Effective Electrodes Position and Features Selection for EEG Based Epilepsy Detection

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This thesis report is submitted to the Department of Electrical and Electronic Engineering, Khulna University of Engineering & Technology (KUET), Khulna, for the partial fulfillment of the requirement for the degree of Master of Science in Electrical and Electronic Engineering

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DECLARATION

This is to certify that the thesis work having title "**Effective Electrodes Position and Features Selection for EEG Based Epilepsy Detection**" has been supervised by Prof. Dr. Mohiuddin Ahmad, Professor, Department of Electrical and Electronic Engineering (EEE), Khulna University of Engineering & Technology (KUET), Khulna-9203, and Bangladesh. As far I know, my thesis work or any part of this work has not been submitted anywhere for the reward of any graduation.

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APPROVAL

This is to certify that the thesis work submitted by Md. Kamrul Hasan Roll No: 1503551 entitled "Effective Electrodes Position and Features Selection for EEG Based Epilepsy Detection" has been approved by the board of examiners for the partial fulfillment of the requirements for the degree of M. Sc. Engineering in the Department of Electrical and Electronic Engineering (EEE), Khulna University of Engineering & Technology (KUET), Khulna-9203, Bangladesh in August 2017.

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TO

MY BELOVED PARENTS AND BROTHER

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August, 2017 Md. Kamrul Hasan

Abstract

Electroencephalogram (EEG) signal is a representative signal that contains information about the brain activity, which is the key identifier and used for the detection of epilepsy since epileptic seizures are caused by a disturbance in the electrophysiological activity of the brain. The prediction of epileptic seizure from the EEG signal usually requires a detailed and experienced analysis of EEG data as well as proper collections of epileptic EEG signal from the effective positions of the scalp. In this thesis, we have introduced a statistical analysis of EEG signal with the optimized electrodes and features that are capable of recognizing epileptic seizure with a high degree of accuracy (96.1 %) and helps to provide automatic detection of epileptic seizure for different ages of epileptic persons. To accomplish the target research, we extract various epileptic features namely Approximate Entropy (ApEn), Kolmogorov–Sinai Entropy (KSE), Spectral Entropy (SE), Standard Deviation (SD), Standard Error (SE), Modified Mean Absolute Value (MMAV), Roll-off (R), and Zero Crossing (ZC) from the epileptic EEG signal. The k-nearest neighbor (k-NN) algorithm is used for the classification of epilepsy then regression analysis is used for the prediction of the epilepsy level at different ages of the patients. Using the statistical parameters and regression analysis, a prototype mathematical model is proposed which helps to find the epileptic randomness with respect to age of different subjects. The accuracy of this prototype equation depends on proper analysis of the dynamic information from the epileptic EEG signal.

Table of Contents

List of Tables

List of Figures

Abbreviations

Acronym	Description of Symbol or Acronym
ApEn	Approximate entropy
ANC	Adaptive noise cancellation
ANN	Artificial neural network
ANFIS	Artificial neural network
BOLD	Blood-oxygen-level dependent
BCI	Brain–computer interface
CSP	Common spatial patterns
CT	Computed tomography
DPSO	Discrete particle swarm optimization
DSLVQ	Distinction Sensitive Learning Vector Quantizer
ERP	Event-related potential
EEG	Electroencephalogram
EOG	Electrooculography
ECG	Electrocardiography
EMG	Electromyography
fMRI	Functional magnetic resonance imaging
FSA	Fast Simulated Annealing
GABA	Gamma-Amino Butyric acid
HEOG	Horizontal Electrooculography
ILAE	International League Against Epilepsy

ICA	Independent component analysis
kNN	k-nearest neighbors algorithm
KSE	Kolmogorov–Sinai Entropy
LORETA	Low-Resolution Brain Electromagnetic Tomography
LARS	Least-angle regression
LDA	Linear Discriminant Analysis
MATLAB	Matrix laboratory
MEG	Magnetoencephalography
MMAV	Modified Mean Absolute Value
MAV	Mean Absolute Value
MRI	Magnetic resonance imaging
NB	Naive Bayes
NN	Nearest Neighbor
PET	Positron emission tomography
PSD	Power spectral density
PNES	Psychogenic nonepileptic seizures
PDF	Probability density function
R	Roll off
RN	Random Neighbor
RBFNN	Radial basis function Neural Network
SD	Standard deviation
SE	Spectral Entropy
SN	Smallest Neighbor
SVM	Support vector machine
STFT	Short-time Fourier transform (STFT)
VEOG	Vertical Electrooculography
WL	Wilks' lambda
WPD	Wavelet Packet Decomposition
ZC	Zero crossing

Chapter 1

Introductions

Chapter Outlines

1.1 History of Seizures and Epilepsy

1.2 Definitions and causes of Epilepsy

1.3 Classifications of Seizures and Epilepsy

1.4 Evaluations and diagnosis of Seizures and Epilepsy

1.5 Significance of diagnosis and treatment of Epilepsy

1.6 Objectives of the thesis

1.7 Structure of this thesis

Epilepsy can be considered as a spectrum syndrome due to its numerous causes, a variety of seizures type, its ability to vary in severity, impact from person to person, and its range of co-existing conditions.

1.1 History of Seizures and Epilepsy

About 2.3 million adults and more than 4,50,000 children and teenagers in all over the world currently live with epilepsy. Each year, an estimated 1,50,000 people are diagnosed and they have found affected with epilepsy. Epilepsy affects both males and females of all races, ethnic backgrounds, and ages. The majority of those diagnosed with epilepsy have seizures that can be controlled with drug therapies and surgery. However, as much as 30 to 40 out of 100 people with epilepsy continue to have seizures because available treatments do not completely control their seizures [1]. The oldest medical records show that epilepsy has been affecting people at least since the beginning of recorded history. Throughout ancient history, the disease was thought to be a spiritual condition [2]. The world's oldest description of an epileptic seizure comes from a text in Akkadian and was written around 2000 BC. The person described in the text was diagnosed as being under the influence of a Moon god and underwent an exorcism. Epileptic seizures are listed in the Code of Hammurabi as a reason for which a purchased slave may be returned for a refund, and the Edwin Smith Papyrus describes cases of individuals with epileptic convulsions [3].

1.2 Definitions and causes of Epilepsy

Epilepsy is a group of neurological disorders characterized by epileptic seizures that are episodes that can vary from brief and nearly undetectable to long periods of vigorous shaking.

These episodes can result in physical injuries including occasionally broken bones and like others. In the case of epilepsy of the epileptic persons, seizures tend to recur and as a rule of thumb, have no instantaneous fundamental causes. Isolated seizures that are provoked by a specific cause such as poisoning are not thought to represent epilepsy. Peoples having epilepsy in some areas of the world involvement with stigma due to the abnormal condition [4]- [6].

The cause of most cases of epilepsy is unknown and in some cases occur as the result of brain injury, stroke, brain tumors, infections of the brain, and birth defects, through a process known as epileptic Genesis. Recognized genetic mutations are unswervingly linked to a small proportion of cases. Epileptic seizures are the result of extreme and irregular nerve cell activity in the cortex of the brain. The diagnosis involves ruling out other conditions that might cause similar symptoms such as fainting and determining if another cause of seizures is present such as alcohol withdrawal or electrolyte problems. This may be partly done by imaging the brain and performing blood tests. Epilepsy can often be confirmed with an Electroencephalogram (EEG), but a normal test does not rule out the conditions. Epilepsy that occurs as a result of other issues may be preventable and are controllable with medication in about 70 out of 100 of cases. Inexpensive options are often available whose seizures do not respond to medication, then surgery, neuro-stimulation, or dietary changes may be considered. Not all cases of epilepsy are lifelong, and many people progress to the point that dealing is no longer desirable [7]- [10].

Epilepsy can have both genetic and acquired causes, with the interaction of these factors in many cases. Established acquired causes include serious brain trauma, stroke, tumors and problems in the brain as a result of a previous infection. In about 60 out of 100 of cases, the cause is unknown. Epilepsies caused by genetic inherited, or growing conditions are more

collective among younger people, while brain tumors and strokes are more likely in older people [11]- [13]. Seizures may also occur as a consequence of other health problems; if they occur right around a specific cause, such as a stroke, head injury, toxic ingestion or metabolic problem, they are known as acute symptomatic seizures and are in the broader classification of seizure-related disorders rather than epilepsy itself [14].

Genetics is believed to be involved in the majority of cases, either directly or indirectly. Some epilepsies are due to a single gene defect about 1-2 out of 100; most are due to the interaction of multiple genes and environmental factors. Each of the single gene defects is rare, with more than 200 in all described. Most genes involved affect ion channels, either directly or indirectly. These include genes for ion channels themselves, enzymes, GABA, and G protein-coupled receptors. In identical twins, if one is affected there is a 50–60% chance that the other will also be affected. In non-identical twins, the risk is 15%. These risks are greater in those with generalized rather than focal seizures. If both twins are exaggerated, most of the time they have the same epileptic condition (70–90%). Other close relatives of a person with epilepsy have a risk five times that of the general population. Between 1 and 10% of those with Down syndrome and 90% of those with Angelman syndrome have epilepsy [15]- [17].

Epilepsy may occur as a result of a number of other conditions including tumors, strokes, head trauma, previous infections of the central nervous system, genetic abnormalities, and as a result of brain damage around the time of birth. Of those with brain tumors, almost 30% have epilepsy, making them the cause of about 4% of cases. The risk is greatest for tumors in the temporal lobe and those that grow slowly. Other mass lesions such as cerebral cavernous malformations and arteriovenous malformations have risks as high as 40–60% [18], [19]. The risk of epilepsy following meningitis is less than 10%; that disease more commonly causes

seizures during the infection itself. In herpes simplex encephalitis the risk of a seizure is around 50% with a high risk of epilepsy following (up to 25%).

1.3 Classifications of Seizures and Epilepsy

The exact apparatus of epilepsy is unknown, but a little is known about its cellular and network mechanisms. However, it is unknown under which circumstances the brain shifts into the activity of a seizure with its excessive synchronization. In epilepsy, the resistance of excitatory neurons to fire during this period is decreased. This may occur due to changes in ion channels or inhibitory neurons not functioning properly. This then results in a specific area from which seizures may develop, known as a "seizure focus". Another mechanism of epilepsy may be the up-regulation of excitatory circuits or down-regulation of inhibitory circuits following an injury to the brain. These secondary epilepsies occur through processes known as epileptogenesis. Failure of the blood–brain barrier may also be a causal mechanism as it would allow substances in the blood to enter the brain [20]- [22].

There is evidence that epileptic seizures are usually not a random event. Seizures are often brought on by factors such as stress, alcohol abuse, flickering light, or a lack of sleep, among others. The term seizure threshold is used to indicate the amount of stimulus necessary to bring about a seizure. Seizure threshold is lowered in epilepsy. In epileptic seizures, a group of neurons begins firing in an abnormal, excessive, and synchronized manner. This results in a wave of depolarization known as a paroxysmal depolarizing shift. Normally, after an excitatory neuron fire, it becomes more resistant to fire for a period of time. This is due in part to the effect of inhibitory neurons, electrical changes within the excitatory neuron, and the negative effects of adenosine. Focal seizures begin in one hemisphere of the brain while generalized

seizures begin in both hemispheres. Some types of seizures may change brain structure, while others appear to have little effect. Gliosis, neuronal loss, and atrophy of specific areas of the brain are linked to epilepsy but it is unclear if epilepsy causes these changes or if these changes result in epilepsy [23]- [25].

1.4 Evaluations and diagnosis of Seizures and Epilepsy

Diagnosis of epilepsy can be difficult. A number of other conditions may present very similar signs and symptoms to seizures, including syncope, hyperventilation, migraines, narcolepsy, panic attacks, and psychogenic non-epileptic seizures (PNES). In particular, a syncope can be accompanied by a short episode of convulsions. Nocturnal frontal lobe epilepsy, often misdiagnosed as nightmares, was considered to be a parasomnia but later identified to be an epilepsy syndrome. Attacks of the movement disorder paroxysmal dyskinesia may be taken for epileptic seizures. The cause of a drop attack can be, among many others, an atonic seizure [26]. Children may have behaviors that are easily mistaken for epileptic seizures but are not. These include breath-holding spells, bed wetting, night terrors, tics and shudder attacks. Gastroesophageal reflux may cause arching of the back and twisting of the head to the side in infants, which may be mistaken for tonic-clonic seizures [27]- [29].

Misdiagnosis is frequent (occurring in about 5 to 30% of cases). Different studies showed that in many cases seizure-like attacks in apparent treatment-resistant epilepsy have a cardiovascular cause. Approximately 20% of the people seen at epilepsy clinics have PNES and of those who have PNES about 10% also have epilepsy; separating the two based on the seizure episode alone without further testing is often difficult [30]. The diagnosis of epilepsy is typically made based on observation of the seizure onset and the underlying cause. An

electroencephalogram (EEG) to look for abnormal patterns of brain waves and neuroimaging (CT scan or MRI) to look at the structure of the brain are also usually part of the workup. While figuring out a specific epileptic syndrome is often attempted, it is not always possible. Video and EEG monitoring may be useful in difficult cases [30]- [32]. Epilepsy is a disorder of the brain defined by any of the following conditions:

i. At least two unprovoked (or reflex) seizures occurring greater than 24 hours apart
ii. One unprovoked (or reflex) seizure and a probability of further seizures similar to the general recurrence risk (at least 60%) after two unprovoked seizures, occurring over the next 10 years
iii. Diagnosis of an epilepsy syndrome

Furthermore, epilepsy is considered to be resolved for individuals who had an age-dependent epilepsy syndrome but are now past that age or those who have remained seizure-free for the last 10 years, with no seizure medicines for the last 5 years. This 2014 definition of the International League Against Epilepsy is a clarification of the ILAE 2005 conceptual definition, according to which epilepsy is "a disorder of the brain characterized by an enduring predisposition to generate epileptic seizures and by the neurobiological, cognitive, psychological, and social consequences of this condition. The definition of epilepsy requires the occurrence of at least one epileptic seizure." It is, therefore, possible to outgrow epilepsy or to undergo treatment that causes epilepsy to be resolved, but with no guarantee that it will not return. In the definition, epilepsy is now called a disease, rather than a disorder. This was a decision of the executive committee of the ILAE, taken because of the word "disorder," while perhaps having less stigma than does "disease," also does not express the degree of seriousness that epilepsy deserves. The definition is practical in nature and is designed for clinical use. In

particular, it aims to clarify when an "enduring predisposition" according to the 2005 conceptual definition is present. Researchers, statistically-minded epidemiologists, and other specialized groups may choose to use the older definition or a definition of their own devising. The ILAE considers doing so is perfectly allowable, so long as it is clear what definition is being used [33]- [36].

1.5 Significance of diagnosis and treatment of Epilepsy

The most significant advance in modern epileptology has been the recognition of epileptic syndromes and diseases, which provides a proper medical diagnosis for patients with epileptic disorders. The inclusive term ‘epilepsy’ is unacceptable because such generalization defines diagnostic precision, which is the golden rule in medicine. The goal of treatment in patients with epileptic seizures is to achieve a seizure-free status without adverse effects. This goal is accomplished in more than 60% of patients who require treatment with anticonvulsants. Many patients experience adverse effects from these drugs, however, and some patients have seizures that are refractory to medical therapy. Monotherapy is desirable because it decreases the likelihood of adverse effects and avoids drug interactions. In addition, monotherapy may be less expensive than poly therapy, as many of the older anticonvulsant agents have hepatic enzyme–inducing properties that decrease the serum level of the concomitant drug, thereby increasing the required dose of the concomitant drug. People with seizures experience psychosocial adjustments after their diagnosis; therefore, social and/or vocational rehabilitation may be needed. Many physicians underestimate the consequences that an epilepsy diagnosis may have on patients. For example, patients with epilepsy may live in fear of experiencing the next seizure, and they may be unable to drive or work at heights. Refer patients with intractable

spells to a neurologist or an epileptologist for further workup, including video-electroencephalographic (EEG) monitoring, to characterize the etiology of their seizures. A neurosurgical consult is recommended when the possibility of surgical management is considered [37]. Abnormalities on an EEG may include any of the following:

i. Epileptiform discharges
ii. Focal slowing
iii. Diffuse background slowing
iv. Intermittent diffuse intermixed slowing

Epileptiform abnormalities and focal slowing are the EEG findings associated with the highest risk of seizure recurrence. Nevertheless, even a normal EEG does not eliminate recurrence risk. The risk of recurrence in a person with 1 generalized tonic-clonic seizure, a normal EEG, a normal brain MRI, and no evidence of focal onset is about 15%; in this case, the patient is not treated. If a patient has all risk factors, the risk is approximately 80%, and the patient is treated. The major unresolved question is how to treat patients with 1 abnormality, whose recurrence risk is 30-50%. One approach is to base the decision on a discussion with the patient that includes the risk of seizure recurrence, the risk of toxic effects from the anticonvulsant, and the benefits of avoiding another seizure. The clinician should also describe seizure precautions, including not driving for a specific time. Treatment with anticonvulsants does not alter the natural history of seizure recurrence; it only reduces the risk for the duration of treatment. The First Seizure Trial Group randomly selected 397 patients with an unprovoked, generalized tonic-clonic first seizure to either receive prophylaxis with a conventional anticonvulsant (i.e., carbamazepine, phenobarbital, phenytoin, valproic acid) or to receive no treatment and reported that about 18% of treated patients had seizure recurrence within 1 year,

compared with 39% of untreated patients. Therefore, patients must be told that anticonvulsants can reduce their risk of having another seizure but will not eliminate that risk [38]- [40].

1.6 Objectives of the thesis

The purpose of this research is to extract EEG signal from effective positions of the scalp and process them to extract optimal features for epilepsy detection. The objectives of the proposed thesis work are mentioned below:

- To select the proper position of the reference and active electrodes by solving inverse method using LORETA to extract the EEG signal. So that, reference position does not impact the degradation of EEG signal of interest.
- To extract the optimal features of EEG signal using Wrapper algorithm that will be used for detecting epilepsy with a higher degree of accuracy.
- To classify the feature vectors that are used for training classifier for detecting epilepsy.
- To formulate the mathematical model using the regression model for the predictions of the presence of epilepsy.

1.7 Structure of this report

The work presented in this thesis is organized in five chapters. These five chapters are structured as follows:

Chapter 1 is entitled **"Introductions"**. This chapter describes the history, definition, causes, classifications, and diagnosis of epileptic of EEG signal as well as the significance of

diagnosis and treatment of Epilepsy. Also, objectives and structures of this thesis are mentioned in this chapter.

Chapter 2 is entitled **"Related works and contributions"**. It introduces related previous researches on electrodes, features selections and epilepsy classifications with their criticisms, proposed work with contributions the thesis.

Chapter 3 is entitled **"Proposed Methodology".** It introduces methodology analysis, preprocessing, processing, noise cancellation, and optimized features selections as well as features extraction and classification (both online and offline) for the epileptic EEG data.

Chapter 4 is entitled **"Results and Discussions"**. All results are summarized here. This chapter is the achievement of the vision.

Chapter 5 is entitled **"Conclusions and Future Work"**. Appropriate conclusion is drawn in this chapter. Future objectives also mentioned in this chapter.

Chapter 2

Related works and Contributions

Chapter Outlines

2.1 Previous works related to electrode positions, features selections and Epilepsy classifications

2.2 Contributions in this thesis

2.1 PREVIOUS WORKS RELATED TO ELECTRODE POSITIONS, FEATURES SELECTIONS, AND EPILEPSY CLASSIFICATIONS

Over the last three decades, a huge variety of approaches pointed at solving the EEG inverse problem for the localization of the sources of brain electrophysiological activity that have been suggested [41], [42]. In the meantime, methods dedicated to the characterization of functional [43] and effective [44] connectivity from EEG signals have substantially established. Clarification of connectivity measures from sensor level recordings is not straightforward, as these recordings suffer from a low spatial resolution and are severely ruined by effects of field spread [45]. To overcome these limitations, several efforts to apply connectivity methods on the temporal dynamics of brain sources reconstructed from scalp EEG signals have been testified [46]. However, it raises a number of methodological issues. Firstly, it requires solving the ill-posed EEG inverse problem. Secondly, a functional connectivity method must be chosen among the many existing ones. Thirdly, volume conduction effects can never be totally eradicated in source space. Subsequently, the central question raised here is related to the choice of the best grouping of methods which is likely to reveal the actual networks that activate during the considered brain progression. In addition, in both steps of the signal processing procedure, some key parameters are also expected to impact the results such as the threshold practical to the adjacency matrices or the considered delay between the time courses of reconstructed sources, among others. In this thesis, quantitative comparison of methods aimed at identifying brain networks from scalp EEG data. We focus on functional connectivity estimated from evoked responses [47]. The novelty of the thesis is threefold: first, the evaluation methodology is based on a well-controlled mental task for which a solid contextual

is available regarding the topology of activated networks that are therefore used as a ground truth. Second, scalp recordings were performed using a high-resolution EEG (Hd-EEG) system characterized by an excellent temporal resolution and by an improved spatial resolution. Third, the comparison consisted of a "two-dimensional" analysis allowing for quantifying the joint effect of the inverse and connectivity methods. Our evaluation methodology involves three main aspects- i) The inverse algorithm used to estimate the cortical sources and reconstruct their temporal dynamics, ii) The connectivity method used to assess statistically significant functional relationships between the temporal dynamics of sources and iii) The cognitive task performed by the subject, which is supposed to activate relatively well-defined brain networks [48].

To select the best features wavelet transform is particularly effective for representing various aspects of non-stationary signals such as trends, discontinuities, and repeated patterns where other signal processing approaches fail or are not as effective [49]. Through wavelet decomposition of the EEG records, transient features can be captured and localized in both time and frequency context [50]. The capability of this mathematical microscope to analyze different scales of neural rhythms is a powerful tool for investigating small-scale oscillations of the brain signals [51]. An important issue that must be addressed when using wavelet transforms to extract features from EEG signals is the feature selection procedure. That is, how many features should be selected and how should they be selected. This is important because with higher levels of decomposition there is an exponential increase in the sub band combinations. The increase in the number of wavelet features can lead to the curse of dimensionality which states that the amount of data required in predicting the classes, using an

induction algorithm, increases with the number of features [52]. It is also found that the time requirements for the induction algorithm can grow exponentially as the number of features increases [53]. To avoid the curse of dimensionality it is important to select the relevant features and reject the correlated or irrelevant features using feature selection methods. Feature selection involves the derivation of optimal features from the raw input data in order to reduce the amount of data used for classification and simultaneously provide enhanced discriminatory power to the classifier. Feature selection approaches can be categorized into two approaches, namely, filter approach and the wrapper approach [54]. In this thesis, our concern is wrapper approach for best features selections.

The first ILAE Epilepsy classification provided a standard system that eventually was accepted worldwide [55]. A major dichotomy between generalized and focal ("partial") epilepsies, based on clinical characteristics of each seizure type linked with EEG features, anatomical substrate, etiology, and age of manifestation, was established [56]. The first revision, in 1985, led to the listing of multiple syndromes defined primarily as a cluster of semiological seizure types, EEG patterns etiologies, age at onset, and seizure frequency [57]. The dichotomy of localization-related versus generalized epilepsies was complemented by a second etiological dichotomy (idiopathic and symptomatic). Four years later, the expression "cryptogenic" was introduced to classify epilepsies that were presumed to be symptomatic, but without definite proof [58].

2.2 CONTRIBUTIONS IN THIS THESIS

In this thesis, first of all the proper position of the electrodes have been selected by solving inverse method using LORETA to extract the EEG signal from the epileptic patients. So that, reference position does not impact the degradation of EEG signal of interest. Secondly, the optimal features which are capable of classifying abnormal and normal EEG signal using Wrapper algorithm have been chosen that will be used for detecting epilepsy with a higher degree of accuracy. After selecting the best electrode positions and features epileptic EEG signal has been classified using k-NN classifier. Finally, mathematical modeling for the prediction of epilepsy has been established. This proposed system provides an approach for automatic online and offline classifications of epileptic EEG signal that will classify EEG signal for normal and abnormal EEG signal.

Chapter 3

Proposed Methodology

Chapter Outlines

The goal of treatment in patients with epileptic seizures is to achieve a seizure-free status of the epileptic patients without adverse effects of them. This goal is proficient in more than 60% of patients who require treatment with anticonvulsants. Many patients experience adverse effects from these drugs, however, and some patients have seizures that are refractory to medical therapy.

3.1 PROPOSED METHODOLOGY

In our proposed thesis work, the proper position of the electrode in the scalp, optimal features have been selected, and finally, the epilepsy condition has been detected using k-NN classifier. For performing the proposed thesis work, the mentioned steps were followed. The proposed flow diagram is shown in Figure 3. 1.

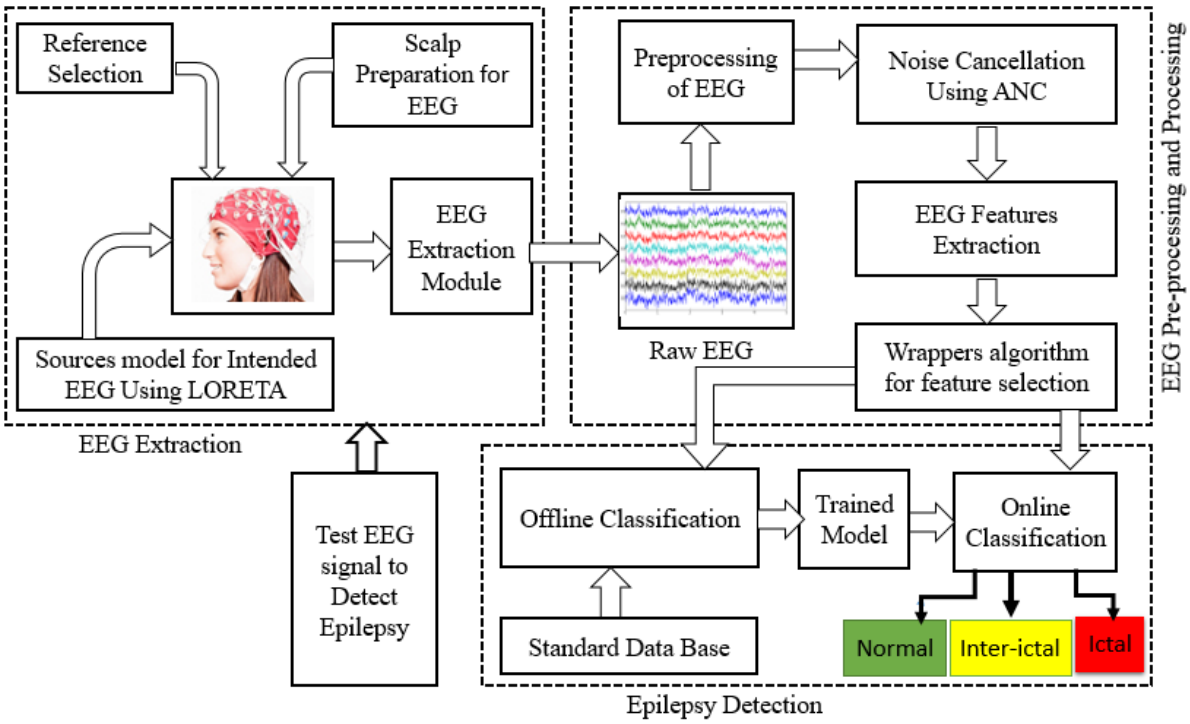


Figure 3.1 Block diagram of the proposed system for epilepsy detection

Step 1: For extracting EEG signal, reference electrode positions should be selected using dynamic selection method. In this regard, all the electrodes were looked upon as active electrodes and while an electrode can result in the maximum sum relative-power of a specific frequency. This particular electrode can be confirmed dynamically as the optimum reference electrode. The proper position of the electrode provides a faithful signal of interest.

Step 2: To identify the effective active electrode, LORETA has been used which is a Laplacian weighted minimum norm algorithm and depends on the existing neuro-anatomical and physiological knowledge with a mathematical constraint. LORETA model is based on the reconstruction of the electrophysiological activity onto all of the points of a 3D grid where every point activity is reformed and considered to be a potential source localization. The smoothest spatial distribution was selected by minimizing the Laplacian of weighted current sources.

Step 3: After selecting reference and the active electrode, preprocessing has been done on raw EEG to prepare it for another processing technique. Adaptive Noise Cancellation (ANC) has been used to eliminate various noise (EOG, EMG, ECG, and Line noise) on EEG due to extraction. The adaptive filter was used due to its capability of adjusting impulse response to minimize an error signal and depend on the filter output. EEG signals are often mixed with artifacts which include EMG, EOG, ECG, and electrical line noise and other external and internal noises. These artifacts are being added in the EEG signal by unknown bodily dynamics, which has a nonlinear property. In our research, these noise reduction is accomplished using adaptive noise cancellation (ANC) based on ANFIS as shown in Figure 3.2. In this system, ANFIS was used to estimate the nonlinear bodily dynamics. The noise was then estimated

using the estimated function by ANFIS taking close to pure EMG, EOG signals and line noise as input. This signal was subtracted from the artifact affected signal to filter it from noise.

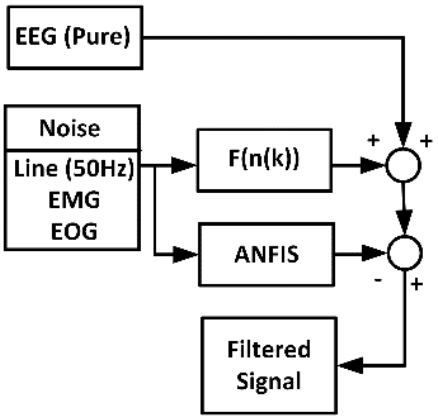


Figure 3.2 Raw EEG Filtering and noise cancellation using ANC implemented in ANFIS

Step 4: Entropy based features e.g. Approximate Entropy (ApEn), Kolmogorov–Sinai Entropy (KSE), Spectral Entropy (SE), Standard Deviation (SD), Standard Error (SE), Modified Mean Absolute Value (MMAV), Roll-off (R), and Zero Crossing (ZC) were extracted as shown in Figure 3.3 and used for optimization using Wrappers algorithm. In Wrapper method, different combinations of the features were prepared, evaluated and compared to other combinations. **Step 5:** A predictive model has been used to evaluate a combination of features and assign a score based on model accuracy and searching was continued until best-first will results. Also, LARS model was used for the feature ranking. Using the selected best feature and standard data base of EEG, trained model was prepared called offline classifications. This model will predict epilepsy either normal or inter-ictal or ictal from the test data sets taking same features used in offline classifications. Finally,

proposed system was compared with other existing system for automatic epilepsy detection. Proposed flow diagram of the research work is shown in Figure 3.4.

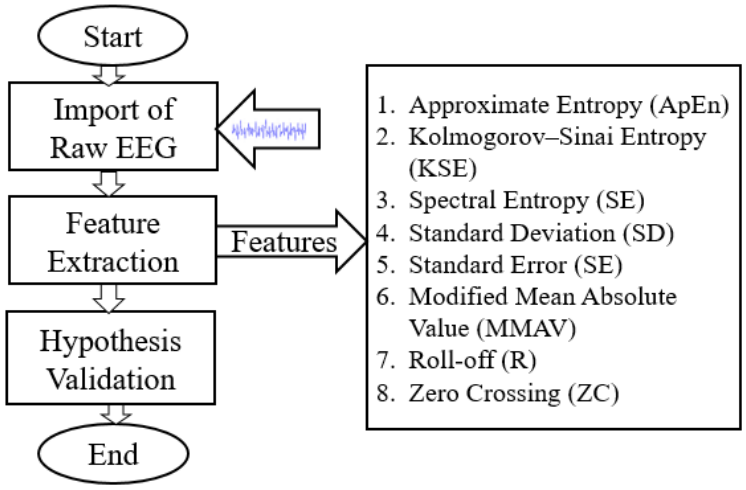


Figure 3.3 Representations of features extraction for hypothesis validation

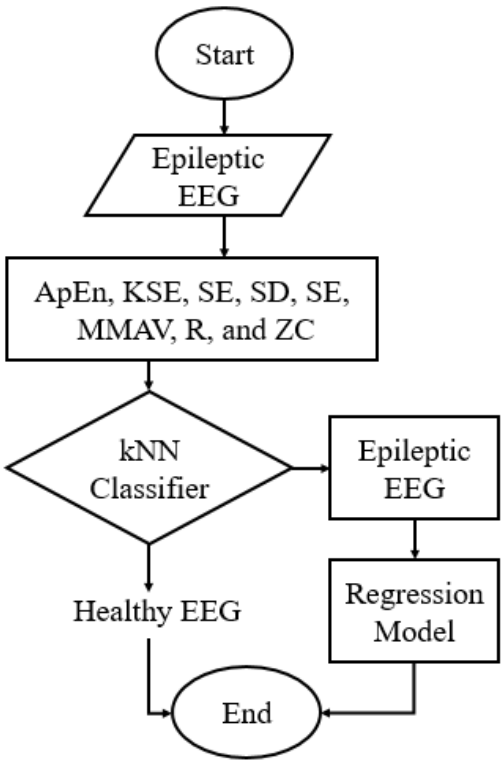


Figure 3.4 Proposed flow diagram of the thesis work

3.2 EPILEPTIC EEG EXTRACTIONS

With the discovery of the electroencephalogram (EEG) in 1924, Hans Berger revealed that one could measure the electrical activity of the human brain by placing electrodes on the scalp and amplifying the signal. The EEG proved to be a useful source in recording brain activity over the ensuing decades. However, it tended to be very difficult to assess the highly specific neural process that is the focus of cognitive neuroscience because using pure EEG data made it difficult to isolate individual neurocognitive processes. In 1964, research by Grey Walter and colleagues began the modern era of ERP component discoveries when they reported the first cognitive ERP component, called the contingent negative variation (CNV). Sutton, Braren, and Zubin (1965) made another advancement with the discovery of the P3 component. Over the next fifteen years, ERP component research became increasingly popular [59], [60]. People with some types of epilepsy have unusual electrical activity in their brain all the time, even when they are not having a seizure. When they have an EEG test, the results can show certain brain wave patterns that doctors recognize. This information is very helpful for doctors when they are making a diagnosis [61]. In a modern decade, various techniques are now available to monitor brain function, e.g., electroencephalography (EEG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), and positron emission tomography (PET) [62]. Among them, EEG provides an excellent temporal resolution and higher precision time measurement, whereas fMRI, PET, and MEG are inherently limited by the slow speed of Blood Oxygenation Level Dependent (BOLD) response. In addition, EEG equipment is relatively inexpensive, simple to operate compared with others. Hence, EEG is the optimal choice for brain diseases detection [63].

3.2.1 Scalp preparation and reference selection

EEG reflects the electrophysiological activity of the brain, which can be recorded directly from the scalp in a noninvasive way using surface electrodes. EEG recording consists of electrodes with conductive media, amplifiers with filters, A/D converter and recording device where electrodes consist of Ag-AgCl disks having 1 to 3 mm in diameter that can be plugged into an amplifier. Time-dependent EEG signal can lose its information due to the wrong position, reference of the electrodes or use of an excessive number of unnecessary electrodes [64], [65]. The ground is used for common mode rejection. The primary purpose of the ground is to prevent power line noise from interfering with the small biopotential signals of interest. By design, amplifiers should not be affected by large changes in potential at both the active and reference sites. A ground electrode for EEG recordings is often placed on the forehead (but could be placed anywhere else on the body; the location of the ground on the subject is generally irrelevant). The reference lead is the lead that connects the reference electrode; in EEG recordings, this electrode is usually placed in the ear or, in the case of "summed ears," to a pair of electrodes, one at each ear. The measured electrical potential differences are ideally the voltage drops from the active electrode (connected to Vin+ on the amplifier) to the reference electrode (connected to Vin- on the amplifier). MEG is reference free but EEG has been using different types of reference for the past few decades. Below are some of the usual EEG reference selections

i. 1 electrode on top of the head
ii. Average between electrodes on the two ears
iii. Average of all connected electrodes (average reference)
iv. Average of two mastoid references

v. Single mastoid (left or right) reference

vi. Nose reference

3.2.2 Source localizations using LORETA

There are two ways to analyze the EEG – (i) the whole cerebral EEG analysis, and (ii) the regional cerebral EEG analysis. In the regional cerebral analysis, the selection of the cerebral region equals to the selection of the electrode on that region of the brain [66]. Now, it is an abundant challenge to select proper electrode positions. Common spatial patterns (CSP) can be used for EEG analysis which is a highly successful algorithm in calculating spatial filters for detecting event-related synchronization and event-related desynchronization effects. So, CSP has been widely used in brain abnormality detection [67], [68]. But, CSP depends on choosing the windows which are time-consuming and may adversely affect the signal qualities. Discrete particle swarm optimization (DPSO) can be used to search the valuable electrode positions [66]. But, DPSO algorithm suffers from the partial optimism, which degrades the regulation of its speed and direction. Statistically, the motivated electrode can select based on Cohen's effect size f2 whose accuracy is only 57.5 % [69]. Also, the electrode can select using Distinction Sensitive Learning Vector Quantizer (DSLVQ). But, for the performance analysis, DSLVQ required model based classifier which is computationally complex [70]. To overcome above limitation, Low-Resolution Electromagnetic Tomography (LORETA) model for the selections of proper electrodes was used in this thesis. LORETA is an inverse method using distributed source models which can derive from the quasi-static approximation of Maxwell equations [71]. LORETA localize the source of EEG with minimal errors using a single inverse matrix. Epilepsy is the fourth most common neurological disorder and affects people of all ages which can be analyzed from EEG signal. In this research work, LORETA has been used to select

effective electrode to extract epileptic EEG in non-invasive approach with a minimum number of channel.

3.3 EPILEPTIC EEG PREPROCESSING AND PROCESSING

When someone has an epileptic seizure their brain activity changes with respect to the time of recording. This change, known as epileptiform brain activity, can sometimes be seen on an EEG recording. Some people can have epileptiform brain activity even when they do not appear to be having a seizure, so an EEG can be particularly useful for them.

3.3.1 Preprocessing and Noise cancellation

In signal processing, a preprocessor is a program that processes its input data to produce output that is used as input to another program. The output is said to be a preprocessed form of the input data. If there is much irrelevant and redundant information present or noisy and unreliable data, then knowledge discovery during the training phase is more difficult. Data preparation and filtering steps can take a considerable amount of processing time. Data pre-processing includes cleaning, Instance selection, normalization, transformation, feature extraction, and selection, etc. The product of data preprocessing is the final training set. In EEG research, the most common type of analysis concerns small voltages that are time-locked to an eliciting event, these small voltage deflections are referred to as Event-Related Potentials (ERPs). Experimental psychologists and neuroscientists have defined a number of ERPs with specified latency (time interval after an event or stimulus), such as the P3 or N400 [72]. ERPs are thought to reflect the processing of stimuli and can be modulated by changes in attention, in expectation, in the recruitment of memory processes or by changes in mental state.

Some ERPs are more robust and easier to elicit than others but all are small compared to the various types of noise and spontaneous EEG that forms part of the EEG signal. Therefore, to deal with this, EEG experiments typically involve the repeated presentation of an eliciting stimulus or event so that the voltage changes in the EEG signal time locked to this event can be averaged together; this averaging has the effect of canceling out unwanted, random noise and revealing the ERPs [73]. While averaging will cancel out a large part of the random noise that is inherent in the EEG signal, it is not sufficient to deal with certain artifacts that contaminate the EEG signal. This can be due either to their large amplitude or to their regularity in time. Such artifacts can be physiological such as eye-blinks, horizontal and vertical ocular movements (HEOG and VEOG, respectively), cardiac rhythm and artifacts related to movement, or they can be environmental such as the line noise (50-60Hz). This means that any reliable analysis and interpretation of ERP effects must be preceded by an initial « pre-processing » stage, in which artifacts are removed. In the following, the various crucial stages of the preprocessing pipeline for ERP analysis will be described in the context of the EEGLAB toolbox, a MATLAB toolbox dedicated to the processing and analysis of EEG data [74]. The following presents an outline of the pre-processing pipeline. For each stage, links are provided to the relevant MATLAB code, which can be used to create one's own pre-processing script as well as to a page in which the pre-processing stage is discussed in greater detail. The pre-processing stages presented are:

- Importing raw data and Re-referencing
- Resampling
- Filtering
- Detection of bad channels

- Detection of high amplitude noise
- Independent Components Analysis (ICA)
- Epoching of the continuous data
- Epoch rejection
- Subject-level Average and Grand Average

3.3.2 EEG features extraction

When the input data to an algorithm is too large to be processed and it is suspected to be redundant (e.g. the same measurement in both feet and meters, or the repetitiveness of images presented as pixels), then it can be transformed into a reduced set of features (also named a feature vector). Determining a subset of the initial features is called feature selection [75]. The selected features are expected to contain the relevant information from the input data so that the desired task can be performed by using this reduced representation instead of the complete initial data. Feature extraction involves reducing the number of resources required to describe a large set of data. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power, also it may cause a classification algorithm to over-fit to training samples and generalize poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy [76]. Mathematical background for statistical features (Approximate Entropy (ApEn), Kolmogorov–Sinai Entropy (KSE), Spectral Entropy (SE), Standard Deviation (SD), Standard Error (SE),

Modified Mean Absolute Value (MMAV), Roll-off (R), and Zero Crossing (ZC)) are described below-

Approximate Entropy (ApEn)

ApEn is a statistical feature that indicates the predictability of the current amplitude values of a physiological signal e.g. EEG based on its earlier amplitude. The value of ApEn drops sharply during an epileptic seizure and this property is used to detect the epileptic seizures. A high value of approximate entropy signifies more irregularity; on the contrary, a low value signifies that the time series is deterministic which reflects the intra-cortical information flow in the brain when applied to EEG signals [77]- [78]. The value of ApEn can be calculated by using Eq. (3.1).

$$\emptyset^m(r) = (N - m + 1)^{-1} \sum_{i=1}^{N-m+1} \log\left(c_i^m(r)\right)$$

$$ApEn = \emptyset^m(r) - \emptyset^{m+1}(r) \qquad (3.1)$$

Mathematical procedures of Approximate Entropy (ApEn) calculation are described below in a flow chart [78], [79] in Figure 3.5.

Kolmogorov–Sinai Entropy (KSE)

The concept of entropy that measures preserving dynamical systems, today is known as Kolmogorov-Sinai-entropy. This entropy turned out to be a strong and far-reaching invariant of dynamical systems. The Kolmogorov-Sinai-entropy provides a rich generalization of Shannon entropy. the Kolmogorov-Sinai entropy measures unpredictability of a dynamical system. The higher unpredictability, the higher entropy. This fits nicely with Shannon entropy, where unpredictability of the next character is equivalent to new information. It also fits with the

concept of entropy in thermodynamics, where disorder increases the entropy and the fact that disorder and unpredictability are closely related. Kolmogorov-Sinai-entropy has strongly influenced our understanding of the complexity of dynamical systems. Even though the formal definition is not that complicated, the concept has shown its strength through the highly adequate answers to central problems in the classification of dynamical systems [80]. The Kolmogorov – Sinai-entropy (KSE) of (X, β, u, T) is defined as in Eq. (3.2).

$$h_u(T) = \sup_Q h_u(T, Q) \tag{3.2}$$

where the supremum is taken over all finite measurable partitions.

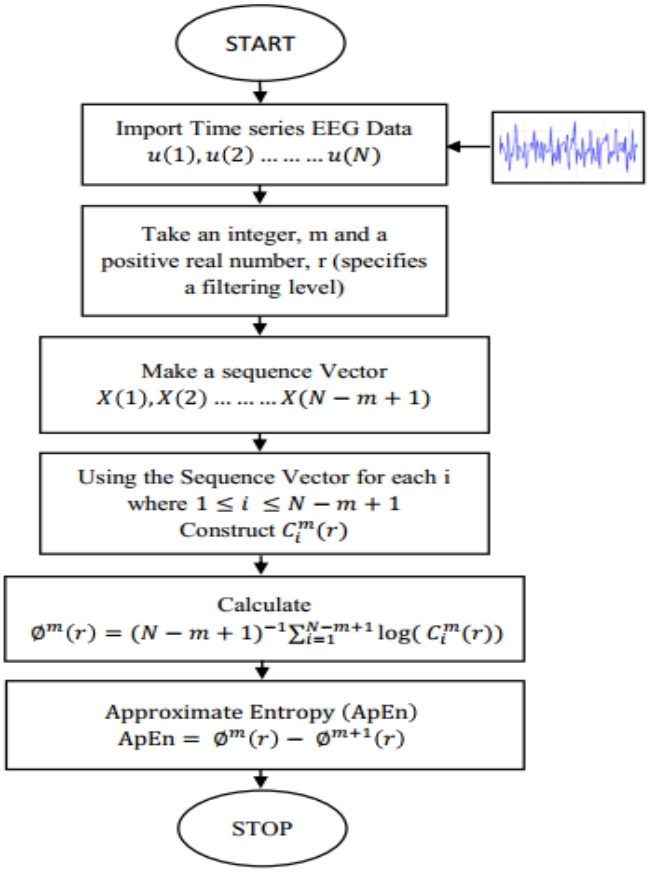


Figure 3.5. Computational flow diagram for ApEn

Spectral Entropy (SE)

Spectral entropy, which is a measure of the hypnotic level of anesthesia, was conceptualized in Finland in 1999 by Viertiö-Oja and colleagues. This assessment of entropy estimates the complexity and irregularity of the signal and quantifies the amount of disorder in the EEG frequency space. In order to optimize between time and frequency resolution, the M-Entropy module utilizes a set of window lengths chosen in such a way that each frequency component is obtained from a time window that is optimal for that particular frequency. In this way, information is extracted from the signal as fast as possible. The approach is closely related to the idea of the wavelet transformation wavelets, being wave packets with finite variable widths containing a roughly constant number of variations to optimize between time and frequency resolution. The selected technique, however, combines this advantage of wavelet analysis with those of fast Fourier analysis, such as the possibility to explicitly consider the contribution from any particular frequency range, and efficient implementation in software [81]. The concept of spectral entropy originates from the measurement of one of the most important metrics of the information theory called Shannon entropy (H) equation Eq. (3.3),

$$H = -\sum p_k \,.\log p_k \qquad (3.3)$$

Standard Deviation (SD) and Standard Error (SE)

The measurements of the square root of a variance of a random variable, statistical population, any kinds of data set, or probability distribution are known as the Standard Deviation (SD) which also known as an absolute deviation. The standard deviation can be defined for any distribution with finite first two moments, which can be measured mathematically by using the Eq. (3.4).

$$Standard\ Deviation, SD = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(x_n - \mu)^2} \qquad (3.4)$$

Where N is the number of samples in data sets, x_n is the actual value of the n^{th} term in data sets and μ is the average value of those data sets. The Standard Error (SE) is defined as the Standard Deviation (SD) of a sample data sets which is the estimation of the sample mean based on the population mean. SE is the mean which is calculated using Eq. (3.5).

$$Standard\ Error\ (SE) = \frac{Standard\ Deviation\ (SD)}{\sqrt{N}} \qquad (3.5)$$

Modified Mean Absolute Value (MMAV)

Mean Absolute Value (MAV) is the moving average of full-wave rectified data sets which is the measurement of average value by taking the average of the absolute value of data sets. So, MMAV is the extension of MAV, in which the individual value is multiplied by weighting function W_n [82] that can be determined by the Eq. (3.6).

$$MMAV = \frac{1}{N}\sum_{n=1}^{N}(w_n \times |x_n|) \qquad (3.6)$$

$$\text{Where } w_n = \begin{cases} 1.0 & 0.25N \le n \le 0.75N \\ 0.5 & Otherwise \end{cases}$$

Roll-off (R)

Roll-off is the steepness of a transmission function with frequency, particularly used in signal feature extraction. The roll-off can be defined as the frequency below which 85% of the magnitude distribution of the data sets is intense [82]. It is also a measure of spectral shape which can be written mathematically in Eq. (3.7).

$$R = 0.85 \times \sum_{n=1}^{n/2}|x_n| \qquad (3.7)$$

Zero Crossing (ZC)

Zero Crossing (ZC) is the frequency domain features of the data sets which measures the number of times that the amplitude value of data sets crosses the zero Y-axis [82]. It can be expressed mathematically in Eq. (3.8).

$$ZC = \sum_{n=1}^{N} sgn\,(x_n \times x_{n-1}) \cap |x_n - x_{n-1}| \geq Threshold \quad (3.8)$$

$$sgn\,(x) = \begin{cases} 1 & x \geq Threshold \\ 0 & Otherwise \end{cases}$$

3.3.3 Optimized Feature selections

Extracted features will use as an input vector to the classifier for detecting epilepsy. If all the extracted features fed to the classifier, it degrades the performance, accuracy of the classifier. Hence, features selection extract a subset of features that are used to select a relevant subset of all available features that reduce noise (irrelevant features) [83], [84]. Features can select using the method based on the statistical parameter Wilks' lambda (WL) where WL compute the ratio of within-group variability to the total group variability by using the discriminator variables [85]. But, the smaller value of WL will result in larger groups dispersion. In Wavelet Packet Decomposition (WPD) method, feature selection algorithm uses Fisher distance function to select each feature individually based on the highest value and forward sequential method which examines the features based on the accuracy [86]. For n levels of decomposition, WPD produces 2n different sets of coefficients which make the classifier computationally expensive. In order to solve the above problem, Wrapper algorithm will be used proposed in this thesis. Wrappers algorithm searches the best features through the space of possible features [87]. Since Wrappers algorithm is based on the recursive feature elimination techniques it will search the optimal features for detecting epilepsy with a higher

degree of accuracy. Generally, a clinician relies on identifying inter-ictal EEG for epilepsy prediction as the ictal segments are obtained rarely. Thus, longer durations of EEG signals are necessary to visually monitor and analyze to localize the normal, inter-ictal and ictal episodes for an epilepsy patient [88]. Epilepsy can be detected traditionally by well-trained and experienced neurophysiologists from a long duration EEG signal. However, long duration inspection of EEG signal is time consuming, tedious, and subjective. Hence, in order to detect epilepsy, a number of entropy based features that describe the behavior (either static or dynamical) of seizures [89] will be extracted to detect normal, inter-ictal and ictal epilepsy. Entropy based features are chosen for separating the useful signal from an intrusive noise [90]. Usually, a high entropy value corresponds to an increased irregularity or unpredictability whereas a low value corresponds to a high regularity [91]. After selecting best electrodes and optimal features from the epileptic EEG, least-angle regression (LARS) method will be used for ranking the features to detect epilepsy more accurately.

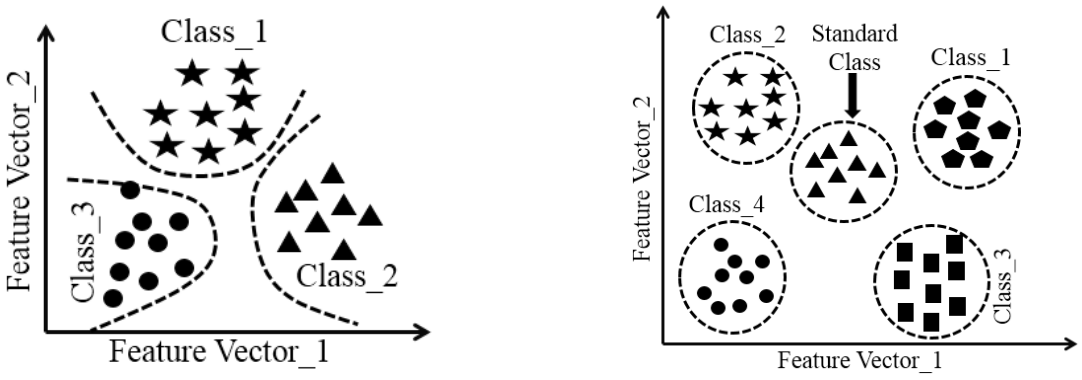
3.4 CLASSIFICATIONS OF EPILEPTIC EEG

EEG signal classification is the process of organizing EEG data into categories for its most effective and efficient use. A well-planned EEG data classification system makes essential EEG data easy to find and retrieve. This can be of particular importance for risk management, legal discovery, and compliance. Data classification is the process of organizing data into categories for its most effective and efficient use. A well-planned data classification system makes essential data easy to find and retrieve. This can be of particular importance for risk management, legal discovery, and compliance. Written procedures and guidelines for data classification should define what categories and criteria the organization will use to classify

data and specify the roles and responsibilities of employees within the organization regarding data stewardship. Once a data-classification scheme has been created, security standards that specify appropriate handling practices for each category and storage standards that define the data's life cycle requirements should be addressed. Mathematical background for the Classifier (k-NN) and regression analysis are described below-

k- Nearest Neighbours (k-NN)

k Nearest Neighbours algorithm (k-NN) is a non-parametric learning algorithm mechanism use mainly used for the classification of signal pattern or pattern recognition as shown in Figure 3.6 (a). The major goals of this mechanism are to assign to an unseen point the leading class among its k nearest neighbours within the training sets of data [92]- [93].



(a) (b)

Figure. 3.6. Architecture of k-NN classifier a) simple classification b) cluster classification

Among all of the method of classification like Support Vector Machine (SVM), Artificial Neural Network (ANN), Linear Discriminant Analysis (LDA), Naive Bayes (NB), and RBF

Neural Network (RBFNN), k-NN is the best classifier statistical pattern recognition or neighbour cluster selection as shown in Figure 3.6 (b) due to its consistently high performance, without a priori assumptions. The k-NN classifier extends this idea by taking the k nearest points and assigning the sign of the majority [94]. The positive integer "k" indicates that how many neighbors guide the classification. The default value k = 1, is called by the nearest neighbor algorithm. In the classification analysis, k-NN is the supervised learning algorithm [95]- [96]. The learning algorithm of k-NN for the classification of any data set X is described below step by step-

1. Consider that training categories are the column vector of the training set. If there are i number of categories in a training set which is denoted by $C_1, C_2, C_3, \dots\dots\dots\dots C_i$. There summation make *m*-dimensional feature vector.
2. The sample data set X should have same dimensional vector for the proper classification which is denoted by $X_1, X_2, X_3, \dots\dots\dots\dots, X_m$.
3. In this state, the similarity between the training set and data set should be calculated. Taking j[th] sample d_j $(d_{j1}, d_{j2}, d_{j3}, \dots\dots\dots, d_{jm})$. The similarity $SIM(X, d_j)$ is mention in the Eq. (3.9)

$$SIM\left(X, d_j\right) = \frac{\sum_{i=1}^{m}(X_i \times d_{ji})}{\sqrt{\left(\sum_{i=1}^{m} X_i\right)^2 \left(\sum_{i=1}^{m} d_{ji}\right)^2}} \qquad (3.9)$$

4. Select the value of k which is larger from N similarity of $SIM\,(X, d_i), (i = 1, 2, 3, \dots\dots\dots\dots\dots, N)$. Now, the probability function has the following mathematical form

$$P\,(X, C_i) = \sum_{d} SIM\left(X, d_j\right) \times y(d_j, C_i)$$

Where, $y\left(d_j, C_i\right)$ is the categories is attribute function which satisfied the following mathematics

$$y\left(d_j, C_i\right) = \begin{cases} 1, & d_j \in C_i \\ 0, & d_j \notin C_i \end{cases}$$

5. Finally, justification of sample X to categories which have larger value of (X, C_i) .

In the k-NN classifier, the distance between two sets of data points is measured by some distance vectors, which are Euclidean Distance, Cityblock Distance, Cosine Distance, and Correlation Distance.

In statistical mathematics, the Euclidean distance is the distance between two points in Euclidean space, which becomes a metric space whose norm form is commonly known as the Euclidean norm. The Euclidean distance, d_{st} is in Eq. (3.10)

$$d_{st} = \sqrt{(x_s - y_t) \times (x_s - y_t)'} \tag{3.10}$$

The distance between two points is the sum of the absolute differences of their Cartesian coordinates is known as the Cityblock distance which also known as Manhattan length [97]. Cityblock distance d_{st} is represented in Eq. (3.11).

$$d_{st} = \sum_{j=1}^{n} \left| x_{sj} - y_{tj} \right| \tag{3.11}$$

Cosine distance is the distance which is used for the compliment in positive space, i.e. $D_c(A, B) = 1 - S_c(A, B)$. Cosine distance d_{st} is represented in Eq. (3.12).

$$d_{st} = \left(1 - \frac{x_s y_t'}{\sqrt{(x_s x_s')(y_t y_t')}} \right) \tag{3.12}$$

Correlation distance is the measure of statistical distance between two random variables or two random vectors of arbitrary, not necessarily equal dimension. Correlation distance d_{st} is represented in Eq. (3.13).

$$d_{st} = 1 - \frac{(x_s - \overline{x_s})\,(y_t - \overline{y_t})'}{\sqrt{(x_t\,\overline{x_s})(x_t\,\overline{x_s})'}\;\sqrt{(y_t\,\overline{y_t})(y_t\,\overline{y_t})'}} \qquad (3.13)$$

$$\text{Where } \overline{x_s} = \frac{1}{n}\sum_j x_{sj} \text{ and } \overline{y_t} = \frac{1}{n}\sum_j y_{tj}$$

The statistical features used for the classification using k-NN classifier in this research are described below-

Regression Analysis

In mathematics, regression analysis is the procedure to find out the mathematical relationship between dependent variables with independent variables. In limited conditions, regression analysis can be used to infer causal relationships between the independent and dependent variables. However, in many applications, especially with small effects or questions of causality based on observational data, regression methods can give misleading results. The function which fits a polynomial regression model as shown in Figure 3.7 by the method of linear least squares is mention below in Eq. (3.14).

$$Y = b_0 + b_1 x^1 + b_2 x^2 + \cdots \ldots \ldots \ldots + b_k x^k \qquad (3.14)$$

Where, *Y* represents predicted outcome value for the polynomial model with regression coefficients b_1 to b_k for k^{th} order polynomial and *Y* intercept b_0.

3.4.1 Off line classification

In machine learning for the classifications of the normal and abnormal conditions, systems which employ offline learning that does not change their approximation of the target function when the initial training phase has been completed. These systems are also typical examples of

eager learning for the classifications. Here, train and test datasets are fixed, and then your model is released/published/deployed. Another way to think of it is in batches. In this case, there is usually no concept of time of the classifier.

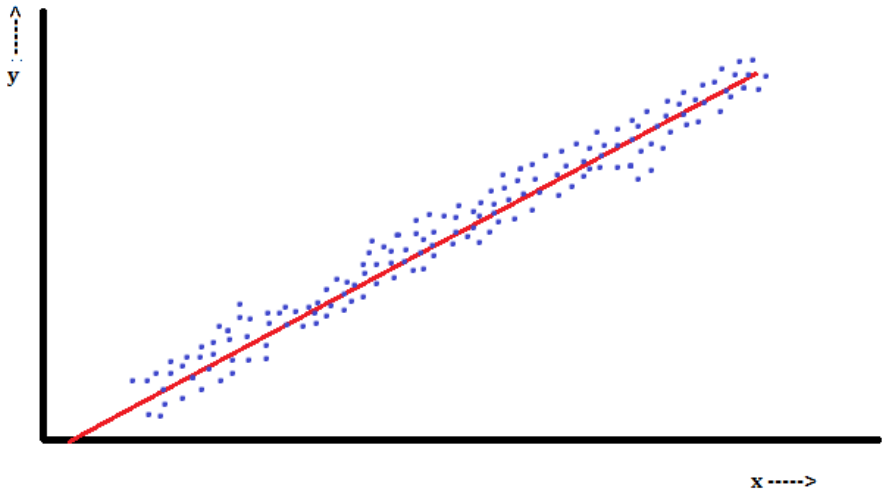


Figure 3.7. Graphical representation of regression equation for regression modeling

3.4.2 On line classification

In computer science, online machine learning is a method of machine learning in which data becomes available in a sequential order and is used to update best predictor for future data at each step, as opposed to batch learning techniques which generate the best predictor by learning on the entire training data set at once. Online learning is a common technique used in areas of machine learning where it is computationally infeasible to train over the entire dataset, requiring the need for out-of-core algorithms. It is also used in situations where it is necessary for the algorithm to dynamically adapt to new patterns in the data, or when the data itself is generated as a function of time, e.g. stock price prediction. Online learning algorithms may be prone to catastrophic interference. This problem is tackled by incremental learning approaches.

Chapter 5

Results and Discussions

Chapter Outlines

4.1 Epileptic EEG signals

4.2 Results of optimized electrode selections

4.3 Reference selections

4.4 Results of optimized features selections

4.5 Epilepsy classifications and performance analysis of the classifier

4.6 Predicting equations modelling and error analysis of epilepsy predictions

4.1 EPILEPTIC EEG SIGNALS

People with some types of epilepsy have unusual electrophysiological activity in their brain all the time, even when they are not having a seizure. When they have an EEG test, the results can show certain brain wave patterns that doctors recognize. This information is very helpful for doctors when they are making a diagnosis. For the detection of epilepsy from the raw EEG signal, proper selection of the references is required. The database (EU database contains annotated EEG datasets from more than 200 patients with epilepsy, 50 of them with intracranial recordings with up to 122 channels. Each dataset provides EEG data for a continuous recording time of at least 96 hours (4 days) at a sample rate of up to 2500 Hz.) used for the analysis to detect epilepsy has the different features that are mentioned in Table 4.1. The epileptic EEG used for the analysis for this research is shown in Figure 4.1.

Table 4.1: Features of the EEG signal used for the epilepsy detections

SL No	Features types	Properties
01	EEG data types	Continuous
02	Channels per frame	32 Nos
03	Frames per epoch	30, 504 Nos
04	Epochs	1 Nos
05	Events	154 Nos
06	Sampling Rate	128 Hz
07	Epoch start (Sec)	0.00 Sec
08	Epoch End (Sec)	238.305 Sec
09	Reference	Unknown
10	Dataset size (Mb)	4.3 Mb

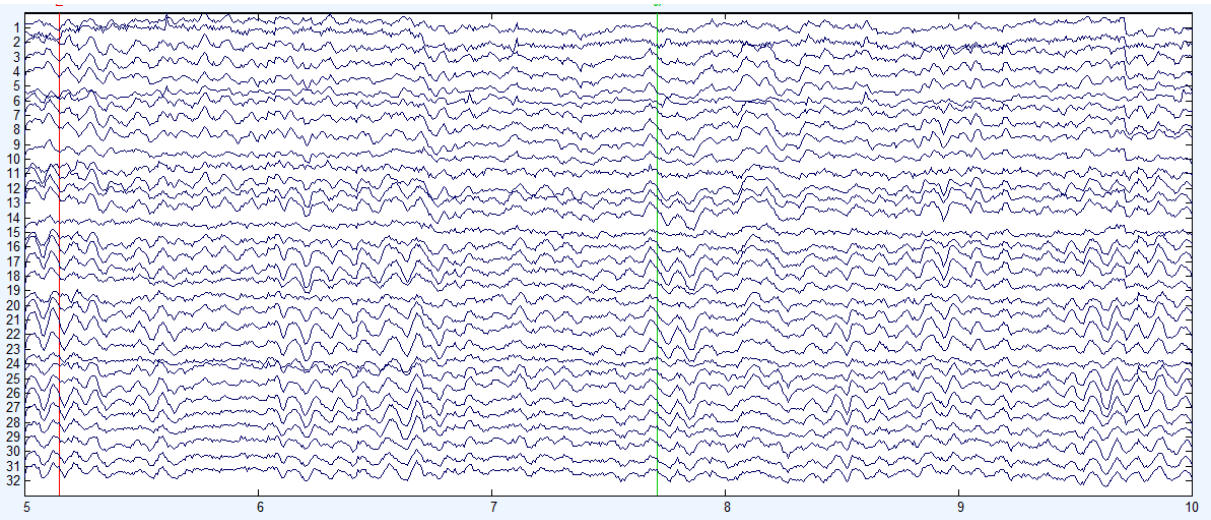


Figure 4.1 Time domain representations of epileptic EEG signal

4.2 RESULTS OF OPTIMIZED ELECTRODE SELECTIONS

At first, all the collected epileptic EEG data (.sat format) files are imported into MATLAB then all the data files are exported as a .txt file which can easily import into the EEGLAB for EEG sources analysis. So that it can be further processed. The block diagram for the EEG sources analysis is represented in Figure 4.2. Figure 4.3 (a) represents the power spectral density (PSD) of the individual channel of EEG signal that is the power of the signal as a function of frequency, per unit frequency as well as the brain spectrum for a particular frequency. From the Figure 4.3 (a), it is clear that for 6 Hz, 10 Hz and 22 Hz activity of the EEG signal, the right sides (Temporal and Parietal), left sides (Parietal and Occipital) and center (Frontal, Parietal) respectively are the best-selected region for the EEG signal. The channel from the locations is the best channel to analyze the EEG signal rather that whole EEG signal from all the signal. In signal processing, time–

frequency analysis is a body of techniques and methods used for characterizing and manipulating signals whose statistics vary in time, such as transient signals.

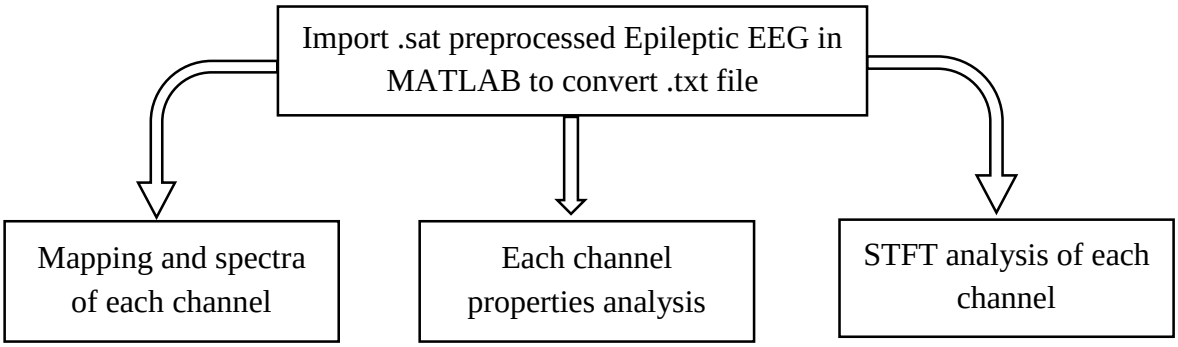
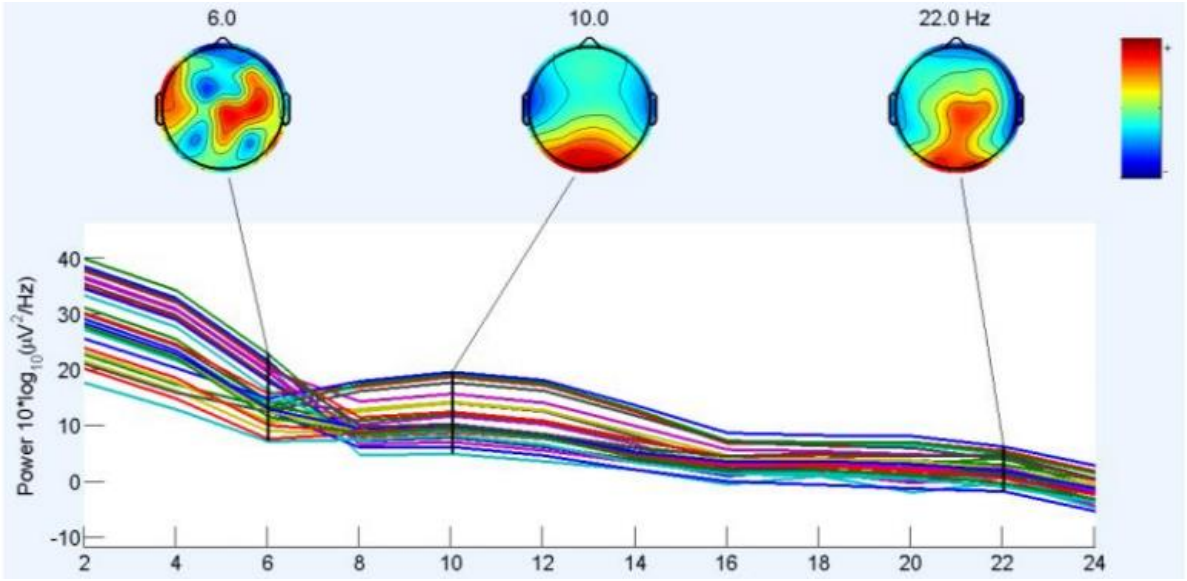
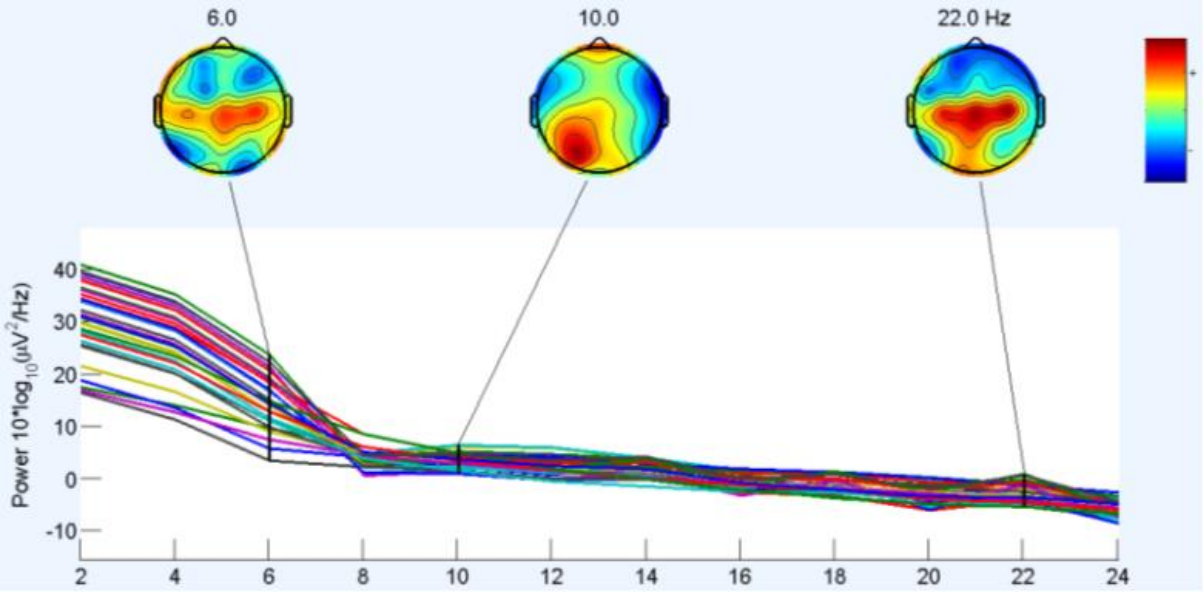


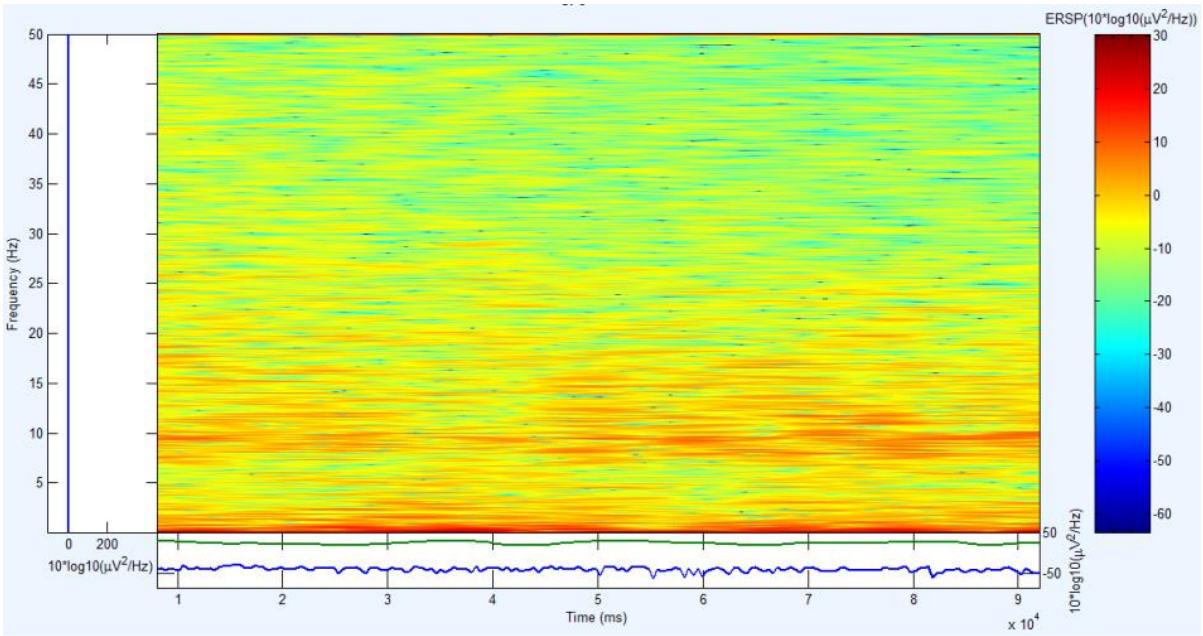
Figure 4.2 Block diagram for EEG sources analysis



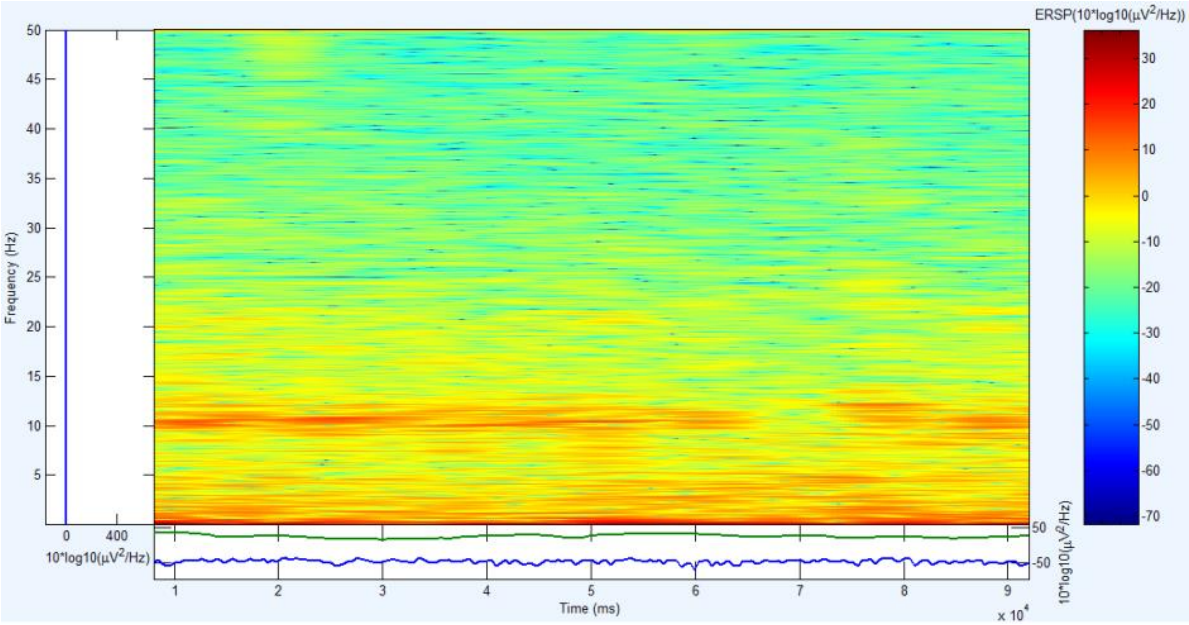
(a)


6.0
10.0
22.0 Hz
Power 10*log10(μV²/Hz)
40
30
20
10
0
-10
2
4
6
8
10
12
14
16
18
20
22
24

(b)


ERSP(10*log10(μV²/Hz))
Frequency (Hz)
50
45
40
35
30
25
20
15
10
5
0
200
10*log10(μV²/Hz)
Time (ms)
1
2
3
4
5
6
7
8
9
x 10⁴
30
20
10
0
-10
-20
-30
-40
-50
-60

(c)



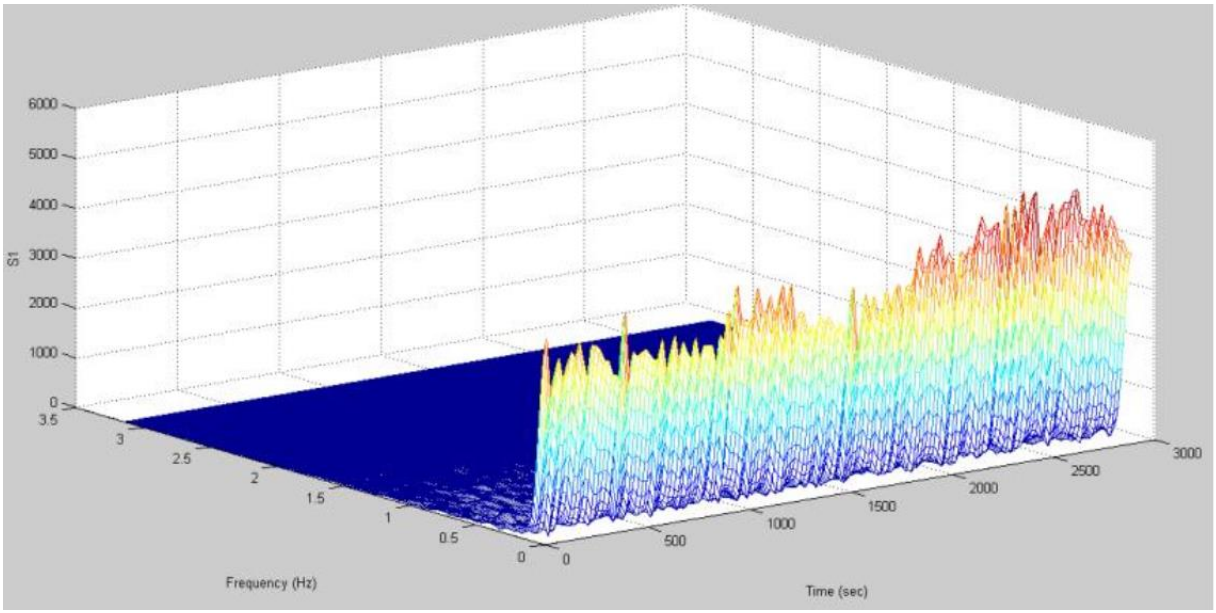
(d)

Figure 4.3 Individual channel PSD and brain spectra for particular frequency a) without considering CSD b) considering CSD and Frequency-time representation of the epileptic EEG c) using all the electrode d) using the selective electrode

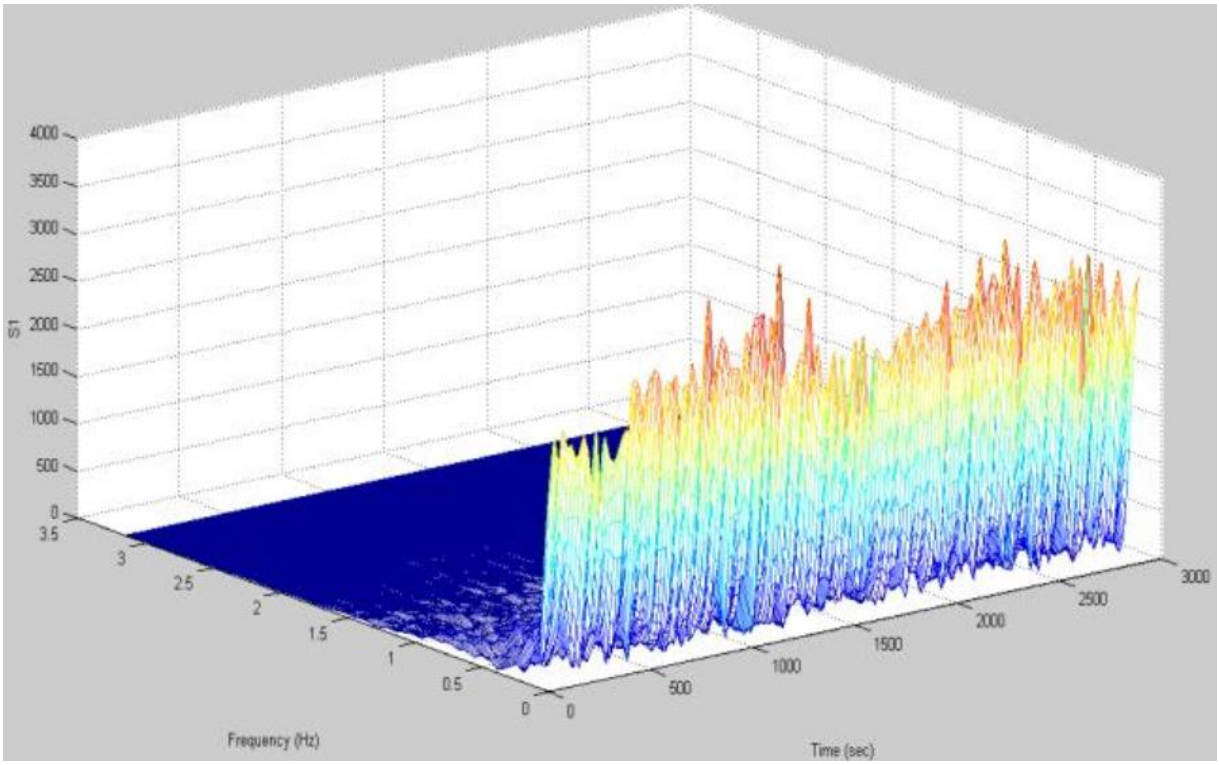
In such a representation the frequency domain will only reflect the behavior of a temporally localized version of the signal. In Figure 4.3, the time-frequency representation of the epileptic EEG is shown b) using all the electrode c) using the selective electrode. Both time-frequency representations show the similar behavior of the EEG signal even they have different numbers of electrodes. But 2nd one having less number of electrode that reduces the computational complexity and required less computational time.

4.3 REFERENCE SELECTIONS

The mesh plot of the EEG is the wireframe mesh with color determined by EEG magnitude in Z axes, so color is proportional to surface height corresponding to time and frequency. The Figure 4.4 (a) and 4.4 (b) show the mesh plot of the epileptic EEG a) using all the electrode b) using the selective electrode. From that Figure, it is clear to prove that 2nd figure has better magnitude response then 1st one. So, from the above discussion we can conclude that selective number of electrode provides better response rather than all the electrode for particular applications of EEG analysis. In case of reference selections, mastoid signal does contain some neural signal, which means that the mastoids are not the ideal references. For high density EEG, the average of activity at all electrodes is often chosen as the reference.



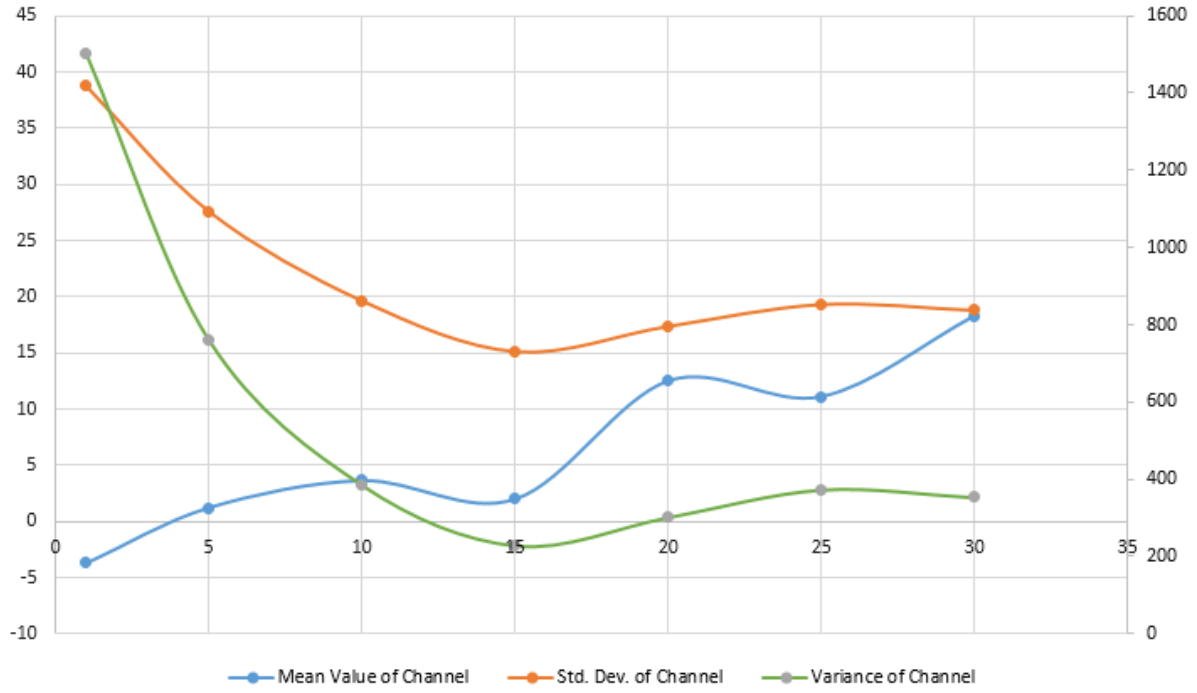
(a)



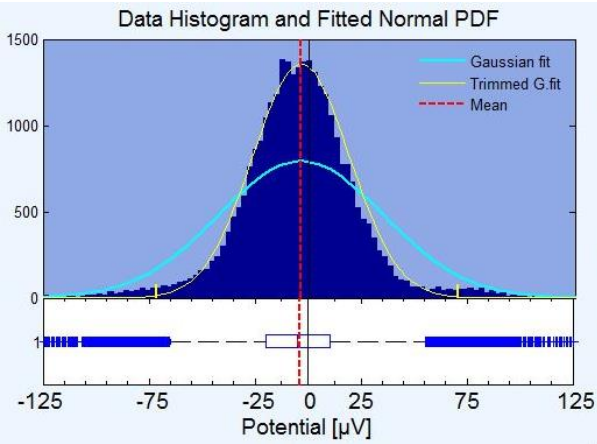
(b)

Figure 4.4 Mesh plot for epileptic potentials, frequency and time a) using all the electrode b) using the selective electrode

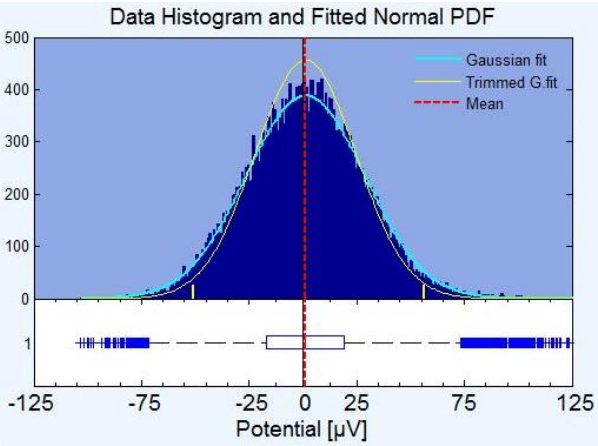
In our research, the activities of each channel is analyzed by observing mean value, standard deviation and variance. The smaller response of these statistical features indicates the better reference for the epilepsy detection faithfully. From Figure 4.5 (a), it is seen that at channel no. 15 the values of the above statistical variables are optimized. Furthermore, others Figures 4.5 (b), (c), (d), (e), (f) and (g) it is shown that at channel no. 15 has sharper distribution of the EEG signal that indicates the sharper response if we use channel no. 15 as a reference.


45
40
35
30
25
20
15
10
5
0
-5
-10
1600
1400
1200
1000
800
600
400
200
0
0
5
10
15
20
25
30
35
Mean Value of Channel
Std. Dev. of Channel
Variance of Channel

(a)


Data Histogram and Fitted Normal PDF
Gaussian fit
Trimmed G.fit
Mean
1500
1000
500
0
1
-125
-75
-25
0
25
75
125
Potential [µV]

(b)


Data Histogram and Fitted Normal PDF
Gaussian fit
Trimmed G.fit
Mean
500
400
300
200
100
0
1
-125
-75
-25
0
25
75
125
Potential [µV]

(c)

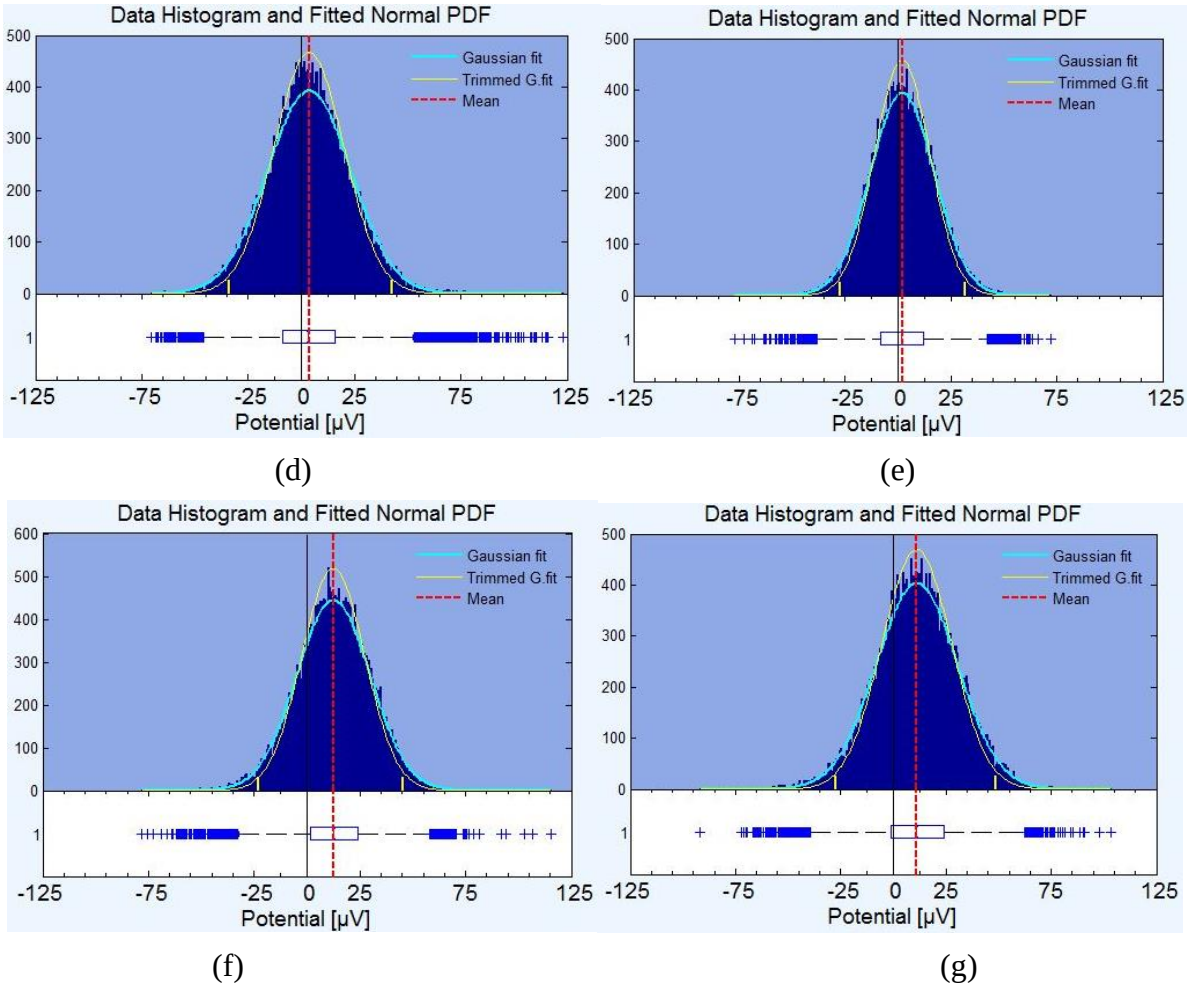


Figure 4.5 a) channel mean, std. dev. and variance response, EEG data distribution for b) channel no. 1, c) channel no. 5, d) channel no. 10, e) channel no. 15, f) channel no. 20, and g) channel no. 25

4.4 RESULTS OF OPTIMIZED FEATURES SELECTIONS

In machine learning and statistics, feature selection, also known as variable selection, attribute selection or variable subset selection, is the process of selecting a subset of relevant features

(variables, predictors) for use in model construction for the faithful classifications. The structure used for best features selection using wrapper algorithm is shown in Figure 4.6.

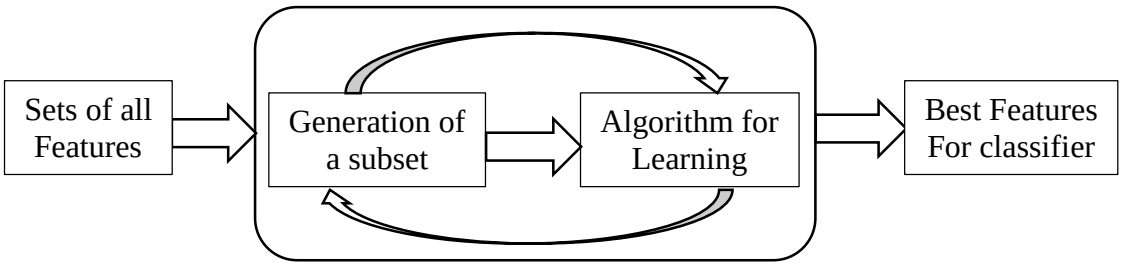
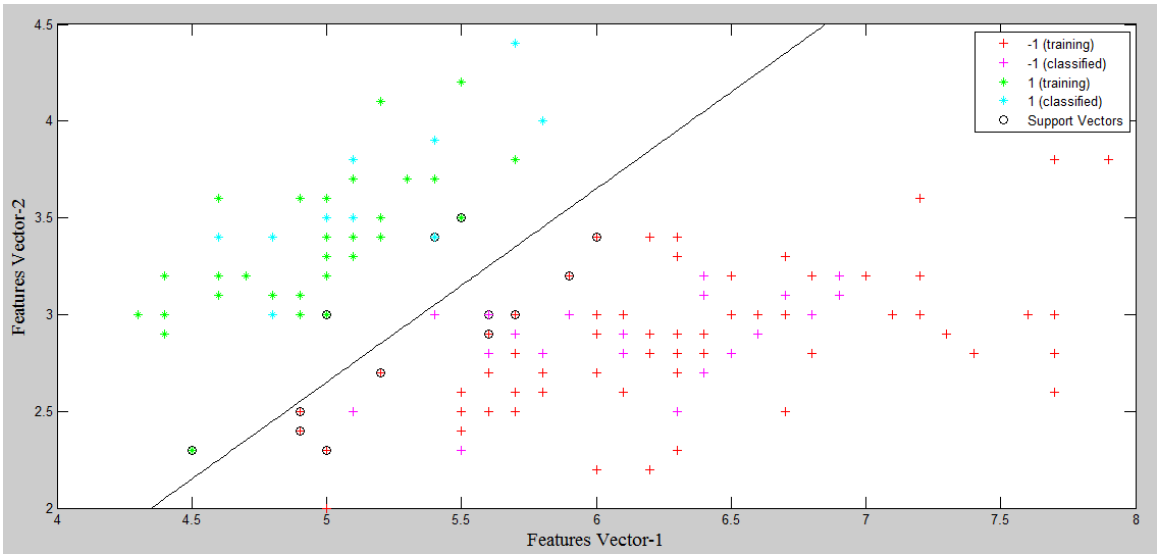
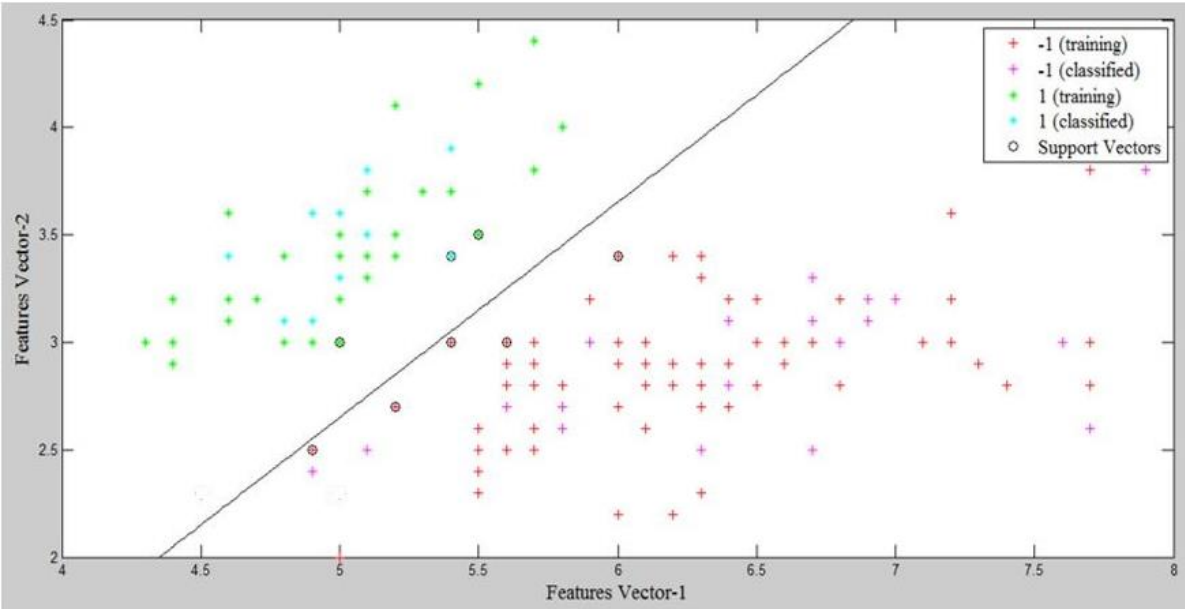


Figure 4.6 Block diagram for Wrapper Algorithm for best features selection



(a)



(b)

Figure 4.7 Classification of normal and epileptic EEG data using best-selected features a) without Sequential forward selection b) with Sequential forward selection

The CFS method that based on the Wrapper principle finds the subsets of features on the basis of the following hypothesis "*Good feature subsets contain features highly correlated with the classification, yet uncorrelated with each other*". The classifications of the normal EEG (Epilepsy free) and abnormal EEG (Epileptic) is shown in Figure 4.7, where Figure 4.7 (a) represents the optimized feature based classifier without Sequential forward selection and Figure 4.7 (b) represents the optimized feature based classifier with Sequential forward selection. Additional sequential forward selection (SFS) is used with Wrapper algorithm in this thesis to increase accuracy rate and a reduced run-time when searching a large number of multidimensional datasets.

From the Figure 4.7, we may claim that if we use only circled feature that will also classify the normal EEG (Epilepsy free) and abnormal EEG (Epileptic).

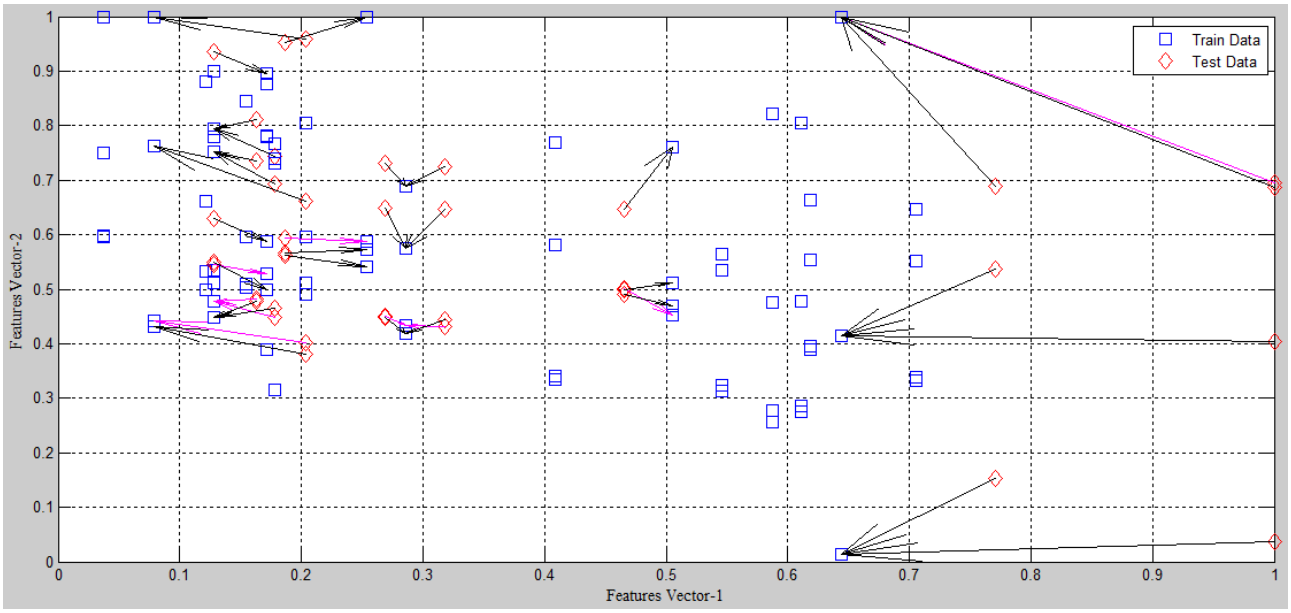
4.5 EPILEPSY CLASSIFICATIONS AND PERFORMANCE ANALYSIS OF THE CLASSIFIER

After extracting the best features, the epileptic EEG data is processed for the achievement of the features vector then a template as mention in Table 4.2 is formed for the train of the k-NN network. In Table 4.2, all columns indicate the normalized features set and each row indicates the subject used for the train of the network. In Figure 4.8 (a), all the nearest neighbor is determined by the trained k-NN network in which all the arrow indicate the nearest neighbor where blue square indicates the train features set and red diamond is the desired point whose nearest neighbor is our goal. On the other hand, in Figure 4.8 (b), the cluster of the feature vectors (ApEn, KSE, SE, MMAV, SD, SE, Roll-off and ZC) is represented using circle from the classification using k-NN classifier. To accomplish this, one standard feature point of desired is set, then from the trained k-NN network, its clustering circle is determined around the point of interest. In Figure 4.8 (b), k=10 nearest neighbor is determined inside the circle to find out the close approximation of epileptic EEG signal using feature vectors (ApEn, KSE, SE, MMAV, SD, SE, Roll-off and ZC) for that one features of vector from the normal EEG data (free from the epilepsy) from the patient is required. In this research work, four distance parameters namely city block, correlation, cosine, and Euclidean are used in our analysis and their performance is analyzed by considering other

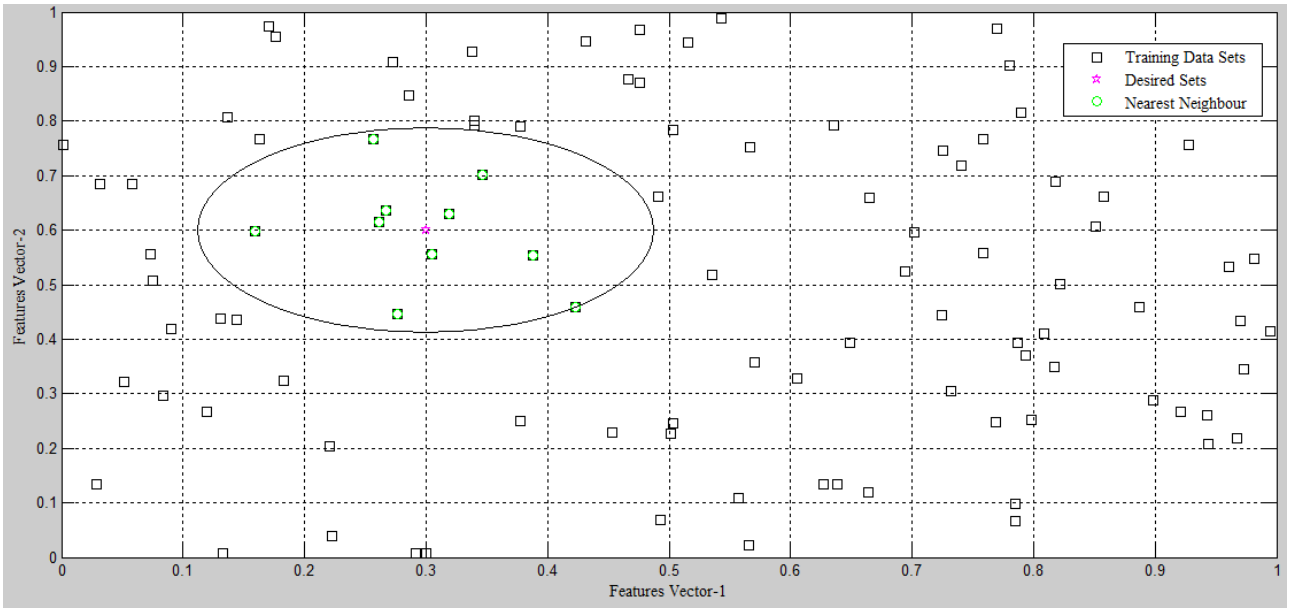
parameters kept constant. Similarly, the performance of classifier rule namely Nearest Neighbor (NN), Random Neighbor (RN), and Smallest Neighbor (SN) as well as different k value is also analyzed keeping corresponding parameters constant. The performance of k-NN classifier which is confusion matrix is shown in Table 4.3, Table 4.4 and Figure 4.9 (a). From the Table 4.3 and 4.4 as well as Figure 4.9 (a), it is concluded that lower classification rate is found at the 'city block' when k=1 and classifier rule is Smallest Neighbor (SN). In Figure 4.9 (b), the first two diagonal elements show the number and percentage of correct classifications by the k-NN networks where 453 samples are correctly classified at the beginning. Out of 475 epochs at the bingeing predictions, 95.4% are correct and 4.6% are wrong and out of 224 epochs predictions, 97.8% are correct and 2.2 % are wrong. Similarly, for 458 and 241, 98.9% correct with 1.1% wrong and 90.9% correct with 9.1% wrong respectively. Overall, 96.1% of the predictions are correct and 3.9% are wrong classifications.

Table 4.2: Training and testing template of features vector of Epileptic EEG data

Normalized Features / **Subjects of Train or Test**	**ApEn**	**KSE**	**SE**	**SD**	**SE**	**MMAV**	**R. off**	**ZC**
S_1	0.17123	0.59125	0.45215	0.87575	0.87574	0.78181	0.77964	0.39014
S_2	0.20376	0.65213	0.35694	0.80575	0.80574	0.51230	0.49013	0.59653
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
S_{20}	0.61815	0.69.785	0.51235	0.66366	0.66367	0.39526	0.39025	0.55392



(a)



(b)

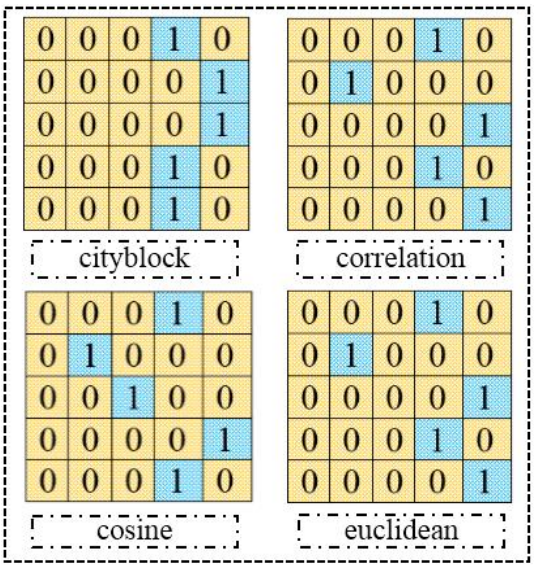
Figure 4.8 Classification using k-NN classifier a) Nearest Neighbour searching b) Clustering with k Nearest Neighbour

Table 4.3: Percentage of accuracy due to variation of Nearest Number k, other parameters kept constant

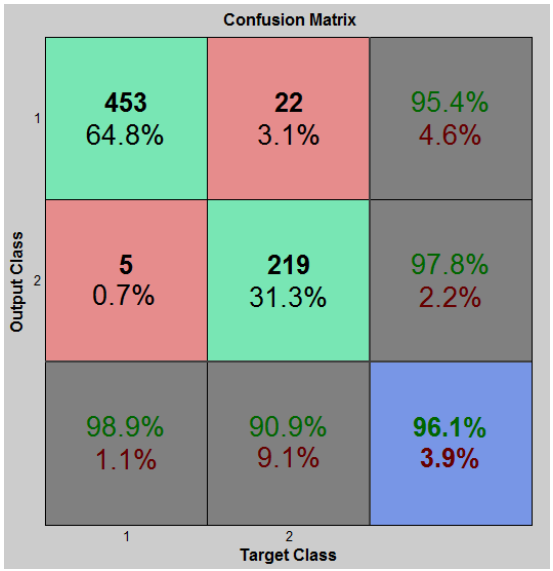
Distance Types	k=1 and Nearest Neighbour		k=2 and Nearest Neighbour		k=3 and Nearest Neighbour	
	Accuracy	Confusion Matrix	Accuracy	Confusion Matrix	Accuracy	Confusion Matrix
'cityblock'	60 %		60 %		60 %	
'correlation'	60 %	Figure 4.9 (a)	60 %	Figure 4.9 (a)	60 %	Figure 4.9 (a)
'cosine'	60 %		60 %		60 %	
'euclidean'	60 %		60 %		60 %	

Table 4.4: Percentage of accuracy due to variation of classification rule other parameters kept constant

Distance Types	k=1 and Nearest Neighbour		k=1 and Random Neighbour		k=1 and Smallest Neighbour	
	Accuracy	Confusion Matrix	Accuracy	Confusion Matrix	Accuracy	Confusion Matrix
'cityblock'	60 %		40 %		20 %	
'correlation'	60 %	Figure 4.9 (a)	60 %	Figure 4.9 (a)	60 %	Figure 4.9 (a)
'cosine'	60 %		40 %		40 %	
'euclidean'	60 %		60 %		60 %	



(a)



(b)

Figure 4.9 a) Presentation of confusion matrix for various k values, distance types and classification rules b) accuracy of training and classifications

4.6 PREDICTING EQUATIONS MODELLING AND ERROR ANALYSIS OF EPILEPSY PREDICTIONS

The 3rd order fittings of the Approximate Entropy (ApEn) is shown in the Figure 4.10 (a). The corresponding regression equation mention in the Eq. (4.1). In this equation, if we put the age of the epileptic people, we may be interpreted the degree of randomness of EEG signal.

$$Y_{3rd\ order\ Fitting} = 1.3277 \times 10^{-07}x^3 - 1.2915 \times 10^{-05}x^2 + 0.00052903x^1 + 0.001932 \quad (4.1)$$

The modification between the predicted value and actual value of the independent value is called the residual which is the measure of the accuracy of prediction. The residual of 3rd order fitting is shown in Figure 4.10 (b) and its regression equation is Eq. (4.2). From this equation, we may find the error of prediction at any age of the epileptic persons.

$$Y_{3rd\ Order\ Res} = -8.6358 \times 10^{-14}x^7 + 2.9924 \times 10^{-11}x^6 - 4.0981 \times 10^{-09}x^5 + 2.8173 \times 10^{-07}x^4 - 1.0201 \times 10^{-05}x^3 + 0.00018623x^2 - 0.0014727x^1 + 0.0032633 \quad (4.2)$$

In a similar manner, 4th order fittings of the Approximate Entropy (ApEn) is shown in the Figure 4.11 (a). The corresponding regression equation mention in the Eq. (4.3). In this equation, if we put the age of the epileptic people, we may be interpreted the degree of randomness of EEG signal.

$$Y_{4th\ order\ Fitting}$$

$$= -3.5815 \times 10^{-10}x^4 + 2.0511 \times 10^{-07}x^3 - 1.7628 \times 10^{-05}x^2$$

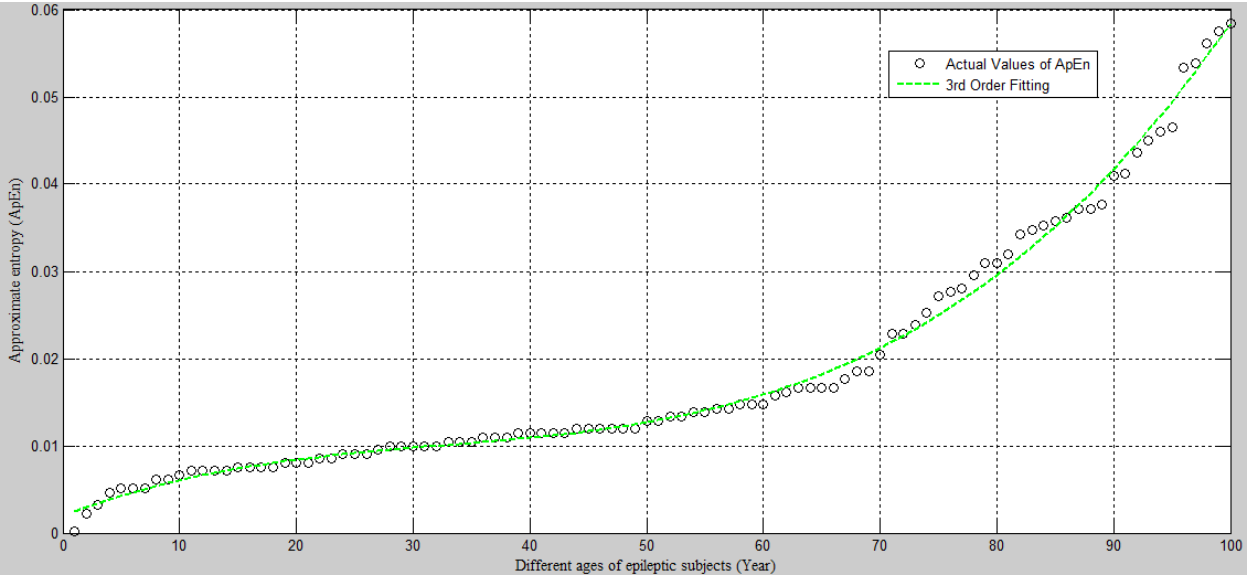
$$+ 0.00063605x^1 + 0.0013676 \qquad (4.3)$$

The residual of 4th order fitting is shown in Figure 4.11 (b) and its regression equation is Eq. (4.4). From this equation, we may find the error of prediction at any age of the epileptic persons.

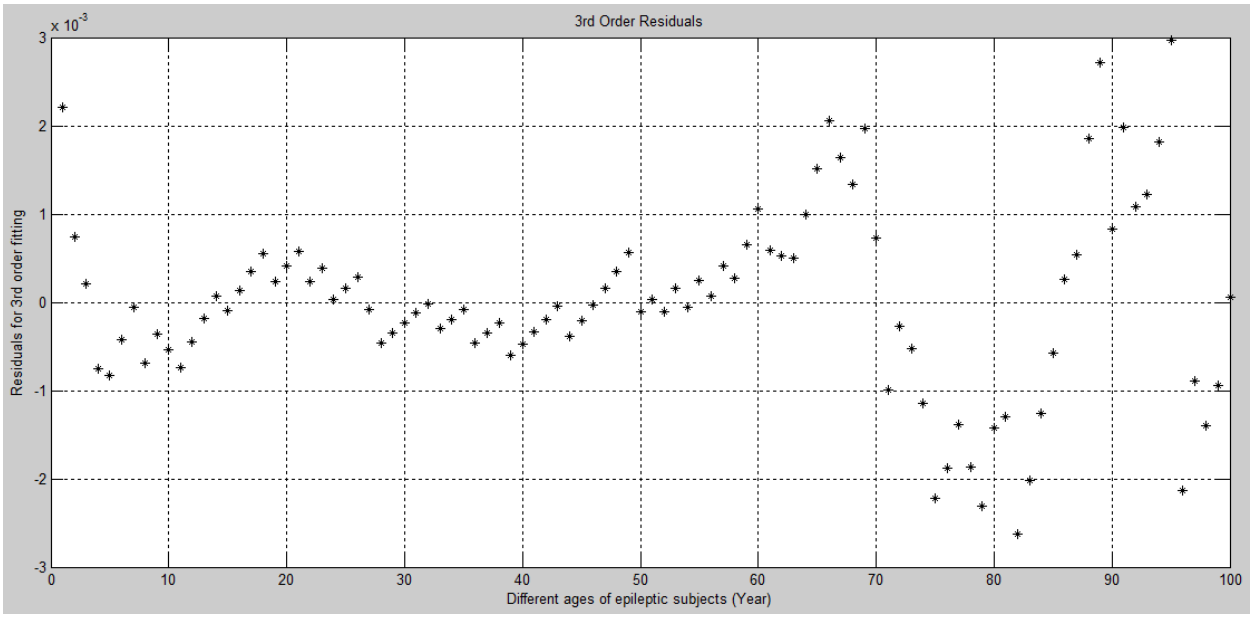
$$Y_{4th\ Order\ Res} = -8.6358 \times 10^{-14}x^7 + 2.9924 \times 10^{-11}x^6 - 4.0981 \times 10^{-09}x^5 + 2.8173$$

$$\times 10^{-07}x^4 - 1.0129 \times 10^{-05}x^3 + 0.00018151x^2 - 0.0013657x^1$$

$$+ 0.0026987 \qquad (4.4)$$

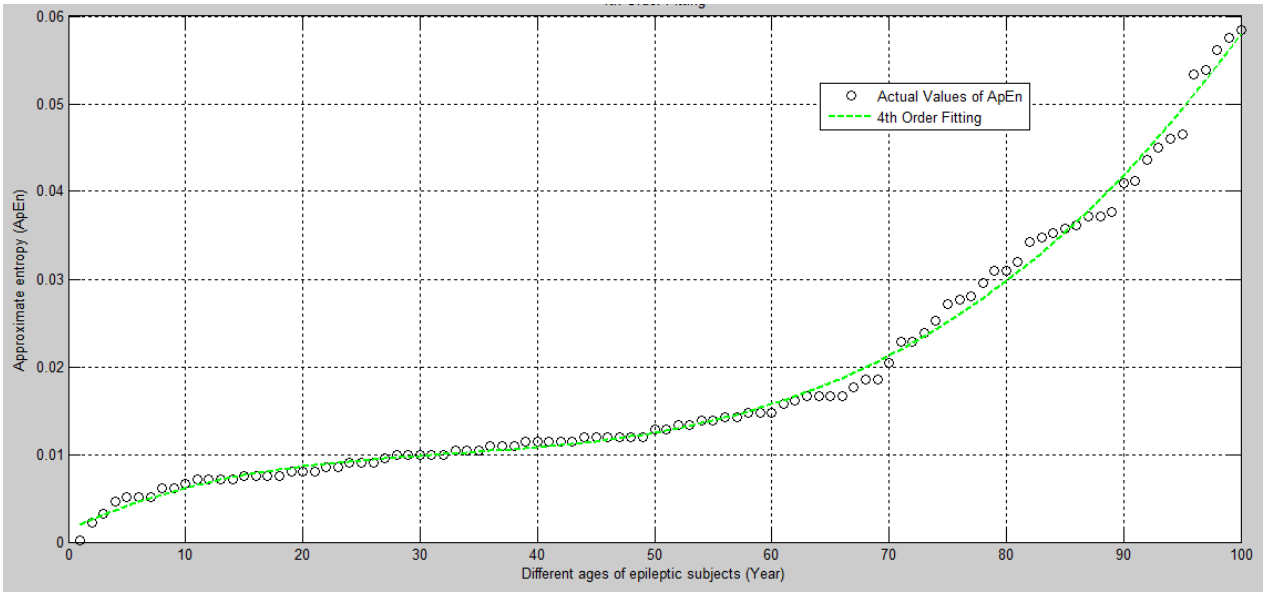


(a)

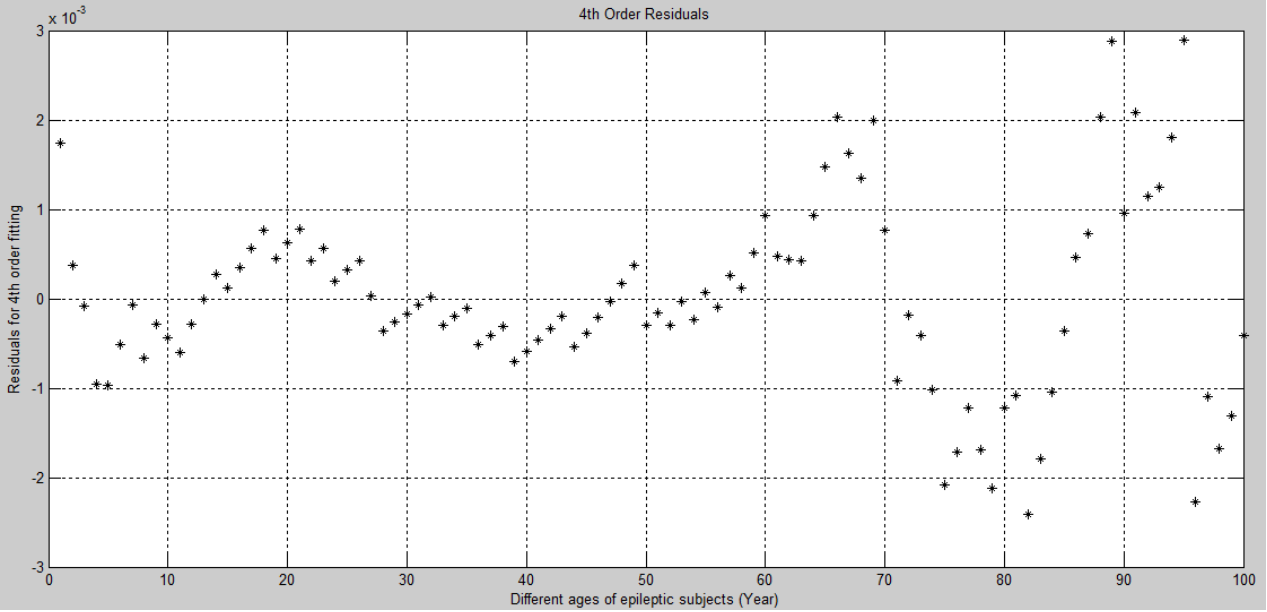


(b)

Figure 4.10 a) 3rd order fitting b) Residual of ApEn with different age of subjects



(a)



(b)

Figure 4.11 a) 4th order fitting b) Residual of ApEn with different age of subjects

In Table 4.5, the error of prediction is shown where the accuracy of prediction is more in 3rd order fitting. From the table, it is noticed that for the increase of the order of fitting may reduce the error probability but after 3rd order fitting the error probability as well as the computational complexity is increased. Hence, optimum prediction equation for the epileptic seizure is a 3rd order which has less computational complexity and less error probability.

Table 4.5: Error (% deviation) calculation for different order of fitting and for different test value (age) of subjects

Order of Fittings	Value of ApEn (20 Years of Subject)		Value of ApEn (40 Years of Subject)		Value of ApEn (60 Years of Subject)		Value of ApEn (80 Years of Subject)	
	Actual	Interpreted	Actual	Interpreted	Actual	Interpreted	Actual	Interpreted
3rd Order	0.008	0.00841	0.0114	0.0109	0.0148	0.0159	0.031	0.0310
	Error = 5.13 %		Error = 4.39 %		Error = 7.43 %		Error = 2.51 %	
4th Order	0.008	0.00862	0.0114	0.0108	0.0148	0.0157	0.031	0.0312
	Error = 7.75 %		Error = 5.26 %		Error = 6.08 %		Error = 2.52 %	

Chapter 5

Conclusions and Future Work

Chapter Outlines

5.1 Conclusions

5.2 Future Work

5.1 CONCLUSIONS

The electrophysiological activity of brain called EEG signal can analyze for the prediction and diagnosis of epilepsy of the human being. The epileptic EEG signal is more and more random in nature and the EEG containing epilepsy is not suitable for the perfect Brain related paradigms or like others applications. Hence, prediction of epilepsy is a vital issue in the modern Bio-medical field of research. For the prediction of epilepsy, a statistical approach was explained in this thesis work. First of all, EEG brain mapping and spectral analysis of the brain was used for the sources modeling that can be helpful for the researcher to select the best electrodes for the EEG extractions. After the position selection of the electrodes, suitable reference and best features among Approximate Entropy (ApEn), Kolmogorov–Sinai Entropy (KSE), Spectral Entropy (SE), Standard Deviation (SD), Standard Error (SE), Modified Mean Absolute Value (MMAV), Roll-off (R), and Zero Crossing (ZC) were selected for the classifications using k-nearest neighbor (k-NN) algorithm. k-NN was used for the classification of epilepsy then regression analysis was used for the prediction of the epilepsy level at different ages of the patients. The regression equation of ApEn with respect to different ages of the epileptic persons may help the BCI researchers or the neural researcher to predict the randomness viz. level of epilepsy corresponding to different ages. This may help the clinical person to provide the treatment of the epileptic person after finding the level of randomness. In our thesis, the epileptic EEG signals for different aged epileptic subjects were analyzed and one of the vital features Approximate Entropy (ApEn) was measured which was the indicator of randomness of any time domain signal.

5.2 FUTURE WORK

Automatic seizure detection is very essential for monitoring and rehabilitation of epilepsy patients and other types of EEG related paradigms. In future, FSA (Fast Simulated Annealing) algorithm will be applied for reducing the dimension of data for the faster classifications with less computational time. The performance of the reduced electrodes and features will the measured using different types of available classifiers and compare with them to select the best one. The robustness of the machine learning algorithm will also be analyzed.

ACHIEVEMENTS

Book Chapter

[1] M. K. Hasan, M. S. H. Sunny, S. Hossain, and M. Ahmad, "**User Independency of SSVEP Based Brain Computer Interface Using ANN Classifier: Statistical Approach**", In: Meesad P., Sodsee S., Unger H. (eds) Recent Advances in Information and Communication Technology 2017. IC2IT 2017. Advances in Intelligent Systems and Computing, vol. 566. Springer, Cham.

International Journal

[1] M. K. Hasan, M. A. Ahamed, M. Ahmad, and M. A. Rashid, **"Prediction of Epileptic Seizure by Analysing Time Series EEG Signal Using k-NN Classifier",** Applied Bionics and Biomechanics [In Press], 2017, *[IF: 0.943]*.

International Conferences

[1] M. K. Hasan, S. M. H. Ullah, S. S. Gupta, and M. Ahmad, "**Drowsiness Detection for the Perfection of Brain Computer Interface Using Viola-jones Algorithm**", Proc. of 3rd International Conference on Electrical Engineering and Information & Communication Technology (iCEEiCT), Sept, **2016**, Dhaka, Bangladesh.

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