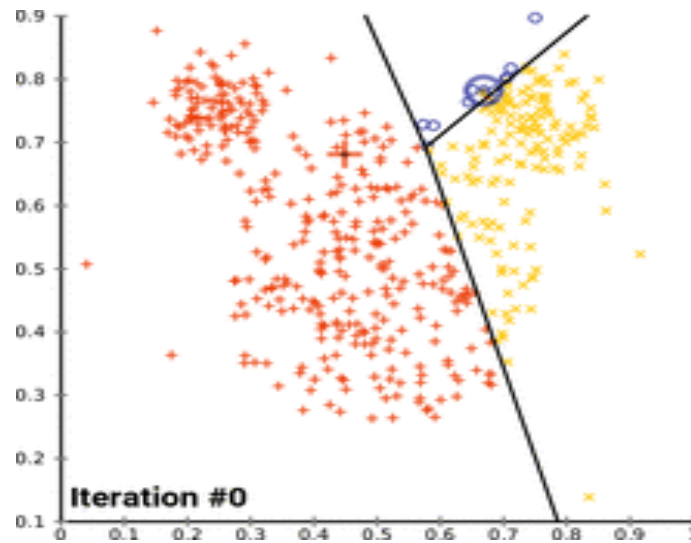


Fig. 3.10 k-means clustering[27].

Figure 3.10 shows an iteration of k-mean convergence.

Hierarchical Clustering

Hierarchical clustering is a calculation that makes gatherings and puts comparable items into same gatherings called groups. The endpoint is an arrangement of groups, where each bunch is particular from one another and the items inside each bunch are broadly like one another. There are two kinds of hierarchical clustering.

Agglomerative Clustering: It works in a bottom-up manner. That is, each object is at first considered as a solitary cluster group or leaf. At each progression of the calculation, the most comparable two groups are consolidated into another greater bunch or hubs. This methodology proceeds until the point that all focuses are individual from only one single enormous bunch which is the root. The outcome is a tree which can be plotted as a dendrogram[43].

Divisive hierarchical clustering: It works in a top-down manner just opposite of agglomerative or an inverse order of that. It starts with the root, in which all items are incorporated into a solitary cluster. At each progression of emphasis, the most heterogeneous group is separated into two[43]. The procedure keeps running until the point when all articles are in their very own isolated groups.

Figure 3.11 shows the hierarchical clustering pointing out bottom-up agglomerative and top-down divisive clustering.

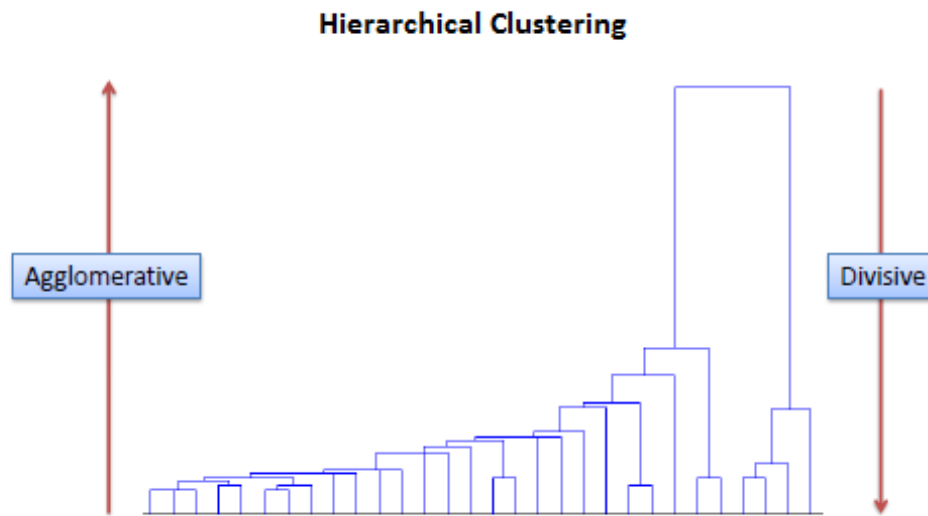


Fig. 3.11 Hierarchical clustering[43].

3.6 Dataset

The data was recorded at Bonn University, Germany[53]. The data set consists of five subsets; each subset contains 100 single-channels recording. Each recording has 23.6 seconds in duration captured by the international 10–20 electrode placement scheme. Among them, two subsets are taken from EEG signals of healthy volunteers, two subsets are taken from intractable EEG signals while at seizure free intervals and the last subset is taken from intractable EEG signals during seizure[53].

After analyzing all the parts of the study, we figure out our approaches and methodology for detecting epileptic seizure. As a classifier, the supervised machine learning (i.e., SVM) is supposedly the best suitable for our research.

Chapter 4

Proposed Model

In order to detect epileptic seizure, first key task is to extract distinguishing features from the EEG signals. The features significantly affect the accuracy for epileptic seizure detection. The optimal features play an important role in the performance of a classifier. This chapter intends to find out the robust feature extraction techniques for epileptic seizure detection. Two time-frequency distribution techniques such as STFT and PWD are used for feature extraction. After the feature extraction, it is processed through a machine learning approach. As a machine learning SVM classifier is chosen as it is convenient and then classified the data into healthy and affected brain signals.

For the experiment, five subsets of data is used where four of them are of healthy brain and one of them is of the affected brain (i.e., seizure). To detect epileptic seizure, this subsets are classified and made a border between healthy and affected signals.

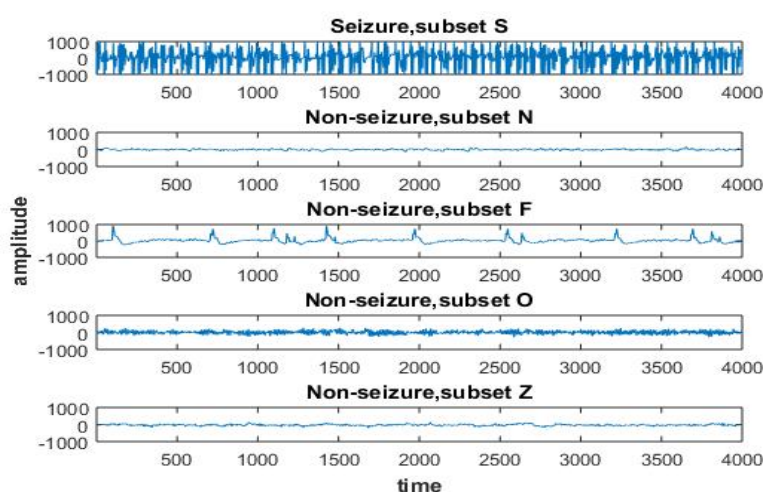


Fig. 4.1 Signals of five subsets of data [53].

It is clearly visible that seizure data shows much difference than the non-seizure ones (see Fig. 4.1). After collecting data, the later steps are followed by signal feature extraction and classification and then classified data is used for detect seizure (see details in Fig. 4.2). Feature extraction and classification were the most challenging task as we needed to manipulate the data as per our requirements.

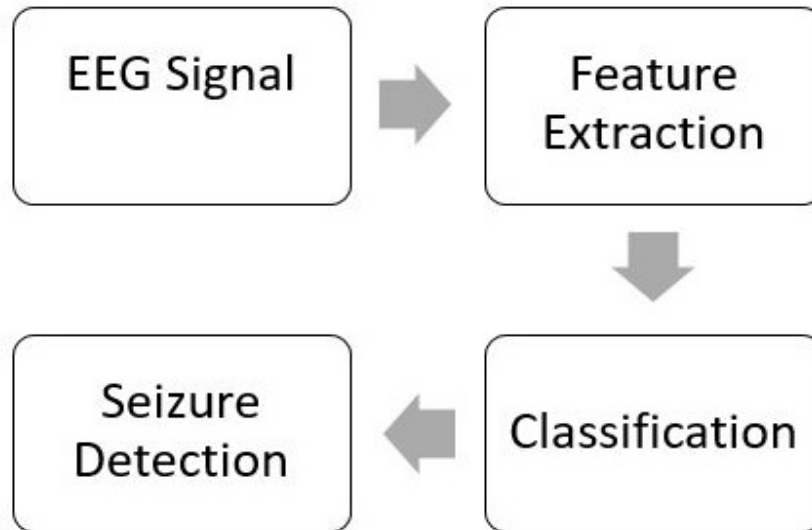


Fig. 4.2 Work-flow of the proposed model.

4.1 Feature Extraction

EEG signal used in this research were recorded on a time domain. To obtain a prominent accuracy, researchers suggest that features need to be extracted in either frequency domain or time-frequency domain. In our thesis, we extracted energy features based on STFT and PWD decomposition techniques in time-frequency domain as it will provide us most distinguishable features.

4.1.1 Time-Frequency Distribution

Time–frequency analysis serves those techniques that needs a signal in both the time and frequency domains simultaneously, using various time–frequency representations. Time–frequency analysis studies a two-dimensional signal whose domain is real plane obtained from signal as a outcome of a time-frequency transform. Extracted features based on STFT and PWD

give the best outcome in classifier due to spatio-temporal resolution. Therefore, we have extracted energy features using spatio-temporal resolution are describe below.

Pseudo-Wigner Distribution (PWD)

PWD is a modified wigner distribution that has three dimensional representation- time, frequency, amplitude. Signals can be analyzed in the time domain, in the frequency domain and in time-frequency domain. The time-frequency domain presents many special characteristics. Due to excellent properties, the wigner distribution has always been a standard distribution method. The distribution gives better auto term localization compared to the smeared out spectrogram [7]. However, when applied to a signal with multi-frequency components, cross terms appear due to its quadratic nature. The wigner distribution can be approximated by discrete signal which is referred to pseudo-wigner distribution.

$$PW_x(t, f) = \int_{-\infty}^{\infty} (t - \frac{\tau}{2})x * (t - \frac{\tau}{2})e^{-j2\pi r f} d\tau \quad (4.1)$$

Cohen's kernel function :

$$\prod(t, f) = \xi_o(t)W_h(t, f) \quad (4.2)$$

$$PW_x(t, f) = \int_{-\infty}^{\infty} ST_x(t, f + \frac{v}{2})ST_x * (t, f - \frac{v}{2})e^{2j\pi vt} dv \quad (4.3)$$

which is concentrate on the frequency axis.

Pseudo Wigner can also be written as the Fourier transform of the “spectral-correlation” of the STFT.

It is not based on a multi-scale decomposition procedure. This method deals with discrete-time signals.

Short Time Fourier Transform (STFT)

STFT is an amazing broadly useful apparatus for signal processing utilized for characterizing a helpful class of time-frequency distributions. The STFT adds a period measurement to the base function parameters by duplicating the infinitely long complex exponential with a window to restrict it. The base function is

$$STFTx(t)(\tau, \omega) \equiv X(\tau, \omega) = \int_a^b x(t)\omega(t, \tau)e^{-j\omega t} dt \quad (4.4)$$

where $w(t)$ is the window function, commonly a Hann window or Gaussian window centered around zero, and $x(t)$ is the signal to be transformed.

It gives time and frequency data. The genuine exchange among time and frequency is dictated by the decision of the window function. The after effect of this change can likewise be viewed as a channel bank with bandpass filters channels that have the Fourier transform as the window $w(t)$ as frequency reaction, yet moved to the middle frequency . Every one of the channels in this manner have the equivalent bandwidth[7].The squared size of the STFT is known as the spectrogram.

4.2 Classification

There are a several machine learning algorithms have been proposed. Among of them, SVM is the most effective classifiers for perceiving EEG signals due to handle non-stationary EEG signals [16][51][19][34]. The essential view of the SVM is to decide a choice hyperplane with the end goal to order information tests into two cases. The ideal hyperplane for separating two gatherings is controlled by expanding the separations between closest information purpose of both the classes and the hyperplane .

For our proposed methods, the seizure and non-seizure EEG signals extracted from Bonn University dataset and then SVM classifier is used to classify them using linear and RBF kernels. In the experiment, 80% of the training set is randomly selected and the remaining 20% is used for testing. 90% of the training set is established in the learning phase and the remaining 10% of the training set is used to check whether the model fitted well. When the data set is well-trained, classification is performed on the unseen testing set. After testing, the performance is evaluated by computing sensitivity, specificity and accuracy.

In this chapter, the decommission techniques have been pros posed based on STFT and PWD and then SVM has applied for classification of seizure and non-seizure EEG signals. Next chapter will explain the experimental results.

Chapter 5

Experimental Result and Discussion

Two feature extraction techniques based on STFT and PWD have been proposed to extract features. Our ultimate target is to classify seizure and non-seizure EEG signals. Therefore, these features are passed into SVM classifier to classify them and finally detect whether it is seizure or not.

Sensitivity, specificity and accuracy are statistical measures the performance of a binary classification result. Performance measurement criteria such as accuracy, sensitivity, and specificity are used to verify the classification outcome of seizure and non-seizure EEG signals. Accuracy is determined as an overall performance measurement where sensitivity measures the proportion of positives i.e., seizure and specificity measures the proportion of negatives i.e., non-seizure.

The sensitivity, specificity and accuracy are defined as

$$Sensitivity = (TP / (TP + FN)) * 100 \quad (5.1)$$

$$Specificity = (TN / (TN + FP)) * 100 \quad (5.2)$$

$$Accuracy = ((TP + TN) / (TP + TN + FP + FN)) * 100 \quad (5.3)$$

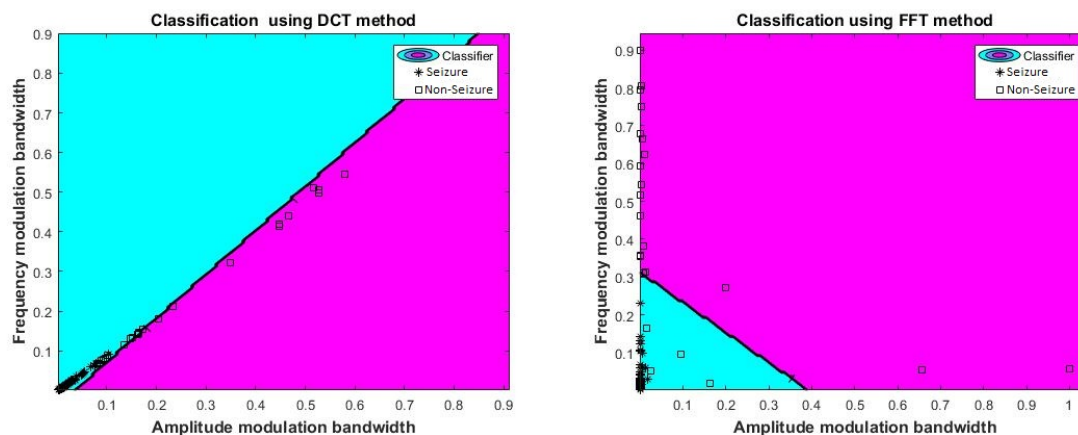
where TP and TF represent the total number of detected true positive and true negative events. FP and FN represent false positive and false negative events.

Two methods, STFT and PWD, have been proposed based on time-frequency analysis to extract features for classification of seizure and non-seizure EEG signals. Besides, we have applied another two well-established method such as discrete cosine transform (DCT) and fast Fourier transform (FFT) to justify our results (see in Table 5.1, Figure 5.1 and 5.2).

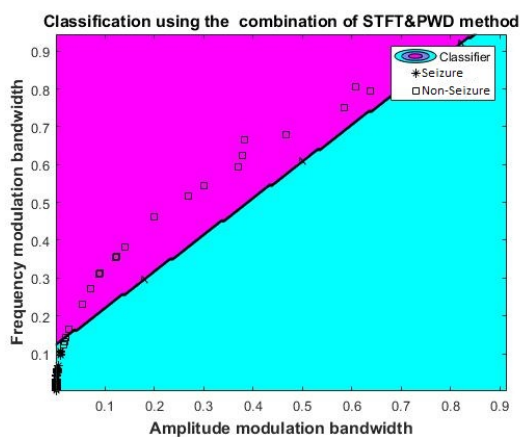
Table 5.1 Sensitivity, specificity, accuracy for different features of seizure and non-seizure EEG signals.

Classifier	Criteria	Proposed System	DCT	FFT
Linear and RBF	SEN	65.00	54.00	44.00
	SPE	99.25	98.00	98.25
Kernel	ACC	92.40	89.20	87.40

For the STFT and PWD based energy, we get 65.00% sensitivity 99.25% specificity, and 92.40% accuracy using Linear and RBF kernel from the Bonn University[53] (see Table 5.1). Besides we have justify our result using another two well-defined methods based on DCT and FFT. Sensitivity, specificity and accuracy based on DCT are 54.00%, 98.00%, and 89.20% respectively. On the other hand FFT based energy, we get 44.00% sensitivity 98.25% specificity, and 87.40% accuracy.



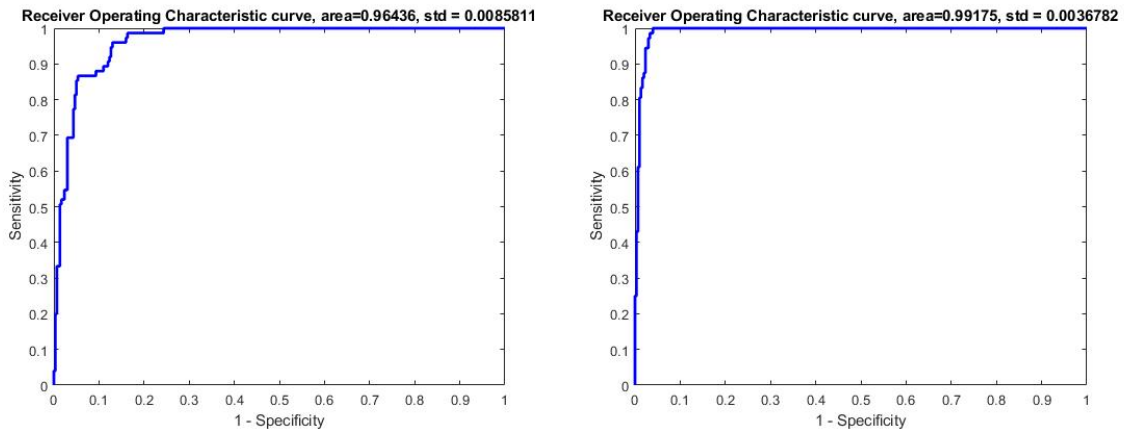
(a) Classification of seizure and non-seizure EEG signals using DCT. (b) Classification of seizure and non-seizure EEG signals using FFT.



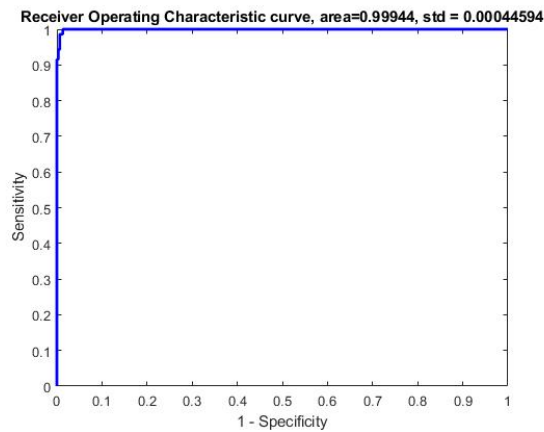
(c) Classification of seizure and non-seizure EEG signals using STFT and PWD.

Fig. 5.1 Classification results of the models.

Figure 5.1 shows the classification results of the models. The classification curve includes the frequency against amplitude at various threshold settings.



(a) ROC curve of Classification using DCT. (b) ROC curve of Classification using using FFT.



(c) ROC curve of Classification using proposed system.

Fig. 5.2 ROC curve of classifications of the models.

A receiver operating characteristic curve (i.e., ROC curve), is a kind of plot and by using it we can illustrate the diagnostic ability of a binary classifier system as its discrimination threshold is varied. The ROC curve includes the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. The true-positive rate is also known as sensitivity and shows probability of detection in machine learning. We have determined the ROC curve based on our proposed method with DCT and FFT based method (see Fig. 5.2). Result demonstrated from Fig. 5.2 that our proposed method is best fitting compared to other two methods.

In this chapter the effective epileptic seizure detection methods are proposed which exploits time-frequency EEG signals. The proposed method outperforms existing state-of-the-art methods considering the sensitivity, specificity and accuracy.

Chapter 6

Conclusion

Lately, identifying epileptic seizure has become a subject of great demand in the field of research and attracted the attention of researchers since it is a commonly happening phenomenon. Human brain is center of anything that involves movements, activities, thinking, awareness and controlling . It is made of signal waves of various frequencies that have power over our activity and conduct. Changes in this signs prompts numerous irregular conditions and epileptic seizure is one of them. Experts utilize electroencephalogram (EEG) to capture the signals and their frequencies in our brain. EEG records the motions and frequency areas from the surface of our brain using the ionic current exhibited in the neurons of brain. EEG component has filled an extraordinary need in locating epileptic seizure. Epileptic seizure is characterized as sudden irregular shaking, vibrating or comparable strange activity and behaviours which goes on for a couple of minutes. This can be risky on the off chance when anybody is in the middle of a certain work. Experiencing this phenomenon frequently should be a matter concern. In this manner, there have been studies and researches regarding this matter up until this point and people are so mindful about this. In our research, we used the dataset gathered from Bonn University where healthy and seizure affected signals are available. The initial step of our examination required the example dataset to be compressed by transferring the information time-frequency area by applying STFT and PWD to extract the energy features that are significant for recognizing the seizure. To the best of our insight, utilizing PWD for extraction has never been attempted. After that, the extracted features were scaled given into the SVM classifier for epileptic seizure recognition. In the way of our methodology, we accomplished 92.40% accuracy in experiment. In future, we will apply signal pre-processing before feature extraction as we have not applied it in this thesis that could have increases the accuracy of our work. We also plan to work with other time-frequency domains together along with diverse classifiers to achieve more efficiency which

can be adopted by medical institutions. We may utilize our concept to research on some other similar brain disorder as well.

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