AUTOMATED EPILEPTIC SEIZURE DETECTION FROM ELECTROENCEPHALOGRAM SIGNALS

A Dissertation Submitted in Fulfillment of the Requirement for the Award of the Degree of

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DECLARATION

I, **Komal Jindal** hereby declare that the work presented in this thesis entitled "**Automated Epileptic Seizure Detection from Electroencephalogram Signals**" in partial fulfillment of the requirement for the award of degree of Master of Engineering submitted at Electronics and Communication Engineering Department, Thapar University, Patiala is an authentic record of work carried out under supervision of **Dr. Rahul Upadhyay** (Assistant Professor, Electronics and Communication Engineering Department, Thapar University) .The matter presented in this has not been submitted either in part or full to any other university or institute for the award of any other degree.

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It is certified that the above statement made by the candidate is correct to the best of my knowledge and belief.

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The study has indeed helped me to explore knowledge and avenues related to my topic and I am sure it will help me in my future.

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ABSTARCT

Epileptic seizure is one of the brain's disorder which can be automatically diagnosed by measuring and analysing the non-linear and non-stationary behaviour of brain electrical activity. It is a transient symptom of excessive or synchronous neuronal activity of human brain. It is a group of disorders of human brain which has affected a large part of world's population. Epileptic seizure disturbs usual pattern of neuronal activity that causes interruption of consciousness, weird sensation and muscle fits. Early recognition of epileptic seizure helps in improving the physiological condition of patient. Human brain electrical activity varies with various physiological and neurological conditions and is recorded by multiple scalp mounted electrodes. The record of human brain electrical activity is called Electroencephalogram (EEG) signals. The Electroencephalogram (EEG) signals are employed to diagnose various human brain disorders. The Electroencephalogram (EEG) signals contain necessary information for early diagnosis of epilepsy and epileptic seizures. In epilepsy, the nerve cells send out high amplitude electrical impulses and the impulses generate events called seizures. In the past, these EEG signals were diagnosed for any brain disorders by visual examination. However, visual examination is susceptible to errors and requires good understanding of EEG activity.

This research work presents an autonomous system, which is capable of detecting epileptic seizure from EEG signals automatically. The proposed system is carried out in three methodological steps viz. pre-processing, feature extraction and classification. The purpose of pre-processing is to organize the data in an orderly manner and to remove noise. Whereas, feature extraction step extracts time-spectral features for proper representation of seizure and non-seizure signals. Further, the extracted features are then fed to the machine learning algorithms for detection of seizure and non-seizure EEG signals. The proposed system of automatic seizure detection is validated on publicly available dataset and the results show high detection ability of the proposed system. In present work, different feature extraction techniques have been employed and analysed for efficient classification. A comparative study for proposed feature extraction methods is performed in terms of classification efficiency. In this work, Support Vector Machine and Artificial Neural Network classifier have been used for classification of Electroencephalogram signals associated with different physiological condition.

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LIST OF ABBREVIATIONS

EEG:	Electroencephalogram
FAWT:	Flexible Analytical Wavelet Transform
TQWT:	Tunable-Q Wavelet Transform
SVM:	Support Vector Machine
ANN:	Artificial Neural Networks
RF:	Random Forest
ApEn:	Approximate Entropy
REN:	Renyi's Entropy
FD	Fractal Dimension
LS-SVM	Least Square- Support Vector Machine
CD	Correlation Dimension
FT	Fourier Transform
CWT	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform
FFT	Fast Fourier Transform
STFT	Short Time Fourier Transform
EMD	Empirical Mode Decomposition
PCA	Principal Component Analysis
ICA	Independent Component Analysis
PE	Permutation Entropy

CHAPTER 1 INTRODUCTION

1.1 OVERVIEW

Epileptic seizure is defined as “a transient symptom of excessive or synchronous neuronal activity generated due to recurrent discharges in cerebral cortex of brain” and is observed using EEG signals. Epilepsy is a group of disorders of human brain by which large section of the world’s population suffers. It is due to recurrent discharge from cerebral cortex of brain because of irregular disturbance in brain functions and it disturbs usual pattern of neuronal activity that causes disruption of consciousness, strange sensation and muscle spasms. This results in disturbance to the normal electrical activity of human brain. Electrical activity of brain can be recorded by placing electrodes on scalp and is called Electroencephalogram (EEG). The Electroencephalogram signals are non-linear and non-stationary in nature that represents electrophysiological activity of human brain. Electroencephalogram (EEG) signals vary largely with different physiological and neurological conditions of human brain. The EEG signals contain vital information about how brain functions and various neurological disorders such as Epilepsy and Alzheimer’s disease.

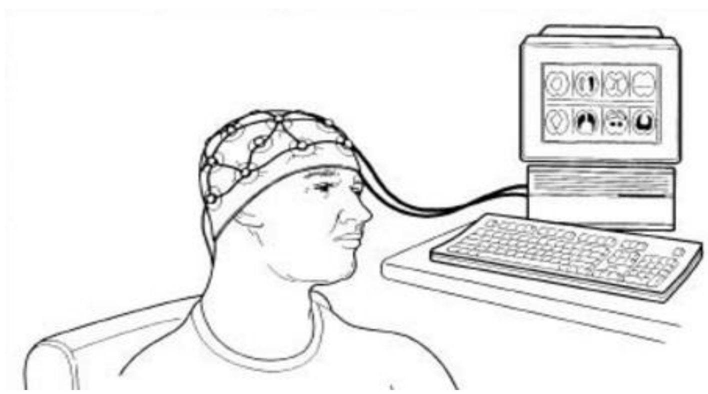


Figure 1.1 Recording of EEG signals by scalp mounted electrodes [10]

Early detection of epileptic seizure helps patients to improve their quality of life. The human brain electrical brain activity can be effectively observed from Electroencephalogram (EEG) signals, which helps in early diagnosis of different physiological and neurological conditions such as epileptic seizure. Visual scanning of EEG signals for epileptic seizure detection is a difficult and inefficient task. So to enhance inadequacies for visual scanning, numerous Computer Aided Techniques (CAD) have been proposed in recent years.

Major objective behind epileptic seizure detection research is to help people suffering from neuronal disorders. Detection of epileptic seizure may save lives of many patients, if detected in early stage of disease.

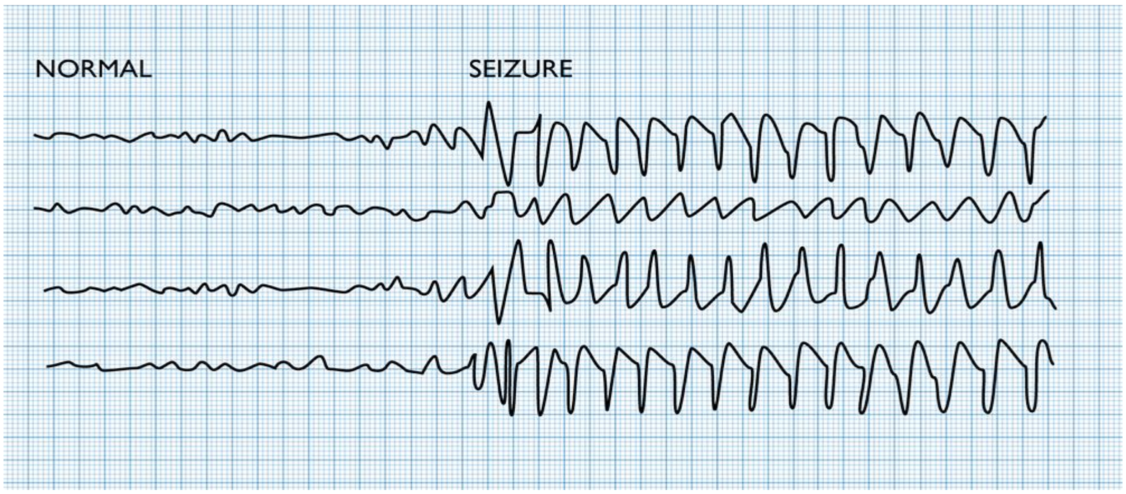


Figure 1.2 Normal and Seizure signal [4]

Many automated epileptic seizure classification/detection techniques have been emerged in recent years. The disease of Epileptic Seizures has been classified into two categories by International Commission on Classification and Terminology of the International League against Epilepsy in 1981, which are partial seizures and generalized seizures.

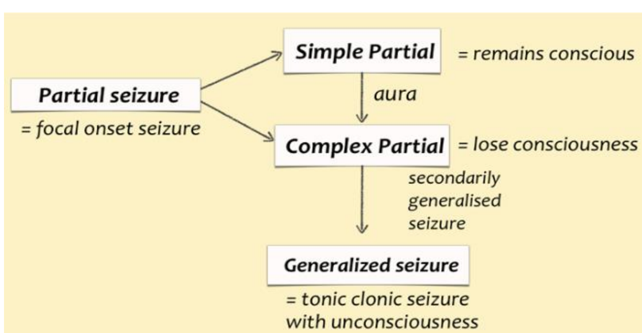


Figure 1.3 Block diagram of partial seizure [5]

Partial seizure is the type of seizure in which clinical and EEG changes suggest initial activation of system of neurons limited to one part of cerebral hemisphere .Fig 1.3 shows the block diagram of partial seizure. The human brain is divided into two hemispheres and further into four lobes i.e. frontal, temporal, parietal, occipital lobes. The partial seizure affects only one hemisphere of human brain. In addition, partial seizure may affect only one lobe of one hemisphere of human brain. Its symptoms vary according to the part of brain which is affected by the seizure. For example, effects in the frontal lobe may cause occurrence of wave like sensation in the head. Further, partial seizures are classified into two types: simple partial seizure and complex partial seizure. Simple partial seizure is a seizure in which only one lobe is affected and person remains conscious and it is called aura. However, in complex partial seizure unilateral cerebral hemisphere is involved and it causes unconsciousness.

On the other side, the generalized seizure is a type of seizure that impedes consciousness and bends electrical movement of bigger part of cerebrum. It is primary because of originally diagnosed condition as opposed to secondary epilepsy, which is an indication of analyzed condition. Most generalized epilepsy begins amid childhood. It grows during adolescence and no longer needs medication. Further, generalized seizures are of six types:

a) **Tonic:** Tonic seizures are due to increase of tonus in body of human and limits longs for about 5-10 seconds.
b) **Clonic:** These seizures contracts muscles rhythmically and occurs repeatedly about 0.2-5 times per second.
c) **Tonic-Clonic:** In this seizure Tonic phase seizure for 10-20 seconds is followed by Clonic phase for 0.5-2 minutes.
d) **Astatic/atonic:** It is due to short loss of axial tonus.
e) **Myoclonia:** Myclonia seizures are jerks in body parts that lasts for 100 miliseconds and these occurs due to synchronous activity. In this person is conscious and it occurs alone or in sequence.
f) **Absences:** It is a kind of blank stare and person faces small consciousness and becomes absent. Behavior of person changes without any effect on posture and muscle tone.

Major breakthrough in the epileptic seizure field was observed after the development of non-invasive systems for EEG signals recording. EEG signals recorded by utilizing obtrusive methods are less boisterous because of less defilement from environment. In this work, we have utilized EEG signals, recorded using noninvasive methods only. The accuracy and efficiency of epileptic seizure detection system depends on accuracy maintained during recording, feature extraction and classification of EEG signals. As EEG signals are boisterous because of extensive defilement from external noises, it turns out to be extremely essential to filter and de-noise EEG signals before extracting features from it. Researches have been performed with various novel algorithms for pre-processing, feature extraction and classification. For pre-processing, techniques like FIR, IIR, low pass, band-pass, Chebyshev, Butterworth filters etc. are commonly used in EEG based disease diagnosis. In order to extract features from EEG signals different researchers extracted different feature like temporal features, spectral features, wavelet transform features and entropy based features etc.

For classification of EEG signals various machine learning techniques have been used in past. The machine learning algorithms are trained with the features of series of EEG data for each class of EEG signals. A well trained classification algorithm can adequately classify among distinctive classes to test EEG signals. Support Vector Machine (SVM) and Artificial Neural Networks (ANN) are the most reliable and efficient classification algorithms.

The epileptic seizure detection is necessary to prevent people suffering from adverse effects of the disease. The major steps involved in epileptic seizure detection includes:

- **Brain Activity Recording:** Electroencephalogram signals are recorded using different kinds of sensors for epileptic seizure detection.
- **Pre-processing:** The recorded EEG signals contain noise and artifacts. Hence, it is preprocessed to enhance the quality of the signal. It includes filtering and de-noising of input signals.
- **Feature Extraction & selection:** It extracts relevant information from pre-processed EEG signals in the terms of features. Out of these extracted features best features are selected for efficient computation.
- **Classification:** A classification algorithm is trained with set of elements for each class's features. Each class represents a sort of mental condition of brain. Once training is over, the classification algorithm is available for validation of input signals.

1.2 RESEARCH OBJECTIVE AND SCOPE

Epileptic seizure is a major brain disorder due to which a large number of people in this world are affected. These patients lose their lives when epilepsy reaches to the un-controlled stage. In addition, patients lose their memory when proper treatments are not provided. Majority of patients suffering from epileptic seizure are less than 30 years of age. The EEG signals are complex in nature, hence, it is difficult for any expert to read the EEG activity for early diagnosis of epileptic seizure. Many researches are being held for automated epileptic seizure detection system. These techniques have been proved efficient in early diagnosis of the epileptic seizure. However, still the improvements can be done in this regards. This thesis work aims to study EEG signal for different physiological conditions and propose effective algorithm to detect epileptic seizure. The overall system of automatic epileptic seizure detection can be expressed by the fundamental block diagram shown in Fig. 1.4.

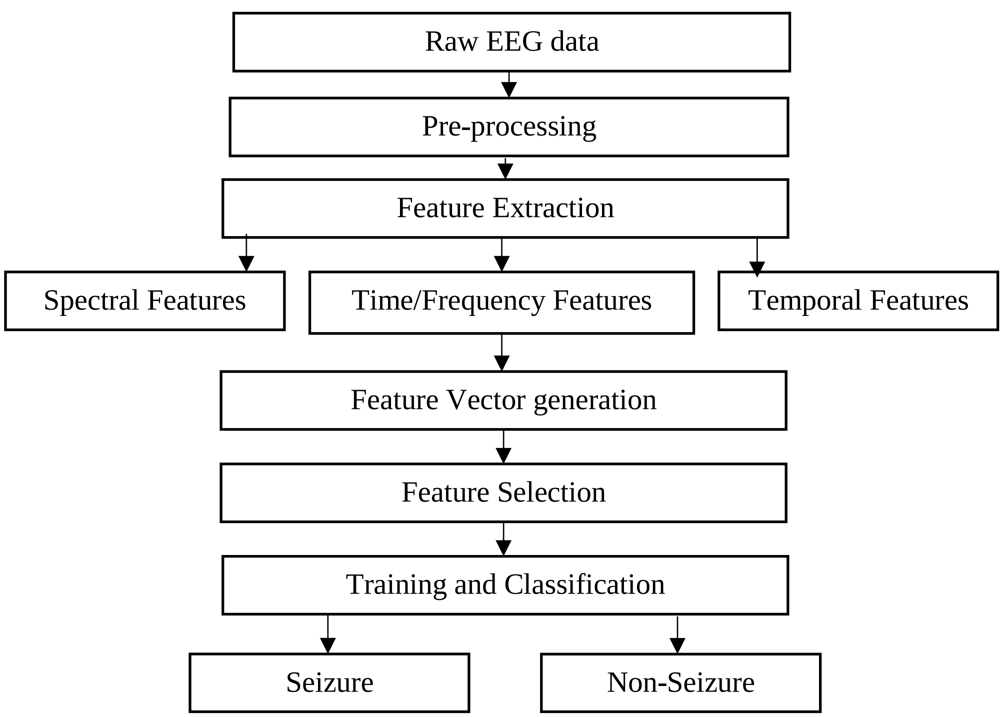


Figure 1.4 Flow chart of Epileptic seizure detection algorithm

1.3 THESIS OUTLINE

In this thesis work, EEG signals are studied under to mental states such as seizure and non-seizure. In order to detect epileptic seizure automatically, algorithms have been proposed for pre-processing, feature extraction and classification of EEG signals. In addition, a survey of different epilepsy detection techniques has been performed for the period of last 17 years. Further, classification efficiencies of different algorithms are compared to find optimized model among all studied models. The present thesis work is divided into five chapters:

In chapter two, a detailed literature survey of previous research work is discussed. Publications which deals with diagnosis of epilepsy or epileptic seizure are considered in this study. The comparison tables are constructed for the suitable comparison between different techniques of pre-processing, feature extraction, feature selection and classification in this chapter.

In chapter three, EEG signals recorded for two different brain states i.e. non-seizure and seizure EEG signals are analyzed using Flexible Analytical Wavelet Transform (FAWT) and statistical features are extracted from Wavelet coefficients. Further, EEG signals are classified for automatic epileptic seizure detection by machine learning techniques. For extracting features from EEG signals, FAWT based methodology is used. The FAWT parameters are optimized on the basis of maximum kurtosis value. Statistical features like mean, kurtosis and skewness are calculated from wavelet coefficients of EEG data. For classification of EEG data three soft computing techniques have been used in this chapter such as SVM, ANN and RF.

In chapter four, previous study is extended to the three classes of EEG signals which includes non-seizure, pre-seizure and seizure EEG signals. In this work, the EEG signals are analyzed using Tunable-Q Wavelet Transform (TQWT) signal decomposition technique. Once the EEG signals are decomposed in the time-frequency coefficients, entropy and FD based features are calculated from the decomposed coefficients. Further, classification of the EEG signals is performed using SVM, ANN and RF machine learning techniques for efficient epileptic seizure detection.

In chapter five, the overall conclusion of the present thesis work is discussed.

2.1 INTRODUCTION

Existence of electrical current in human brain was discovered by Liverpool surgeon named Richard Caton in 1875. After this discovery, a German neuropsychiatric named Hans Berger discovered the recording of EEG signals from electrical activity of brain first time in 1929[6]. He discovered that electric currents of brain can be recorded from scalp of human brain without opening skull. Dr. John Hughlings, a British neurologist discovered about epilepsy and found that epilepsy causes seizures. Hans Berger, also discovered first method of testing electrical hypothesis of epilepsy in 1930. To detect epilepsy, first step is recording of human brain activity using intrusive or non-obtrusive techniques[7]. Fig 2.1 shows epileptic seizure and normal image comparison.

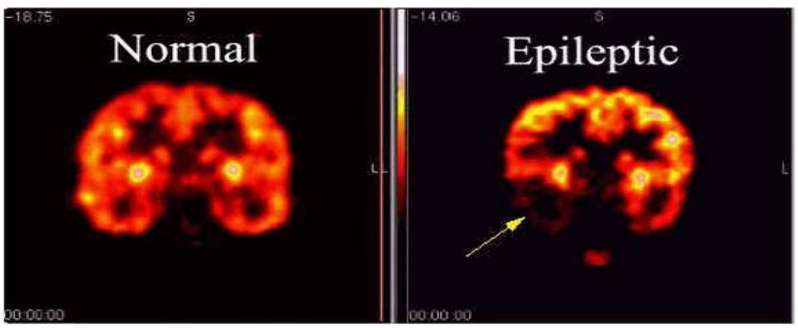


Figure 2.1 Epileptic Seizure and Normal image comparison

Epileptic Seizure is the most common abnormal synchronous neurological activity in brain that affects 50 million people worldwide. Every year around 2.5 million new cases of epileptic seizure occurs globally and are increasing drastically in adults as well as in elder generation. It is an unexpected repetitive interruption of behavior due to excessive synchronization of cortical neural network. It is a recurring abnormal outbreak of electric discharges that a person experiences unexpectedly in the brain. Epilepsy can occur once in a year or several times a day. According to world health organization (WHO) epilepsy is repetitive seizures, which are physical responses to unexpected, uncontrolled electrical discharges in group of brain cells. Epileptic seizure can be focal or generalized. Focal seizure affects only cerebral hemisphere and if whole brain is involved, it is generalized seizure. Epilepsy is due to ‘Epileptogenesis’ in which normal neural activity turns into hyper-excitable one that affects cerebral cortex. It is highly unpredictable and unmeasurably risky. Characteristics of seizures depends on specific region of brain that is involved, spread and extent of abnormal electric discharge. Suddenly occurring and recurrent seizures are dangerous and can lead to life-harming situations. Hence, epileptic seizure detection should be a continuous process and it involves several engineering researches.

This thesis work suggests EEG processing techniques and various classifiers are used for epilepsy detection. Seizure detection system is divided into four methodological stages: EEG data acquisition, pre-processing, feature extraction, selection and classification.

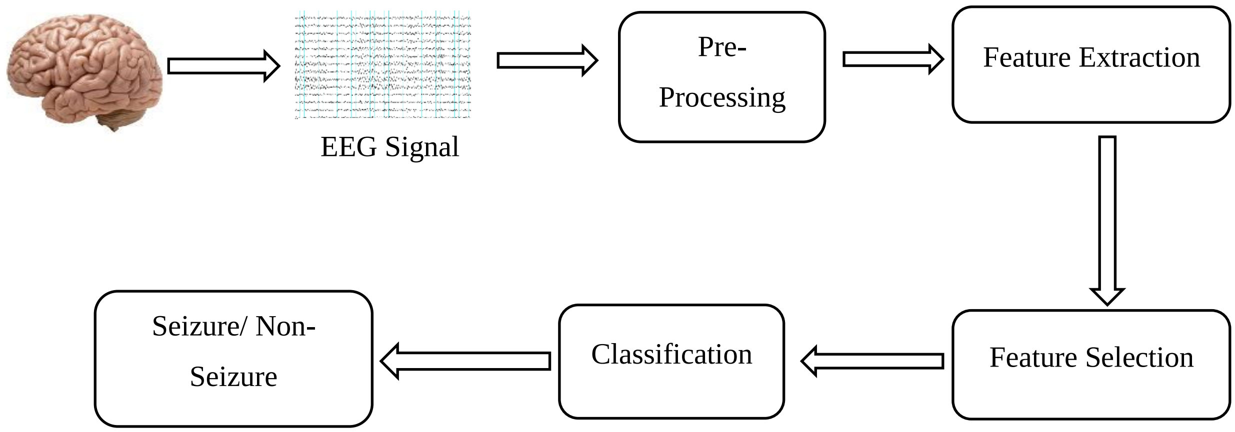


Fig. 2.2 Block Diagram of epileptic seizure detection

In the block diagram of fig 2.2, the process which is followed by all the researchers working on epileptic seizure detection is represented. The EEG signal of brain is used for detection of epileptic seizure. EEG signal indicates the electrical activity of brain which is random and contains useful information about brain condition. EEG signal is non-linear and non-stationary so, advanced signal processing methods are used to diagnose the diseases. Several studies were conducted on EEG seizure detection. To carry out seizure detection, there is a need to create models for EEG signals, for which pre-processing, feature extraction, selection and classification is carried out. Pre-processing block normalizes the signal to make it noise and artifacts free to be used for feature extraction. It is necessary to determine noise and artifacts present in raw EEG signal so that its influence in feature extraction is minimized. To pre-process data various techniques were used by many authors which is mentioned in preprocessing block. Next block used is feature extraction which is necessary for distinctiveness of EEG signal before, during and after seizure has to be determined and evaluated. Several feature have been identified to better describe behavior of seizures. Selection of features best describes the behavior of EEG signal which is important for seizure detection and classification so next step carried out is feature selection. Next block is classification of EEG signal. Objective of classification is to describe a boundary between classes and label them based on measured features. Classifier can be as simple as fixing a threshold or as sophisticated as machine learning algorithms. After classification block we get data classified as seizures or non-seizure which is helpful in determining patients suffering from epileptic seizure so that their treatment is carried out at early stage.

2.2 PRE-PROCESSING:

Data preprocessing refers to a set of activities that are performed to make raw data suitable for further information extraction. Before feature extraction, data is needed to be pre-processed to remove noise from the raw EEG signal. EEG recordings have a wide variety of artifacts like technical original or other physiological origin. Some researchers used only feature extraction and classification stages for epileptic seizure detection and omitted the pre-processing stages. However, in many research studies, one or other kind of filter is used for artifacts removal and noise suppression. Various techniques were used to minimize these artifacts in the past. The techniques are described in this section.

a) **Chebyshev filter:** Chebyshev filter is used to remove nonlinear phase distortion. In Chebyshev's filters data is divided into different frequency bands and data is processed in both forward and backward direction. Chebyshev filter has a sharp roll-off, introducing ripples in its pass band. Frequency bands are selected to use harmonic signals in seizure detection as harmonics of the frequency in one band were always located in another band. In [8] raw EEG data is filtered into seven adjacent frequency bands using Chebyshev filter with no overlap above 40 DB between adjacent filters. In [9] he Chebyshev band-pass digital IIR filters are used to filter the EEG epochs into three consecutive frequency bands. In [10] a 4th-order Chebyshev band-pass digital filter was first used in order to reduce the effect of artifacts.

b) **Notch Filter:** Notch filter is used to remove noise from the signal. Notch filter removes any part of a signal that is at a specific frequency and attenuates signal with narrow band of frequencies. In [11] to remove line noise in raw EEG signal, 60 Hz digital Notch filter is used. In [12] a 50Hz notch filter is used to eliminate electrical interferences for all recordings. In [13] the 50 Hz notch filter is used to remove the power-line interference. In [14 A fourth order Chebyshev notch filter was applied to the EEG data in order to remove the 50 Hz mains component from the EEG. In [15] the line frequency interference was removed with a 50 Hz notch filter.

c) **Butterworth filter:** It has smooth response at all the frequencies. Butterworth filter is flat frequency response filter. When the Butterworth filter was developed, it was found that as the number of stages in a low pass filter is increased, the frequency response became more and more flat in the pass band. For the low pass Butterworth filter, there are no ripples in the gain curve in either the pass band or the stop band. in [15] Raw EEG signal is sampled at 200Hz and bandpass filtered b/w 0.1-100Hz and then, to minimize potential artifacts due to aliasing data is band pass filtered using 4th order butterworth filter with forward backward filtering b/w 0.1-85Hz. In [17] to remove noise 2nd order butterworth filter is used at a sampling rate of 169Hz to remove small sharp spikes. In [19] to remove line noise due to electric supply and stray spikes due to noise 4th order butterworth band pass filter is used with lower and upper cutoff frequencies 0.35 and 30.5Hz respectively. . In [18] 4th order digital butterworth bandpass filter is used to filter raw EEG data b/w 0.5-100Hz. In [20] Most of the seizure activity is within 30Hz so 5th order butterworth low pass filter is used to remove unwanted high frequency interferences. In [14] to remove DC component present in the signal butterworth high pass filter is used with cutoff frequency of 1Hz. In [15] the EEG signals were band-pass filtered with a bi-directional Butterworth second order filter with a bandwidth between 0.5 and 60 Hz. In [21] butterworth band pass filter is used to remove the artifacts from the EEG signal and to avoid the introduction of redundant information.

d) **Band pass filter:** Bandpass filter is a combination of low pass and high pass filter. It passes frequencies within a certain range and rejects all other frequencies. The band pass filter is used to remove most of artifacts and retain the EEG signals within a particular band of interest. Band pass filter allows to pass only a specific frequency range signal and remove all the data above or below that frequency. In [12] and in [13] band pass filter is used to remove artifacts. In [8] chebyshev band pass filter is used. In [16] butterworth band pass filter is used.

e) **FIR and IIR filter:** Finite Impulse Response filter is a filter in which impulse response is finite due to which it becomes zero in finite time. FIR filter is stable as output is a sum of a finite number of finite multiples of the input values. It requires no feedback. FIR filter is used in different papers for preprocessing as in [22] low pass FIR filter is used in which the energy of the frequency band eliminated by the filter is negligible compared with that of the retained band in the range 0–60 Hz. In [23], [24] and in [25] FIR low pass filter is used. Since the sampling frequency of the EEG is 173.61 Hz, according to the Nyquist sampling theorem, the maximum available frequency is half of the sampling frequency or 86.81 Hz. Thereby, from a physiological standpoint, frequencies greater than 60 Hz can be classified as noise and discarded. Infinite impulse response filter is digital filter with feedback and called recursive digital filter. In [9] the Chebyshev band-pass digital IIR filters are used to filter the EEG epochs into three consecutive frequency bands.

f) **DWT:** The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. Discrete Wavelet Transform is also used as a preprocessing technique to remove noise artifacts from the EEG signal as it improves spatial resolution and SNR. DWT has temporal as well as spatial information. De-noising can be achieved by thresholding the wavelet coefficients. In [26] EEG epochs are analyzed using 3rd level wavelet decomposition for both normal and epileptic patients to analyze the EEG signal. In[27] 5th level wavelet decomposition is applied on EEG epochs for both normal and epileptic subjects for frequency approximation. In [28] the EEG is broken down into epochs using a moving window to capture main stationary characteristics of data and short enough to capture burst of seizures and then DWT is applied on the EEG epochs. Table 2.1 presents the various pre-processing methods available in the literature.

Table 2.1 Pre-processing Methods Available in the Literature

Pre-processing Methods	**Reference ID**
Chebyshev Filter	(Zhang *et al* 2015[10], O'regan *et al* 2013[14], Yuan *et al* 2012[9], Greene *et al* 2008[29], Greene *et al* 2007[30], Grewal *et al* 2005[8])
Notch Filter	(Garces Correa et al 2015[21], El Menshawy et al 2013[13], O'regan *et al* 2013[14], Yuan et al 2012[9], Grewal et al 2005[8], Alessandro et al 2003[11])
Butterworth Filter	(Orosco *et al* 2016[21], Garces Correa *et al* 2015[21], O'regan *et al* 2013[14], Holgado *et al* 2012[17], Gardner *et al* 2007[16])
Band pass Filter	(El Menshawy et al 2015[13], Niknazar *et al* 2013[23], Aarabi et al 2007[12], Gardner et al 2007[16], Greene *et al* 2007[29], Grewal et al 2005[8])
Low pass Filter	(Naghsh-Nilchi et al 2010[24], Adeli et al 2007, Ghosh-Dastidar et al 2007[25])
FIR and IIR Filter	(Niknazar et al 2013[23], Yuan et al 2012[9], Naghsh-Nilchi et al 2010[24], Greene *et al* 2005[8], Adeli et al 2007[25], Ghosh-Dastidar et al 2007[25], Greene *et al* 2007[29], Grewal *et al* 2005[8])
Discrete wavelet Transform(DWT)	(Faust *et al* 2015[31], Kumar *et al* 2014[27], Niknazar *et al* 2013[23], Ocak *et al* 2009[26])

2.2 FEATURE EXTRACTION:

To develop automatic epilepsy detection technique, various feature are used to explain behavior of seizures are to be extracted. In this field, a variety of features based on various methods have been attempted to detect epileptic seizure in EEG signals and differentiate EEG signals into normal, inter-ictal & ictal classes such as entropies, CWT/DWT, Spectral and energy features, time domain features, frequency domain features, S-transform and SVD based features and fractal features.

a) **Temporal features:** EEG signals are function of time so, directly extracted features are called time domain features. Time domain features include amplitude, complexity, interval analysis and mobility of EEG signal. Amplitude is instantaneous energy of signal. Amplitude square i.e. signal power detects changes more than energy but is more affected by noise. Interval analysis is to extract information that how much signal lies in that interval. In [9] amplitude and interval analysis are used to extract time domain features. In [32] hjorth parameter which is variance of signal amplitude, mobility i.e. square root of first derivative of signal to original signal and complexity that is mobility of first derivative to mobility of original signal are extracted. Different time domain based features are extracted in different papers to detect epileptic seizure in EEG signal. In [39] time domain features like complexity, energy, fractal dimension, kurtosis, sharpness, mobility etc. are extracted.

b) **Spectral features:** During epileptic seizure there is a change in frequency components of signal. Frequency domain features are used to isolate brain activity at different frequencies. To extract spectral features signal should be in frequency domain which is done using fourier transform. Power spectral density is used to extract relevant features. In [32] fourier spectrum is calculated using FFT and features extracted are spectral entropy, skewness and kurtosis. In [9] AR modeling is used to estimate spectrum of quasi-stationary segments. In [12] normalized power, maximum power and relative power are used for feature extraction of EEG signal.

c) **Fourier transform:** Fourier transform is a transform which analyze time series for stationary signal. EEG signals are non-stationary so it converts EEG signals into small epochs that acts like stationary. Fourier spectral analysis is applied on these epochs. The advantage of fourier transform is it is less susceptible to signal quality variations. In [44] many features like peak frequency, root mean square, average power etc. are calculated using fourier transform.

d) **Time-frequency analysis:** Time-domain analysis can be used to assess the exact location of events but it cannot distinguish that which frequencies are involved in those events. Frequency-domain analysis differentiates the frequencies present in a signal but not the time moment of their occurrence. Due to these limitations, time-frequency analysis techniques have been developed.

e) **Wavelet transform:** A wavelet is a small wave of finite duration and finite energy which is correlated with the EEG signal to obtain the wavelet coefficients. Initially the mother wavelet (a reference wavelet) is shifted continually along the time scale to obtain a set of coefficients at all instants of time. The wavelet coefficients represent the signal in both the time and frequency domains. Next the wavelet is dilated for a different width and then normalized so as to contain the same amount of energy as the mother wavelet. Then the first process of shifting this dilated wavelet along the time scale and evaluating the corresponding set of coefficients is done. Advantage of wavelet transform is it has varying window which can be broad at low frequency and narrow at high frequency. Discrete Wavelet Transform (DWT), Continuous Wavelet Transform (CWT) and Wavelet Packet Decomposition (WPD) are the three types of wavelet transforms. [40] used CWT in their work for automatic epileptic seizure detection. In CWT, various features like texture, fractal dimension, entropies and higher order spectral features are extracted. It improves accuracy in detection of EEG epileptic transients and decrease false detections. 30% of papers used DWT for feature extraction. DWT is compact representation of signal in time and frequency that can be computed efficiently. DWT provides high time resolution and low frequency resolution for high frequency and vice-versa for low frequencies. Using DWT, various features like energy, entropy, mean, curve length, skewness, standard deviation etc. are calculated for feature extraction.

   Some of the papers used both CWT and DWT for feature extraction. In [43] DTCWT (dual tree complex wavelet transform) is used. It is approximate shift invariant and directionally selective in higher dimensions which is useful in pattern recognition and signal analysis. Redundancy is less in DTCWT as compared to DWT.

f) **Empirical Mode Decomposition:** EMD is a data dependent decomposition technique in which temporal signal into bandlimited amplitude and frequency modulated (AM-FM) oscillating components termed as intrinsic mode functions (IMF). It does not require conditions about stationary linearity of signal. In [46] EMD is used for decomposition and then IMF bases are calculated. It works as adaptive high pass filter. EMD is accurate with less computation.

Hilbert-Huang transform is also used with EMD to process high dimensional is also used with EMD to process high dimensional EEG signals. HHT is non-linear and non-stationary method based on EMD which is intuitive, adaptive and direct decomposition method. In [45] HHT based EMD is used which is based on local characteristics of local time domain of data and makes creative improvement of frequency. It removes imperfectness of non-stationary signals processed by fourier transform. In (2015, Fu) Hilbert marginal spectrum (HMS) analysis based on HHT is used. HMS analysis based method has better classification performance as compared with fourier analysis based method.

g) **Principal Component Analysis:** Principal Component Analysis is a dimensionality reduction method to transform d-dimensional data to lower dimensional space. PCA reduces degree of freedom, space and time complexity. PCA is useful in segmenting signals from multiple sources and extracting relationship among multiple variables.

h) **ICA**: Independent Component Analysis (ICA) transforms multivariate random signal into signal components which are mutually independent that is information carried by one component cannot be inferred by others.

i) **AR modelling**: Autoregressive modelling specifies that output variable depends linearly on its own previous values AR modelling is used for a signal with sudden peaks in the frequency spectrum modelled as output of causal, all pole discrete filter whose input is white noise. AR parameter estimation process is considered to get the stable and high performance AR method. A sequence of parameters are obtained from parameter spectral analysis such as power spectrum, peak frequency and bandwidth.

j) **Fractal Dimension**: Fractal dimension (FD) is a measure of complexity and self similarity of time series. As the fractional dimension increases complexity and self similarity of signal increases. It meets the computational requirements of real time implementation. The vertical intercept of fitted straight line to calculate fractal dimension is called fractal intercept. In [32] Higuchi's algorithm is used for calculating fractal dimension. In [9] differential box counting (DBC) approach is used for estimating fractal dimension and fractal intercept of an image. Different FD algorithm interpret irregularity and self similarity differently and compute FD in different ways. Computational burden of FD is reduced by eliminating logarithmic computation. Table 2.2 presents the various feature extraction methods available in the literature.

Table 2.2 Feature Extraction Methods Available in the Literature

Methodology	**Detail of Methodology**	**Reference ID**
Entropy	Approximate Entropy	Kumar *et al* 2014[27], Yuan *et al* 2012[9], Ocak *et al* 2009[26], Aarabi *et al* 2009[12], Greene *et al* 2008[29], Paivinen *et al* 2005[32]
	Sample Entropy	Zeng *et al* 2016[33], Xiang *et al* 2015[34], Kumar *et al* 2011[27], Aarabi *et al* 2009[12]
	Permutation Entropy	Zeng *et al* 2016[33]
	Fuzzy Entropy	Xiang *et al* 2015[34]
	Spectral Entropy	R. Mathieson *et al* 2016[35], El Menshawy *et al* 2015[13], Kumar *et al* 2011[27], Temko *et al* 2011[36], Chua-Chua *et al* 2011[37], Greene *et al* 2008[29], Greene *et al* 2007[30], Paivinen *et al* 2005[32], Alessandero *et al* 2003[11]
	Wavelet Entropy	Kumar *et al* 2011[27]
Wavelet Transform	Discrete Wavelet Transform (DWT)	EL Menshawy *et al* 2015[13], Kumar *et al* 2014[27], Ramgopal *et al* 2014[38], Logesparan *et al* 2012[39], Liu *et al* 2012[40], Guo *et al* 2011[41], Adeli *et al* 2007[25], Aarabi *et al* 2007[9], Aarabi *et al* 2006[12], Subasi *et al* 2006[42], Adeli *et al* 2003[25]
	Continuous Wavelet Transform (CWT)	Logesparan *et al* 2012[39], Guo *et al* 2011[41], Sheng Liu *et al* 2002[40]
	Dual tree complex wavelet transform (DTCWT)	Chen *et al* 2014[43]
Fourier Transform	STFT	Kang *et al* 2015[44], Kai Fu *et al* 2014[45]
	FT	El Menshawy *et al* 2015[13], Ramgopal *et al* 2014[38], Logesparan *et al* 2012[39]

	FFT	Chen *et al* 2014[43], Temko *et al* 2011[36], Greene *et al* 2008[29], Paivinen *et al* 2005[32]
Empirical Mode Decomposition	IMF	Sharma *et al* 2015[46], Pachori *et al* 2014[47]
	HHT	Fu *et al* 201[45], Kai Fu *et al* 2014[45]

k) **Non-linear Parameters:** Non-linear parameters like Correlation Dimension, Fractal Dimension. Lyupanov exponents were used by various researchers to extract features using these parameters.

l) **Statistical parameters:** Parameters like mean, median etc. are used as features for the detection of epileptic seizure detection after using any transform on the EEG data. Mean is an average of the values used by many authors to detect seizures in patients. Median is middle value in the list of values. Standard deviation is the parameter that shows deviation from the mean value of all the values. Many statistical parameters are relative energy, curve length etc are evaluated in different papers as mentioned in the table 2.3.

Table 2.3 Time Domain and Frequency Domain Methods Available in the Literature

Methodology	**Detail of Methodology**	**Reference ID**
Nonlinear parameters	Correlation Dimension (CD)	Ghosh-Dastidar *et al* 2007[25]
	Fractal Dimension	Zhang *et al* 2015[10], Faust *et al* 2015[31], Logesparan *et al* 2012[39], Yuan *et al* 2012[9], Paivinen *et al* 2005[32], Alessandro *et al* 2003[11]
	Lyapunov Exponents	Cheng Hsu *et al* 2010[43], Ghosh-Dastidar *et al* 2007[25], Mormann *et al* 2005[66], Paivinen *et al* 2005[32]
	SVD	R. Mathieson *et al* 2016[35], Xia *et al* 2015[64], Temko *et al* 2011[36]
Statistical parameters	Mean	Orosco *et al* 2016[21], Menshawy *et al* 2015[13], Abualsaud *et al* 2015, Yuan *et al* 2012[9], Chua-Chua *et al* 2011[37], Guo *et al* 2011[41], Naghsh-Nilchi *et al* 2010[24], Aarabi *et al* 2007[12], Greene *et al* 2007[29], Paivinen *et al* 2005[32]

	Median	El Menshawy *et al* 2015[13], Paivinen *et al* 2005[32]
	Mode	Kabir *et al* 2016[19]
	PCA	Kevric *et al* 2014, Ramgopal *et al* 2014[38], Subasi *et al* 2010[42], T.Tzallas *et al* 2009, Ghosh-Dastidar *et al* 2008[25]
	ICA, LDA	Subasi *et al* 2010[42]
	Standard Deviation	El Menshawy *et al* 2015[13], Yuan *et al* 2012[9], Guo *et al* 2011[41], Naghsh-Nilchi *et al* 2010[24], Greene *et al* 2007[30]
	Coefficient of Variation	El Menshawy *et al* 2015[13], Li *et al* 2013[34], Chua *et al* 2011[37], Chua *et al* 2011[37], Aarabi *et al* 2009[12], Aarabi *et al* 2007[9]
	Relative Energy	Grewal *et al* 2005[8]
	Line Length/Curve Length	R. Mathieson *et al* 2016[35], El Menshawy *et al* 2015[13], Ramgopal *et al* 2014[38], O'Regan *et al* 2013[14], Alessandero *et al* 2003[11], Logesparan *et al* 2012[39], Chua *et al* 2011[37], Temko *et al* 2011[36], Chua *et al* 2011[37], Guo *et al* 2011[41], Greene *et al* 2008[29], Greene *et al* 2007[30]
	RMS Amplitude	R. Mathieson *et al* 2016[35], El Menshawy *et al* 2015[13], O'Regan *et al* 2013[14], Temko *et al* 2011[36], Chua *et al* 2011[37], Greene *et al* 2008[29], Aarabi *et al* 2006[9]

2.3 FEATURE SELECTION:

Feature Selection techniques are used to improve classification accuracy effectively where there we have many features. It is a search technique for proposing new feature subset. Various feature selection techniques are used to select optimized subset of features like ANOVA test, K-S test, BSI, GD etc.

a) **Anova Test:** One way analysis of variance is statistical technique which signifies difference between mean of independent groups. Anova test is used to split a group into smaller groups. It compares two means from two independent groups. To observe that differences are significant or not one way anova test is performed. It is to filter out best features out of all the features extracted to detect epileptic seizure.it is used to test general differences rather than specific differences in mean. The advantage of anova test is that there are many complex types of analyses thata are done by anova rather than any other test and it is commonly used technique for comparing means.

b) Wilk's Lambda: It is probability distribution used in multivariate analysis of variance to test difference between mean of identified groups. It is to measure ratio of variability in the group with respect to total variability of different variables. It is to test whether there is difference between means of groups on combination of dependent variables. Advantage of Wilk's Lambda test is that it performs all univariate tests simultaneously as compared to anova test.

$$WL = \frac{|W|}{|B+W|}$$

Equation (2.6)

where $B \; and \; W$ are matrixes that represents square sum and cross products with in groups and between groups respectively.

c) **K-S Test:** Kolmogorov-Smirnov test is a stable non-linear test to check whether two datasets differ significantly or not. It does not make any assumption about distribution of data. To compare two datasets it uses D statistic and enables to view data graphically. Advantage of K-S test is it has strong anti-noise performance and high sensitivity to non-linear signals. Disadvantage is other test are more sensitive when data meets requirements of test.

d) **Correlation and forward sequence based feature selection:** correlation selection is a filter selection method in which correlation of two variables is calculated and it measures degree of dependency between two features. It tells whether there is direct linear relationship or inverse linear relationship between two features.

$$Corr(x,y) = \frac{cov(x,y)}{\sqrt{cov(x,x).cov(y,y)}}$$

Equation (2.7)

where $cov(x,y)$ is covariance of two features x, y .

e) **Forward sequence based feature selection:** Forward sequence based feature selection is a forward and backward search process in which forward search is faster than backward one. It automatically selects subset of features that are more relevant to the problem. It improves computational efficiency and reduce generalization error by removing non-relevant features.

f) **Genetic Algorithm:** It is a search algorithm to select relevant features to enhance efficiency and accuracy of classifiers based on natural selection process. It uses a series of iterative computations to get optimal solution in search space using Charles Darwin's "Survival of Fittest" theory. Best solution in each iteration is saved and passed on to next iteration without any variation in it. The process is repeated until solution dominates the population. It increases sensitivity and decrease false negative. Advantage of genetic algorithm is that it solves problem with multiple solutions and it is easy to understand with no requirement of mathematics knowledge. Disadvantage of genetic algorithm is it takes more time to converge and it is trial and error based method.

g) **Mutual Information:** Mutual Information uses correlation between two features as a goodness measure. If the features are highly correlated it assigns feature as a good feature otherwise not select that feature for classification. Mutual information uses joint probability distribution to compute linear as well as non-linear features.

$$I(X;Y) = \sum_{i,j} log \frac{p(x_i,y_j)}{p(x_i)p(y_j)}$$

Equation (2.8)

where $I(X;Y)$ information that one feature reveals about another feature.

h) **Brain Symmetry Index:** Brain Symmetry Index is a measure of symmetry to assist visual interpretation of EEG for quantification of both spatial and temporal spectral characteristics. Electrical activity of brain has symmetrical relationships so in (2005, Putten) BSI is used to select the features for the classification process. To select features based on relevance and redundancy analysis in [12] reduntant features are selected and removed from all the features and after that non relevant features are also removed which leads to decrease the number of features as far as possible and best features are selected for classification. Representation and distinction are also used to select the best features out of all the features. As in [22] selection of features is carried out on basis of representation of a given class of signals as well as best distinction between classes. Table 2.4 shows feature Selection methods available in literature.

Table 2.4 Feature Selection Methods Available in Literature

Methodology	**Reference ID**
ANOVA Test	Zeng *et al* 2016[33], Adeli *et al* 2007[25]
Wilk's Lambda	Orosco *et al* 2016[21]
K-S test	Xiang *et al* 2015[34]
Correlation selection	El Menshawy *et al* 2015[13]
Forward sequential feature selection	El Menshawy *et al* 2015[13], Alessandro *et al* 2003[11]
Genetic Algorithm	Cheng Hsu *et al* 2010[43], Alessandro *et al* 2003[11]
Mutual Information	Aarabi *et al* 2007[12]
BSI	Putten *et al* 2005[17]
Based on relevance and redundancy analysis	Aarabi *et al* 2006[9]
Representation and distinction	Fatma *et al* 2005[22]

2.4 FEATURE CLASSIFICATION

a) **SVM:** Support Vector Machine is a supervised learning based classifier to classify seizure and non-seizure data. It is discrimination kernel based classification technique that depends on transformation of data from high dimensional space so that it can convert complex classification problems to simpler problems that can use linear discriminant function. It also utilizes those training patterns that are near decision surface as those provide useful information for classification. It can perform both linear and non-linear classification by changing the kernel function. It maps the data into feature sets where a decision boundary separating the classes exist. SVM works in two steps i.e. training step in which algorithm determines optimal decision function from a set of inputs and classification step in which it classifies new input data according to learned decision function. Advantages of SVM are it uses kernel, it does not have local minima and sparseness in solution of SVM. Disadvantage of SVM is it is a binary classifier and to do multistage classification, pair wise classification is carried out. SVM is expensive and runs slow. In around 50% of papers SVM is used. LISVM and RBFSVM are Linear and Radial Basis Function Kernels used in SVM.

b) **Artificial Neural Network:** Neural Network is a computerized computational model based on human brain and nervous system. It is composed of large number of interconnected elements working together to solve problems. Neural network has ability to learn from data given for training and creates its own organization and representation of information. Neural Networks works in real time and tolerate faults using redundant information. It takes samples rather than entire data sets to get solutions. It consists of three interconnected layers. First layer is input layer that send data to second layer which sends output neurons to third layer. RBFNN is Radial Basis Function Neural Network which uses radial basis function as activation function. MLPNN is Multilayer Perceptron Neural Network is commonly used feedforward neural network due to its fast operation and ease of implementation as well as smaller training set requirements. MLPNN consists of three layers i.e. input layer, hidden layer and output layer. Hidden layer processes the information and transmit it to output layer. MLPNN with less or more number of neurons in hidden layer causes problem in bad generalization and overfitting. PRNN, LMBPNN, PNN, EPNN etc are different prediction models that uses neural network to classify data.

c) **KNN:** k Nearest Neighbor algorithm which is non-parametric method used to classify data. KNN is instance based learning which classify data on majority votes using Euclidian distance. KNN is nonparametric, nonlinear and produces multiple thresholds and decision boundaries which makes it suitable for multidimensional and multimodal problems with simple and easy training process. KNN has simplicity, interpretability and good performance. It is used to find k- nearest neighbors in training sets to test sample and classifier.

d) **Discriminant Analysis:** It is a statistical analysis method used to perform supervised dimensionality reduction and to predict category dependent variable by using one or more independent variables. Input data is projected to linear subspace having directions which maximizes separation between classes. Linear Discriminant Analysis is closely related to ANOVA used in statistics, pattern recognition and machine learning to find linear combination of features that separates two or more classes of objects. LDA is effective when measurement is made on independent variable of each observation is continuous. Quadratic Discriminant Analysis is a Bayesian classifier that tries to minimize probability of misclassification. It is a modification of LDA for heterogeneity of classes when matrices substantially differs. QDA is similar to LDA except that covariance matrix which is not common to all k-classes in QDA. It estimates a separate covariance matrix for each class so as to increase number of predictors. So, number of computations in QDA increases with increase in flexibility as compare to LDA. ELDA and MLDA are LDA with Euclidian distance and Mahalanobis distance respectively. Discriminant analysis has closed form solutions that can be computed easily and works well for multiclass.

e) **Decision Tree:** It is a flow chart like decision support tool having tree like structure in which each node represents test on an attribute, each branch represents output of test and each leaf represents label of the class. Decision tree is used to create a model for prediction of target variable by learning decision rules inferred from data features. Decision is simple to interpret and understand with small data preparation. It is cost effective and able to handle both numerical and categorical data with multiple output problems whereas, it creates over complex trees that do not generalize data called overfitting. It creates biased trees when some classes dominates. It becomes unstable when small change in data results in different tree formation. Table 2.5 shows the classification methods available in literature.

Table 2.5 Classification Methods Available in Literature

Classification Methodology	**Details of Methodology**	**Reference ID**
SVM	Support Vector Machine	Mathieson *et al* 2016[35], Zeng *et al* 2016[33], Sharma *et al* 2015[46], Faust *et al* 2015[31], Ramgopal *et al* 2014[38], Xiang *et al* 2012[34], Liu *et al* 2012[40] Temko *et al* 2011[36], Chua-Chua *et al* 2011[37], Temko *et al* 2011[36], Chen Hsu *et al* 2010[43], Subasi *et al* 2010[42]
NN	ANN	Ramgopal *et al* 2014[38], Chen *et al* 2014[43], Kumar *et al* 2014[27], Santaniello *et al* 2011, Aarabi *et al* 2006[12], Subasi *et al* 2005[42], Subasi *et al* 2005[42], Sheng Liu *et al* 2002[40]
	RBFNN	Ghosh-Dastidar *et al* 2008[25], Ocak *et al* 2005[26]
	MLPNN	Kang *et al* 2015[44], Pachori *et al* 2014[47], Naghsh-Nilchi *et al* 2010[24], Subasi *et al* 2007[42], Sheng Liu *et al* 2002[40]
	PRNN	Orosco *et al* 2016[21]
	LMBPNN	Ghosh-Dastdar *et al* 2007[25]
	PNN	Faust *et al* 2015[31], Alessandro *et al* 2003[11]
	EPNN	Faust *et al* 2015[31]
	MuSpiNN	Dastidar *et al* 2009[25]
	BNN	Aarabi *et al* 2007[12]
	DFNN	Subasi *et al* 2006[42]
	RNN	Fatma *et al* 2005[22]
	FFNN, QNN	Karayiannis *et al* 2006[26]
k-NN		Orosco *et al* 2016[21], Zeng *et al* 2016[33], Faust *et al* 2015[31], Guo *et al* 2011[41]
Discriminant Analysis	LDA	Zeng *et al* 2016[33], Orosco *et al* 2016[21], Yuan *et al* 2014[28], Greene *et al* 2008[29], Greene *et al* 2007[30]
	MLDA, ELDA	Ghosh-Dastdar *et al* 2007[25]
	QDA	Kang et al 2015[44], Yuan *et al* 2014[28], Chua *et al* 2011[37], Ghosh-Dastdar *et al* 2007[25]
Decision Tree		Zeng *et al* 2016[33]

CHAPTER 3 | EPILEPTIC SEIZURE DETECTION FROM EEG SIGNAL USING FLEXIBLE ANALYTICAL WAVELET TRANSFORM

3.1 INTRODUCTION

The Electroencephalogram (EEG) signals are non-linear and non-stationary in nature. Hence, temporal and spectral domain features are unable to extract complete information from EEG signals effectively [46, 47]. The limitation of temporal and spectral domain based feature extraction techniques can be overcome by Time-Frequency (TF) based techniques viz. Short Time Fourier Transform (STFT), Wavelet Transform (WT) [48, 49]. STFT has fixed window size, which restrains it in providing optimum resolution in time and frequency domains [49]. The limitation of STFT is improved in WT as it has ability of varying window size. However, WT is not very computationally efficient technique and requires optimum selection of the mother wavelet to maintain consistency in the extracted features. In addition, it has rigid TF behaviour with dynamic dilation and translation parameters [50-52]. The Flexible Analytical Wavelet Transform (FAWT) overcomes the limitations of WT. It contains Hilbert Transform pairs of Wavelet bases which is suitable for processing of oscillatory signals [53]. Flexible Analytical Wavelet Transform (FAWT) allows employing arbitrary sampling rates in both low pass and high pass channels and leads to flexible TF partition behaviour. The dilation and translation factors of FAWT can be easily set in the decomposition process.

In present chapter, an automated technique of epileptic seizure detection using FAWT based sub-band decomposition of EEG signals is proposed. Two classes of EEG signals are considered in this chapter viz. seizure and non-seizure EEG signals. The statistical parameters such as mean, kurtosis, skewness are computed from decomposed sub-bands of EEG signals. Further, three different soft computing techniques viz. Support Vector Machine (SVM), Artificial Neural Network (ANN), Random Forest (RF) are employed for classification of extracted features for automatic recognition of epileptic seizure. Figure 3.1 shows the proposed methodology of feature extraction and classification of EEG signals for automated epileptic seizure detection.

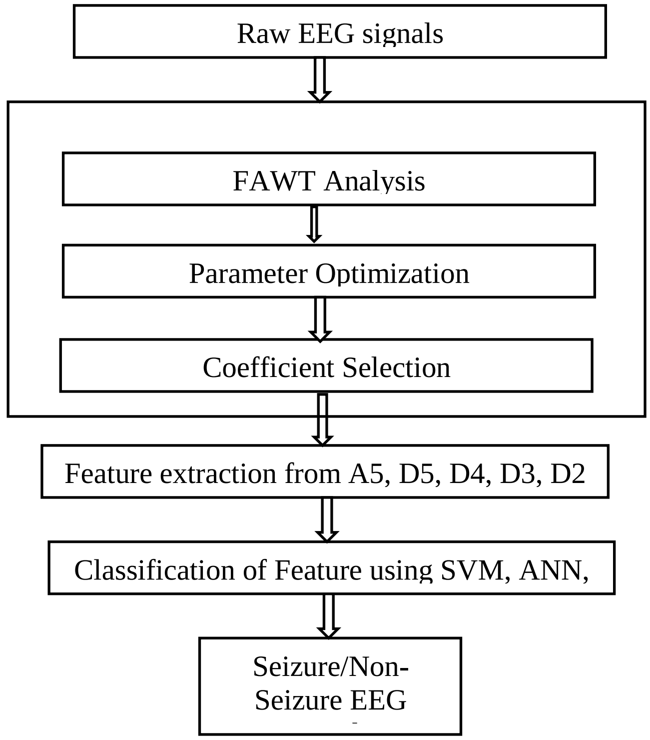


Figure 3.1 Block Diagram of FAWT based automated epileptic seizure detection methodology

3.2 ANALYSIS OF EEG SIGNALS

3.2.1 EEG Database

Electroencephalogram (EEG) data used in present study is taken from online available EEG database of Department of Epileptology, University of Bonn [54]. The EEG database has three subsets (Z, O and S) of artifact free EEG time series of two categories viz. epileptic seizure and non-seizure [55]. Subset Z and O have been measured from EEG recordings of five healthy volunteers and subset S contains signals from five epileptic seizure patients. Each subset has 100 single-channel EEG signals of 23.6s duration. Figure 3.2 shows the exemplary EEG time series for seizure and non-seizure EEG signals.

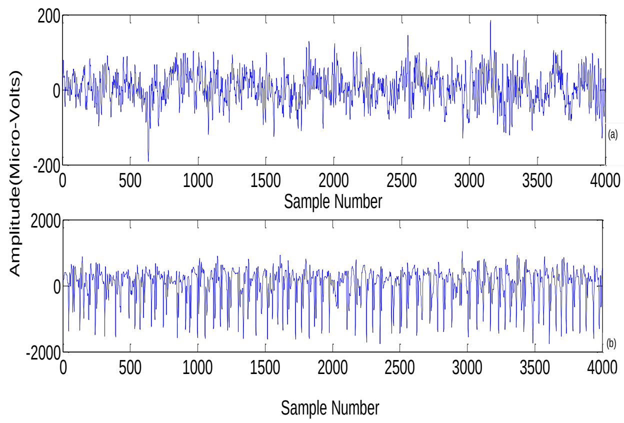


Figure 3.2 Exemplary EEG time series (a) subset non-seizure EEG signal (b) subset seizure EEG signal

3.2.2 Flexible Analytical Wavelet Transform (FAWT)

Flexible Analytical Wavelet Transform (FAWT) is an extension of WT. It is a significant Time-Frequency (TF) representation technique which is having flexible TF partitioning capabilities with easily adjustable dilation and translation parameters. In addition, it regulates the width of the frequency transition bands and attains desirable oscillatory bases to detect different oscillatory signals. The selection of optimal wavelet bases is data-driven process as prior knowledge of impulse being extracted is not known commonly [53]. Flexible Analytical Wavelet Transform [FAWT] separates positive and negative frequencies with a Hilbert transform pair of wavelet bases that allows easy control over parameters such as dilation factor, redundancy and Q-factor [56]. It consists of invertible “constant Q” Iterative Filter Banks (IFB) [53]. Iterative Filter Bank (IFB) has one low pass and two high pass channels [55]. One of these high pass channel analyzes positive frequencies and other analyzes negative frequencies. The flexibility of FAWT is used to get fast implementation of perfect reconstruction for finite length signals with adjustable parameters i.e. p, q, r, s and β. Here, p and q are up and down sampling parameters for low pass channel, whereas, r and s are up and down sampling parameters for high pass channel [53].

Frequency response of low pass filter is given as

$$H(w) = \begin{cases} \sqrt{pq} & |w| < w_p \\ \sqrt{pq}\,\theta\left[\frac{w-w_p}{w_s-w_p}\right] & w_p \le w \le w_s \\ \sqrt{pq}\,\theta\left[\frac{\Pi-w+w_p}{w_s-w_p}\right] & -w_s \le w \le -w_p \\ 0 & |w| > w_s \end{cases}$$ Equation (3.1)

Frequency response of high pass filter is given as

$$G(w) = \begin{cases} \sqrt{rs}\,\theta\left[\frac{\Pi-w+w_0}{w_1-w_0}\right] & w_0 \le w \le w_1 \\ \sqrt{rs} & w_1 < w < w_2 \\ \sqrt{rs}\,\theta\left[\frac{w+w_0}{w_1-w_0}\right] & w_2 \le w \le w_3 \\ 0 & w\epsilon[-\Pi, w_0] \cup [w_3, \Pi] \end{cases}$$ Equation (3.2)

where, $w_p = \frac{1-\beta}{p}\pi + \frac{\epsilon}{p}$, $w_s = \frac{\pi}{q}$, $w_0 = \frac{1-\beta}{r}\pi + \frac{\epsilon}{r}$,

$w_1 = \frac{p}{qr}\,\Pi$, $w_2 = \frac{\Pi}{r} - \frac{\epsilon}{r}$, $w_3 = \frac{\Pi}{r} + \frac{\epsilon}{r}$, $\epsilon = \frac{1}{32}\left(\frac{p-q+\beta q}{p+q}\right)\pi$

where, β and ϵ are nonnegative constants and $\beta < 1$. The transition bands $\theta(w)$ are constructed using Daubechies' orthonormal wavelet filters using two vanishing moments.

$\theta(w) = \frac{1}{2}(1+\cos w)\sqrt{2-\cos w} \quad for \quad \in [0, w]$

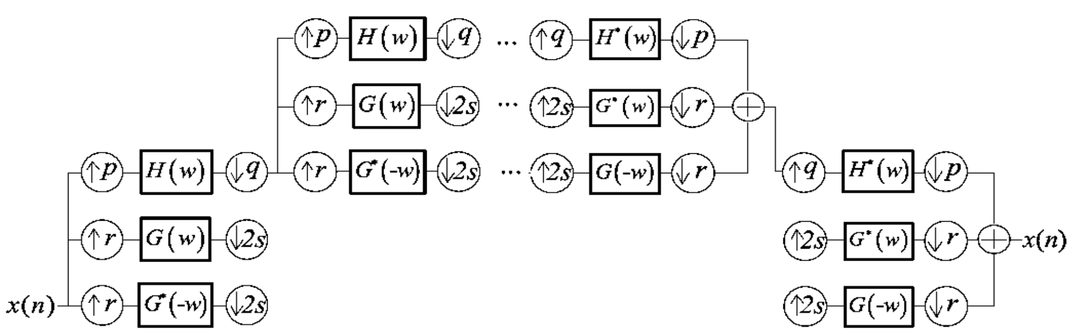


Figure 3.3 Two-stage FAWT decomposition and reconstruction algorithm

To have the perfect reconstruction filter bank, following conditions must be satisfied.

$$\left|\theta(\pi - w)\right|^2 + \left|\theta(w)\right|^2 = 1, \left(1 - \frac{p}{q}\right) \leq \beta \leq \left(\frac{r}{s}\right) \quad \text{Equation (3.3)}$$

To avoid information loss during signal decomposition, the redundancy of FAWT should be greater than *1*. Assume there are n input samples and output samples at j^{th} stage decomposition level is $\frac{ns}{r}.(\frac{p}{q})^{j-1}$, the redundancy factor *(R)* of transform is given by

$$R = \frac{samples(output)}{samples(input)} = \frac{r}{s}\sum_{j=1}^{\infty}(\frac{p}{q})^{j-1}\ ;\ 1 - \frac{p}{q} \leq \frac{r}{s} \quad \text{Equation (3.4)}$$

Q-factor of FAWT is defined as ratio of center frequency to bandwidth and given as

$$Q = \frac{2-\beta}{\beta} \quad \text{Equation (3.5)}$$

here, β is the quality factor of FAWT which lies in range $1 - \frac{p}{q} \leq\ \beta \leq \frac{r}{s}$. In figure 3.3 the schematic diagram of FAWT decomposition and reconstruction is presented.

In order to select the optimum values of FAWT bases p, q, r, s and β , the criterion of *'maximum kurtosis value'* based parameter selection is proposed in this work. Under this criterion, EEG signals are divided into six sub-bands using different values of $p(1 \leq p \leq 10)$, $q(1 \leq q \leq 10)$, $r(1 \leq r \leq 10)$, $s(1 \leq s \leq 10)$ and β, maintaining the following relation

$$\beta = k.\frac{r}{s}\ ; 0 < k \leq 1 \quad \text{Equation (3.6)}$$

Using the values of FAWT basis, the low pass and high pass filters are created and corresponding wavelet coefficients are calculated. Further, kurtosis value is obtained from FAWT coefficient for each set of bases parameters. The criterion of 'maximum kurtosis value' relies on the fact that, as the value of kurtosis increases, the amount of information present in the signal also increases. Hence, those values of FAWT bases for which the yielded kurtosis value is maximum, are employed for calculation of FAWT here. In order to identify optimum number of decomposition levels in FAWT, a separate approach is followed. It is attained that the EEG signal shows significant oscillations for frequency less than 30 HZ and are known as rhythms of EEG signals. In order to extract useful information, it is reasonable to decompose EEG signals maintaining maximum correlation with the bands of these rhythms. It is observed that keeping number of decomposition levels less than *5*, there is no separation between lower rhythmic activities. Also, keeping value greater than *5* is also not useful. Hence, the number of decomposition levels used in this work are set to be *5* [57].

Once, the optimum FAWT bases parameters are attained, the EEG signals are decomposed in five levels of approximate and detailed coefficients for seizure and non-seizure classes only. Figure 3.4 represents the approximate and detailed coefficients of non-seizure and seizure EEG signals.

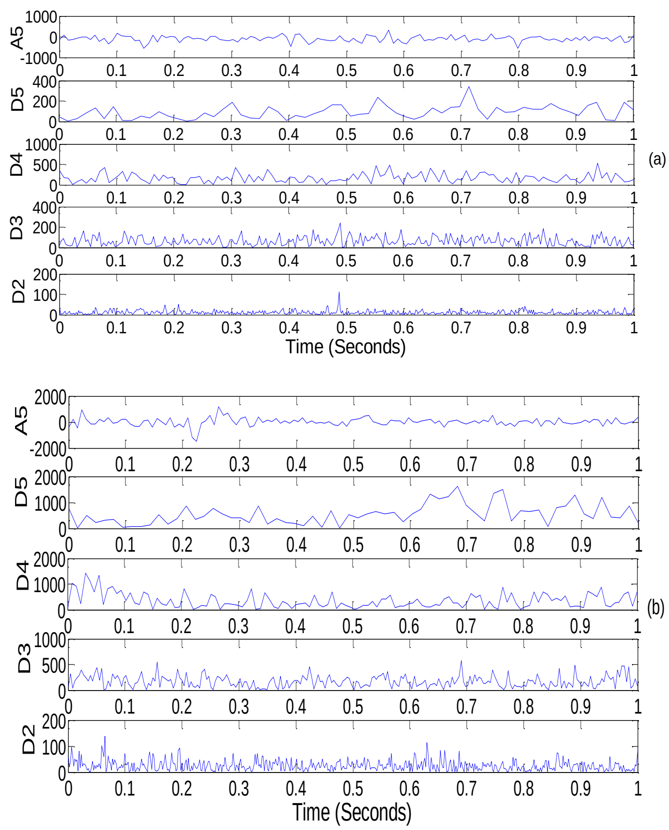


Figure 3.4 Wavelet coefficients of (a) Non- seizure EEG signal

(b) Seizure EEG signal

3.3 SOFTCOMPUTING TECHNIQUES

Soft computing techniques provide information processing capability to handle real life problems. In present chapter, three supervised soft computing techniques i.e. SVM, ANN and RF are used for automated detection of seizure EEG signals. The description of each of the techniques is given in this section.

3.3.1 Support Vector Machine

Vapnik proposed the supervised machine learning technique SVM in 1995 [58]. Support Vector Machine (SVM) is a statistical learning algorithm based on the principle of structural risk minimization. In SVM, a hyperplane is plotted between two different classes of data and positioned such as that it maintains the maximum distance from the support vectors of two linearly separable classes. Let (xi, yi) is sample data set, with i= 1 to M training points. Each sample input xi has D attributes and belong one of two classes yi = -1 or +1. Hyperplane is achieved after solution of an optimization problem under linear inequality constraints, which can be given as Eq. (3.7).

$$\text{Minimize } \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{M}\xi_i \qquad \text{Equation (3.7)}$$

Subject to

$$\begin{cases} y_i(w^T x_i + b) \geq 1 - \xi_i \\ \xi_i \geq 0;\, i = 1,2,\ldots,M \end{cases} \qquad \text{Equation (3.8)}$$

Here, C is an error penalty constant.

3.3.2 Artificial Neural Network

Artificial Neural Network (ANN) is a non-linear statistical data modelling technique, which learns from experimental data. It consists of three layer structure composing of input layer, hidden layer and output layer. The input layer serves data to the network and output layer produces the response of the network. Artificial Neural Network (ANN) learns from the experiences and modifies its structure with newly input set of data. The mathematical model of a single neuron of ANN can be represented as:

$$N_k = \emptyset(\sum_{j=1}^{p} wt_{kj} q_j + wt_{k0}) \quad \text{Equation (3.9)}$$

N_k is the output of k^{th}node, wt_{kj} is the synaptic weight between hidden and output layer, q_j is the j^{th} input and $\emptyset$ is activation function [59].

3.3.3 Random Forest

Random Forest (RF) is an aggregate learning algorithm for classification and regression problems. It keeps a combination of tree predictors. The response of each tree depends on the value of random vector sampled independently and with the equal distribution for every tree in the forest. The algorithm of RF was proposed by Breiman [60], which was forthright modification of bagging method.

3.4 FEATURE EXTRACTION AND CLASSIFICATION OF EEG SIGNALS

3.4.1 FAWT Based Feature Extraction Methodology

Once the EEG signals are decomposed to approximate and detailed FAWT coefficients, the statistical parameters i.e. mean, skewness and kurtosis are calculated from these coefficient as features of the EEG signals. These parameters characterize the location and variability of the EEG data set. Mean is a measure of arithmetic average of a set of values of data. It refers to the sum of all the values divided by total number of values. Mean has very less complexity. It has very good estimate of data values. Skewness is the measure of lack of symmetry in the probability distribution of a real-valued random variable and kurtosis is the measure of peakedness or flatness of probability distribution of a real-valued random variable. These three statistical parameters are combined together to form the feature vector. In present work, the statistical parameters are calculated from four detailed (D2, D3, D4, D5) and one approximation coefficient (A5) only. This makes the size of feature vector as *15* i.e. in each feature vector there are *15* features of the corresponding EEG signals.

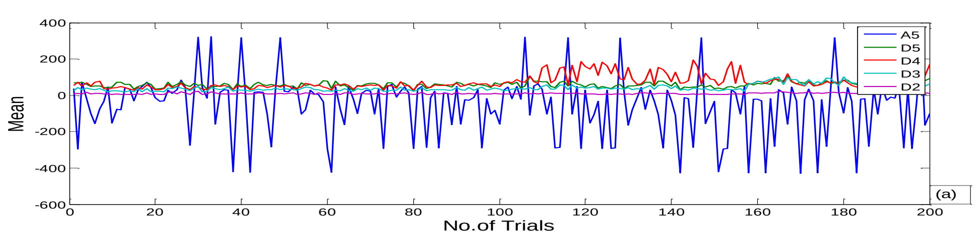
3.4.2 Results and Discussion

Feature vectors are gathered and applied to the classifier algorithm as input. The features calculated from *200* trials of non-seizure EEG signals and *100* trials of seizure EEG signals are fed to the classifier algorithm for training purpose. Fig. 3.5 shows the plot of the FAWT based statistical features extracted from seizure and non-seizure EEG signals. Training and testing of the classifier is performed using 10-fold cross validation to ensure no statistical biasing present in the classification results.

It can be observed from Fig 3.5 that mean of approximation coefficient A5 shows less variation for seizure signal, whereas for non-seizure EEG signals, A5 has large variation. On the contrary, kurtosis value shows a large variation for all coefficients (i.e. A5, D5, D4, D3 and D2) for non-seizure EEG signals and less variation for seizure EEG signals. Once all the statistical features are calculated from the EEG signals, these features are fed as input to the classifier algorithm to test efficiency of proposed feature extraction technique. The confusion matrices for classification of EEG data with 10-fold cross validation using SVM, ANN, RF classifiers is shown in Table 3.1. Further, the classification performance of the classifiers is also evaluated by sensitivity, specificity, F-measure and precision values which are presented in Table 3.2.

Table 3.1. Confusion Matrix calculated from SVM, ANN and RF

Classifier Type	**Non-Seizure**	**Seizure**	**Classified as**
Support vector Machine	200	0	**Non-Seizure**
	8	92	**Seizure**
Artificial Neural Network	200	0	**Non-Seizure**
	3	97	**Seizure**
Random Forest	200	0	**Non-Seizure**
	2	98	**Seizure**



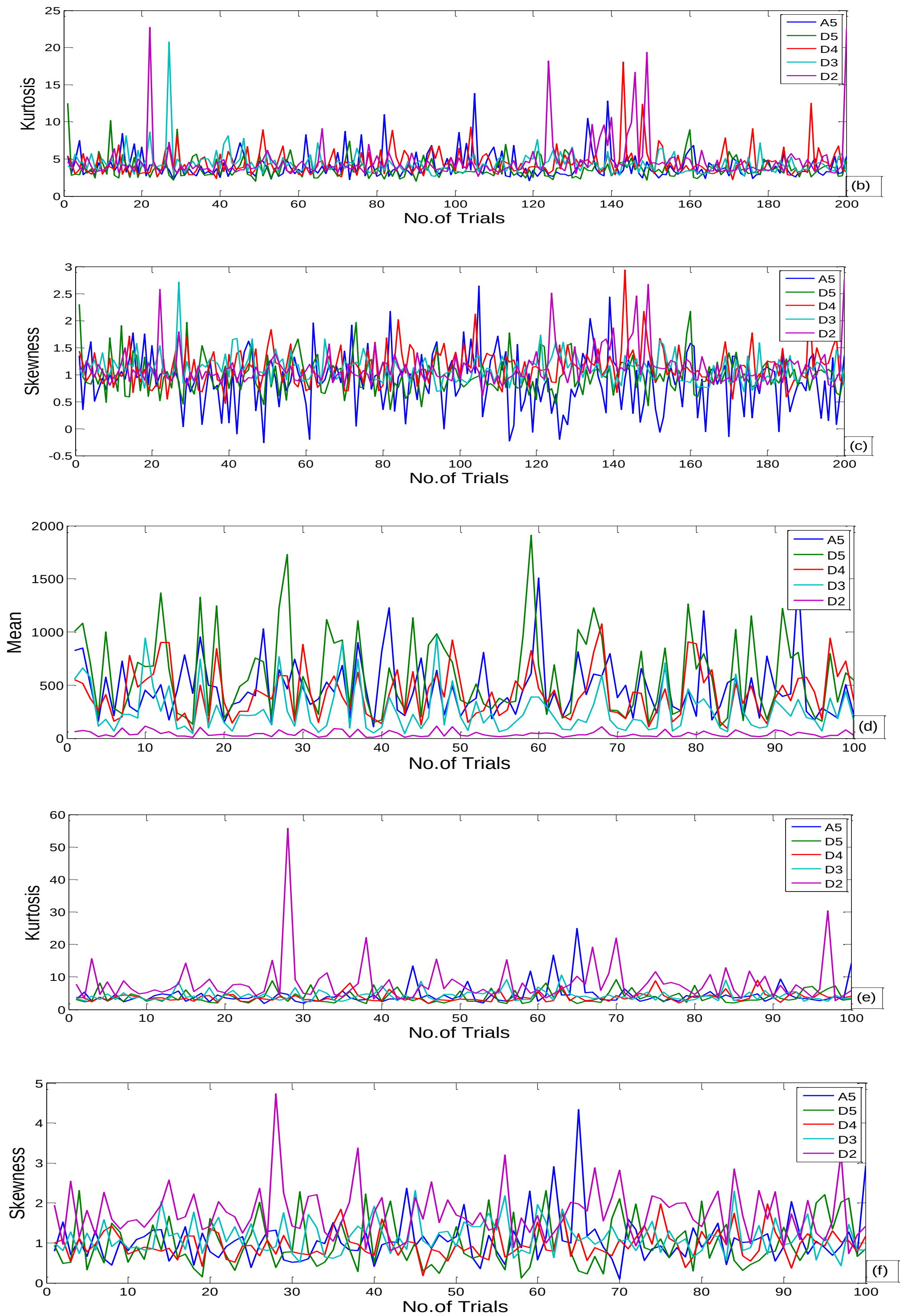


Figure 3.5 (a-c) Plot of extracted features for non-seizure EEG signals (d-f) Plot of extracted features for seizure EEG signals

Table 3.2. Classification performance of SVM, ANN and RF

Classifier Type	**Sensitivity**	**Specificity**	**F-measure**	**Precision**
SVM	92%	100%	0.973	0.974
ANN	97%	100%	0.990	0.990
RF	98%	100%	0.993	0.993

Table 3.1 and Table 3.2 gives that, RF classifier efficiently classifies the seizure and non-seizure EEG signals and shows best results among all three classifiers. In addition, ANN classifier performs better than SVM in terms of classification results. Confusion matrix is a table that is used to describe the performance of classification model on EEG data in which true values are already known. The two important parameters of classification performance i.e. sensitivity and specificity are given as equations 3.10 and 3.11 respectively. Table 3.2 gives the results of different parameters for classification.

$$Sen = \frac{TP}{TP+FN}$$ Equation (3.10)

$$Spe = \frac{TN}{TN+FP}$$ Equation (3.11)

TP is True Positive and FN is False Negative, TN is True Negative and FP is False Positive.

Table 3.3. Summary of recent automated methods for epilepsy diagnosis

Authors	Features/Method	classifiers	Accuracy%	Sensitivity %	Specificity %
Subasi[61]	Wavelet Transform (T-F features)	MLPNN, ANFIS	94	93.7	94.3
Pachori and Patidar[62]	Empirical Mode Decomposition	LS-SVM	97.75	97.68	98.07
Xia et al.[63]	S-Transform and SVD	BLDA	96.40	99	99.01
The proposed work	**FAWT and mean, kurtosis, skewness**	**LS-SVM, ANN and RF**	**99.33**	**98**	**100**

Table 3.3 shows the comparison of present methodology of automatic seizure detection with those studies available in the literature. It is evident from Table 3.3 that the proposed technique is more accurate in terms of seizure detection compared to other methods. It is apparent from the classification results that the proposed technique of automated epileptic seizure detection is capable of recognizing seizure and non-seizure EEG signals efficiently.

3.5 SUMMARY

This chapter aims to propose an effective methodology for the automatic detection of epileptic seizure using EEG signals. In this chapter, FAWT technique is used for TF decomposition of EEG signals and the FAWT bases parameters are optimized by using maximum kurtosis value criterion. The statistical parameter i.e. mean, kurtosis and skewness are calculated from decomposed FAWT coefficients and feature vectors are constructed to classify EEG data using SVM, ANN and RF classifiers. It is evident from the classification results that FAWT transform based feature extraction technique is an efficient method in detection of epileptic seizure. The results of classification indicates very high classification efficiency of 97.33%, 99% and 99.33% is achieved by SVM, ANN and RF classifiers correspondingly.

CHAPTER 4	EPILEPTIC SEIZURE DETECTION USING TQWT

4.1 INTRODUCTION

Visual scanning of EEG signals for disease diagnosis is an inefficient and time consuming process. Also, it requires expertise in reading the temporal distribution of EEG activity. In order to overcome the limitations of visual scanning techniques, numerous Computer Aided Diagnosis (CAD) techniques have been suggested in recent past [64, 65]. The methodology of disease diagnosis using EEG signals integrates three methodological steps viz. pre-processing, feature extraction and classification. Here, pre-processing is responsible for removal of excessive noise and artifacts from EEG activity. It helps in recognizing vital EEG features and improves the classification efficiency. Feature extraction step is involved in extracting significant features from sampled EEG data and preparation of feature vectors. This is followed by training and validation of various soft computing techniques for classification of recorded EEG activity.

Transforms like Short Time Fourier Transform (STFT) [66] and Wavelet Transform (WT) [67] are commonly used techniques for time-frequency representation and feature extraction of EEG activity in epilepsy diagnosis [68]. However, STFT has a limitation of time resolution at high frequencies and frequency resolution at low frequency due to fixed window size [69]. The limitations of STFT restricts it's applicability in epilepsy detection. Wavelet Transform (WT) is used to overcome the drawbacks of STFT as WT has varying window size. It is evident from past studies that WT is a more appropriate time-frequency domain decomposition technique for observing transient phenomenon of EEG signals [70]. In recent studies, WT based approaches have been developed for de-noising, artifacts removal and feature extraction of biological signals [71]. The WT should have a low value of Q-factor when physiological activity shows little or no oscillatory behavior. On the contrary, the WT should have a relatively high Q-factor for the analysis and processing of highly oscillatory physiological activity [75].

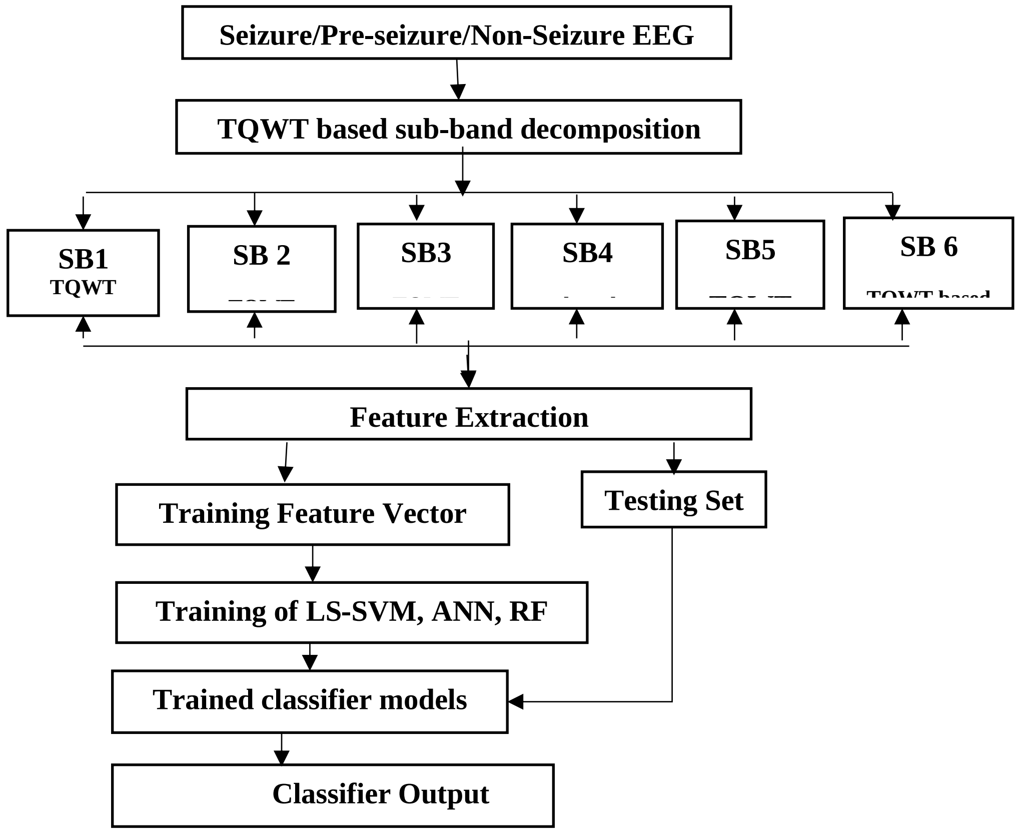


Figure 4.1 Flow chart of proposed methodology of feature extraction and classification

However, other than the CWT, WT have little ability to tune the Q-factor of the wavelet. WT based techniques have limitations of selection of appropriate mother wavelet function and fixed Q-factor [72]. In some studies, Rational Dilation Wavelet Transform (RADWT) has also been used for EEG signal decomposition, however it also has a limitation of rational dilation factor [73]. In order to overcome the limitations of these time-frequency decomposition techniques, the Tunable-Q Wavelet Transform (TQWT) based EEG feature extraction technique is proposed in present chapter [76]. Tunable-Q Wavelet Transform (TQWT) is completely discrete and provides perfect reconstruction of EEG signals [77]. In addition, it samples the time-frequency plane densely while maintaining discrete estimation of Continuous Wavelet Transform (CWT) [74].

In this chapter, two types of epilepsy detection (two class/three class) tasks have been performed using TQWT as the base phenomenon of signal decomposition. In the first study, classification is performed using Entropy based features only and the classification problem is binary in nature i.e. seizure and non-seizure classes. However, classification is performed using Entropy and Fractal Dimension (FD) based features in the second study. The classification problem is of three classes i.e. seizure, pre-seizure and non-seizure classes. Once feature vector is prepared after feature extraction stage, three soft computing techniques viz. support vector machine (SVM), artificial neural network (ANN) and random forest (RF) have been used for training and validation in both the tasks. A unified flow chart of proposed methodology for automated seizure detection is shown in Fig. 4.1.

4.2 TUNABLE-Q WAVELET TRANSFORM

In order to detect epileptic seizure, a complete methodology of feature extraction and classification is described in this section. In this section, the methodology of TQWT based entropy feature extraction is illustrated for epileptic seizure detection. The proposed methodology offers benefits of entropy based features for two class and entropy as well as FD based features for three class problem. In this approach, segments of EEG signals are decomposed into sub-bands using TQWT. Thereafter, features are calculated from the decomposed sub-bands of the EEG signal. The efficacy of proposed techniques is investigated using LS-SVM, ANN and RF classifiers.

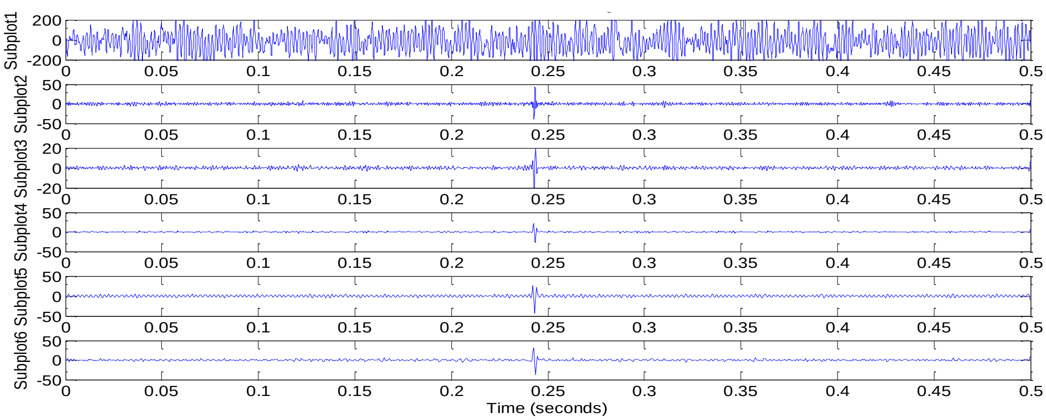
4.2.1 TQWT based EEG decomposition

The method of Discrete Wavelet Transform (DWT) is an efficient technique for Time Frequency (TF) representation since it is capable of capturing variations in morphologies like sharpness, spikes and slow waves [85]. Tunable-Q Wavelet Transform (TQWT) is a type of DWT for which various parameters can be adjusted to obtain desired TF region. The various parameters of TQWT are Q-factor (Q), redundancy or oversampling rate (r) and number of decomposition levels (j). Parameter Q controls number of oscillations of wavelet, parameter r controls undesired excessive ringing and localize wavelet in time without any effect in shape of waveform [79].

The TQWT filters consist of non-rational transfer functions. Therefore, it is easy to perfectly reconstruct and implement TQWT using Fast Fourier Transform (FFT) with adjustable Q-factor [87]. The multi-arrange TQWT based decomposition (TQWD) can be effectively accomplished by more than once appending two band channel banks to the low-pass sub-band signals [80]. The advantages of TQWT over DWT makes it more powerful for analysis of oscillatory physiological signals like EEG [84]. The various merits of TQWT encouraged its use in present study for extracting feasible features from EEG signals.

. EEG signals contains useful information in its rhythmic components i.e. alpha (8-13 Hz), beta (13-30 Hz) and gamma (> 30 Hz) frequency bands [81]. So, it is essential to decompose EEG signals to maximally correlate with these frequency bands. Keeping decomposition level $j = 5$, separates the upper rhythmic activities and extract information embedded in these sub-bands effectively [83]. Hence, in this chapter, the decomposition level is set to 5 for both the problems i.e. two class and three class problem.

Tunable Q Wavelet Transform (TQWT) coefficients for non-seizure, pre-seizure and seizure EEG signals is represented in Fig. 4.2.



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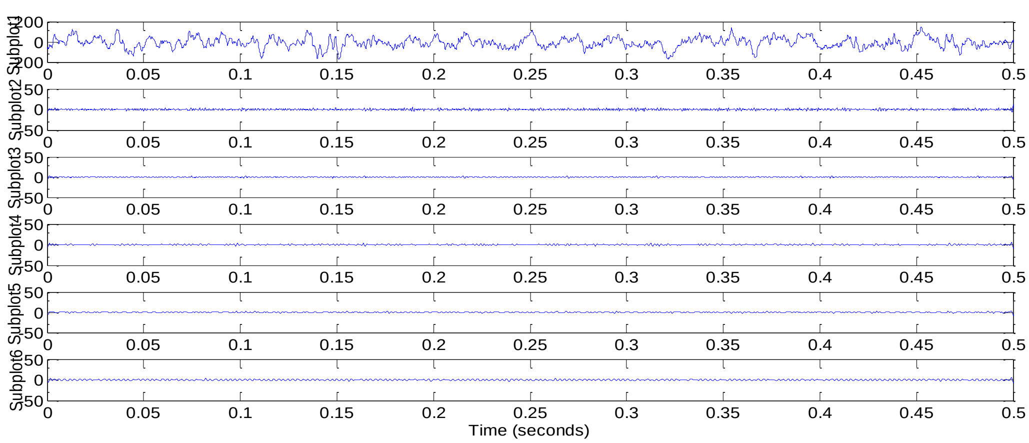

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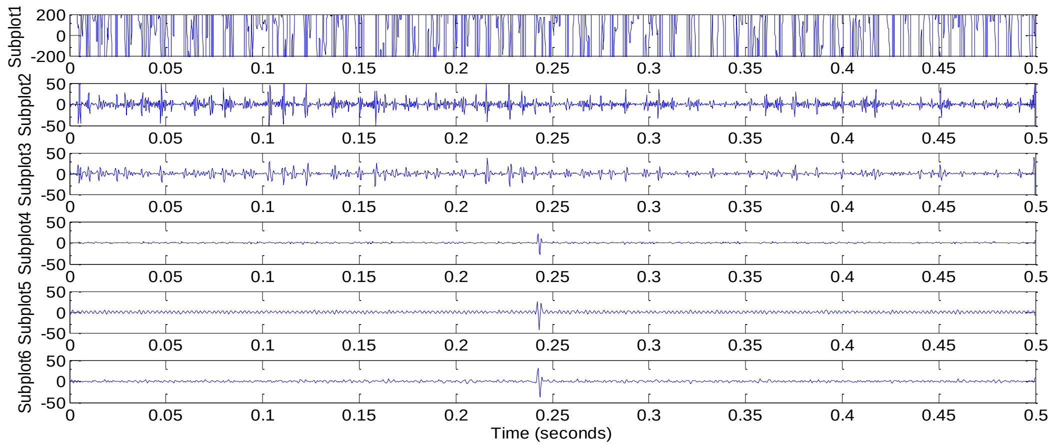
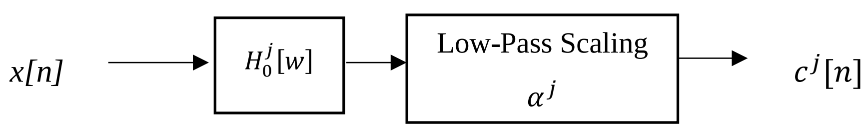


(c)

Figure4.2 (a) TQWT coefficients of seizure EEG signals **(b)** TQWT coefficients of pre-seizure EEG signals **(c)** TQWT coefficients of non-seizure EEG signals



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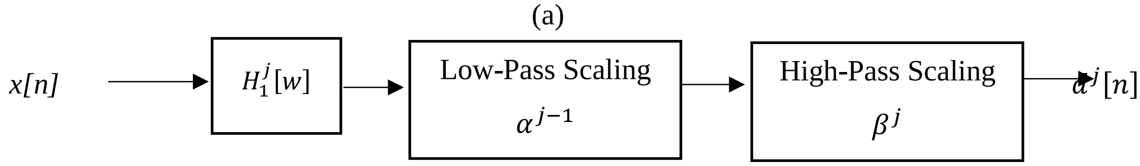


(b)

Figure 4.3 Equivalent System of *jth* level TQWT based decomposition of input signal *x[n]* to generate (a) low-pass sub-band signal $c^j[n]$ and (b) high-pass sub-band signal $d^j[n]$.

Figure 4.3 represents the Equivalent System of *jth* level TQWT based decomposition. $H_0[w]$ and $H_1[w]$ are equivalent frequency response generated after *j*-level for low-pass and high-pass sub-band signals respectively which are expressed mathematically as follows.

$$H_0^J(w) = \begin{cases} \prod_{m=0}^{J-1} H_0\left(\frac{w}{\alpha^m}\right), & if\ |w| \leq \alpha^J \pi \\ 0 & if\ \alpha^J \pi \leq |w| \leq \pi \end{cases} \qquad \text{Equation (4.1)}$$

$$H_1^J(w) = \begin{cases} H_1\left(\frac{w}{\alpha^{J-1}}\right) \prod_{m=0}^{J-2} H_0\left(\frac{w}{\alpha^m}\right), & if (1-\beta)\alpha^{J-1}\pi \leq |w| \leq \alpha^{J-1}\pi \\ 0 & for\ other\ w \in [-\pi, \pi] \end{cases}$$ Equation (4.2)

where $H_0(w) = \theta\left(\frac{w+(\beta-1)\pi}{\alpha+\beta-1}\right)$ $\quad H_1(w) = \theta\left(\frac{\alpha\pi - w}{\alpha+\beta-1}\right)$

$\theta(w)$ is frequency response of Daubechies filter with two vanishing moments and is expressed as

$$\theta(w) = 0.5(1+\cos(w))\sqrt{2-\cos(w)}, |w| < \pi$$ Equation (4.3)

r and *Q* can be expressed in terms of scaling parameters α and β as follows:

$$r = \frac{\beta}{1-\alpha}, \quad Q = \frac{2-\beta}{\beta}$$

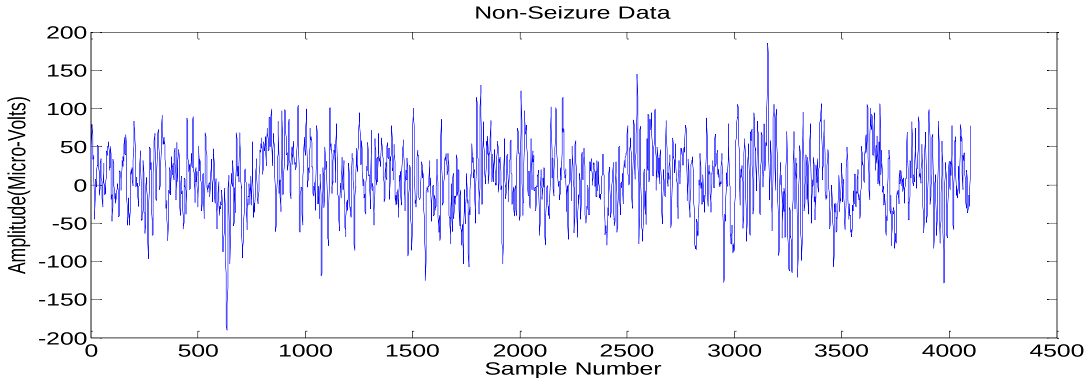
Tunable Q Wavelet Transform (TQWT) should have low Q-factor when signal shows n-oscillatory behavior whereas it should have high Q-factor for analysis and processing of oscillatory signals. The TQWT has an ability to tune Q-factor unlike CWT. Tunable Q Wavelet Transform (TQWT) resolves this problem by adjustment of Q-factor. Hence, it is powerful tool for oscillatory signal analysis like EEG.

4.3 TWO CLASSES CLASSIFICATION PROBLEM

4.3.1 EEG Database

The EEG data used in present study is obtained from online available EEG database of department of Epileptology, University of Bonn [54]. The EEG database consists of three subsets (Z, O and S) of artifacts free EEG time series registered under two categories viz. seizure and non-seizure. Subsets Z and O contains the surface EEG records of five healthy subjects recorded under eyes open and close conditions respectively. The subset S consists of EEG data recorded from five epileptic patients under seizure condition. Each subset consists 100 single-channel EEG record of 23.6 sec duration with the same 128-channel amplifier system, and digitized at a sampling rate of 173.61 Hz with 12-bit resolution. In this chapter, the subsets Z and O are combined to form Non-Seizure (NS) class and subset S forms the Seizure (S) class.

Fig. 4.4 demonstrates the exemplary EEG time series for seizure and non-seizure EEG signals.



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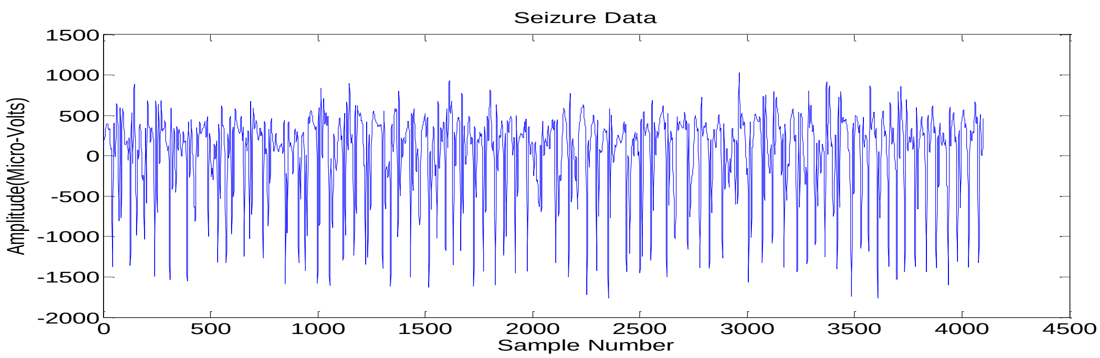
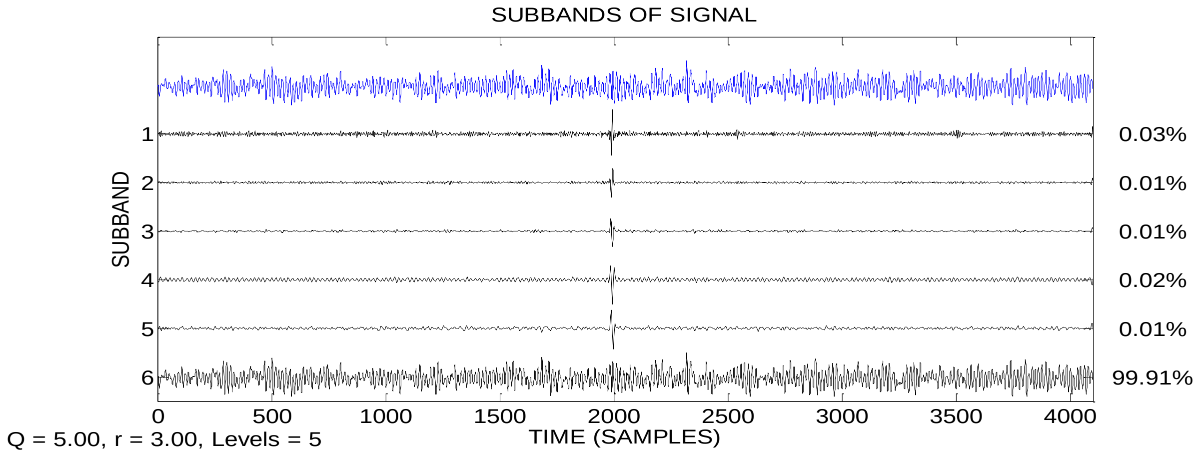


(b)

Figure 4.4 Exemplary EEG time series (a) subset Non-seizure (b) subset Seizure

4.3.2 Feature Extraction for Two Classes

Tunable Q Wavelet Transform (TQWT) coefficients energy distribution over sample values is presented in Fig. 4.5. However, Fig. 4.6 represents the total energy distribution of non-seizure and seizure EEG signals. It can be easily deduced from Fig. 4.5 and Fig. 4.6 that low as well as high frequency sub-bands possess significant amount of energy. Therefore, all these frequency sub-bands have been used in calculation of features. After decomposing EEG epochs to TQWT sub-bands, entropy based features are extracted from decomposed sub-bands in this study.



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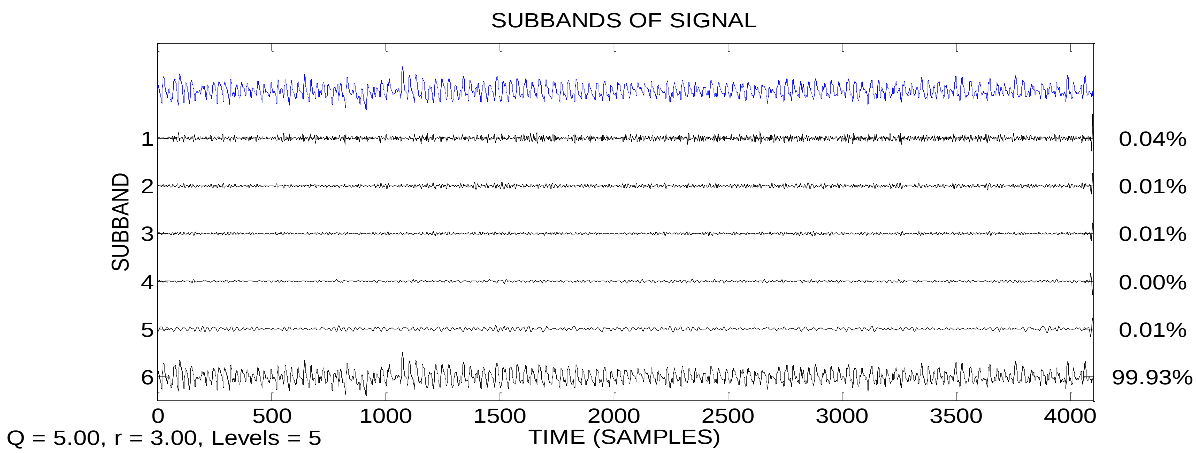

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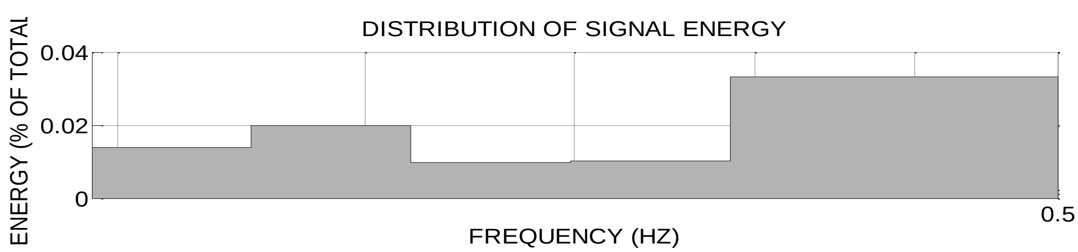
Figure 4.5 TQWT coefficients energy distribution over sample values (a) Non-Seizure (b) Seizure



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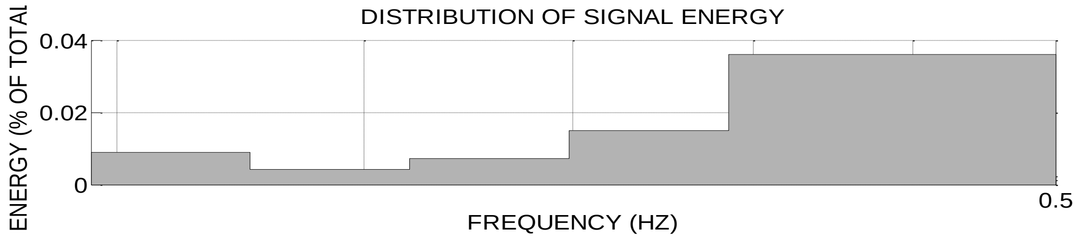


(b)

Figure 4.6 Total energy distribution (a) Non-Seizure (b) Seizure

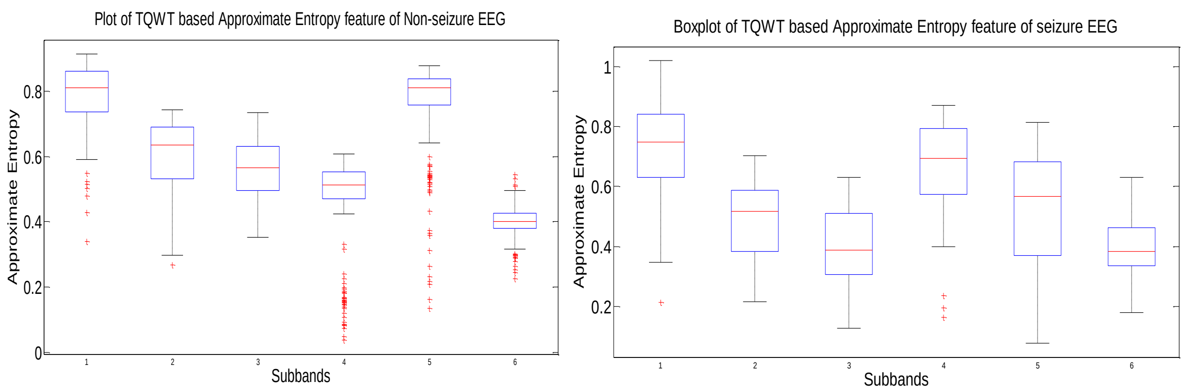
Entropy is a measure of rate of information generated which can be used in signal processing to separate out useful signal from noise signal. It is a non-linear index that reflects degree of chaos in the signal. High entropy value indicates the expanded abnormality and unpredictability whereas low value corresponds to high normality. Selecting features that explains the behavior of EEG signals is important for automatic detection of epileptic seizure. Entropy can easily identify complexity present in the EEG signal using computerized techniques. So, we used entropy features to extract information from EEG signals. Approximate and Renyi's entropies gives accurate results as compared to other entropies so these are used to extract features from sub-bands of EEG signals.

4.3.2.1 Approximate Entropy

Approximate Entropy (*ApEn*) is a measure of instability of variation in any signal. It identifies changes in underlying episodic behavior. In addition, it compares closeness of samples by pattern length *m* and similarity coefficient *r*. It is scale invariant measure because similarity rule is equivalent to standard deviation of information. Very irregular time series gives high *ApEn* whereas time series with more number of similar patterns gives low *ApEn* esteem. Approximate Entropy is calculated as

$$ApEn = \ln\left(\frac{C_m(r)}{C_{m+1}(r)}\right) \qquad \text{Equation (4.4)}$$

where $C_m(r)$ is pattern mean of length m and $C_{m+1}(r)$ is pattern mean of length $m+1$. The pattern mean is computed by comparing similar patterns of length *m* and length $m+1$. Approximate entropy (*ApEn*) relies on pattern length, which is inconsistent and counts the sequence that matches itself to stay away from condition *ln(0)*. In this paper, value of embedded dimension is *dim = 2*, delay time for down-sampling *tau* =1 and tolerance is *r* = 0.2*standard deviation of wavelet coefficients. Advantages of *ApEn* is that it can be figured for a moderately short series of noisy data and it can potentially differentiate a variety of systems such as periodic and multiple periodic systems, chaotic systems and stochastic systems. Fig. 4.7 shows the boxplot for *ApEn* values calculated from non-seizure and seizure EEG signals. On comparing the boxplot shown in Fig. 4.7, it can be illustrated that the boxplot of *ApEn* is more negatively skewed for seizure EEG signals compared to non-seizure one.



(a) (b)

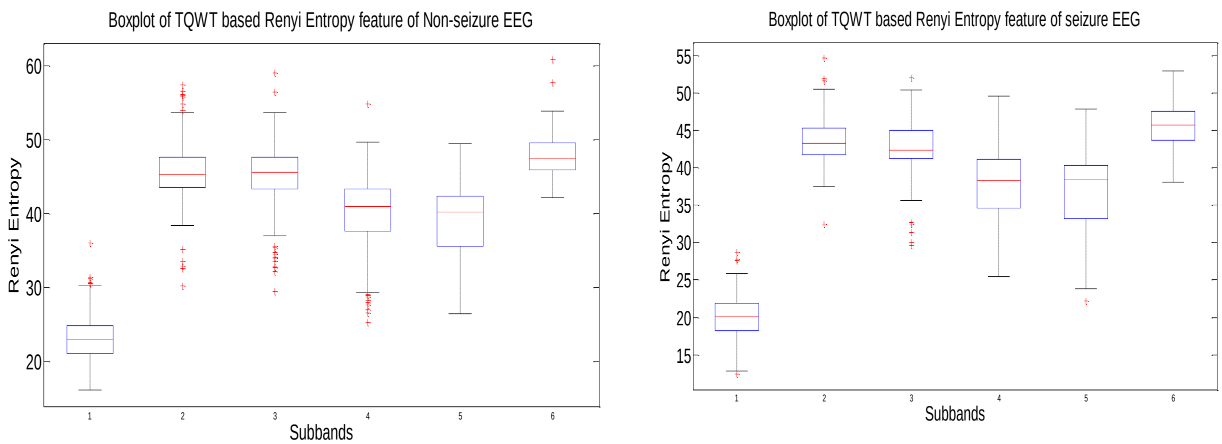
Figure 4.7 (a) Boxplot of *ApEn* feature for non-seizure EEG signals (b) Boxplot of *ApEn* feature for seizure EEG signals

4.3.2.2 Renyi's Entropy Estimation

Renyi's Entropy (*REN*) is an accumulation type of Shannon Entropy and is utilized for evaluating the spectral complexity of time series signal. The *REN* is calculated as:

$$REN(\alpha) = -\frac{\alpha}{1-\alpha}\sum \log p_i^{\alpha} \qquad \text{Equation (4.5)}$$

where $\alpha \neq 1$, p_i is total spectral power. The *REN* with order, $\alpha \geq 2$ provides a lower bound to its smooth entropy as *REN* with order $\alpha = 1$ is similar to Shannon Entropy and it produces shallow measure of smooth entropy. Here $\alpha = 2$ is used for *REN*. The advantages of *REN* includes rescaling of variables and flexibility against additive constant. In this work, maximum value of *REN* is considered as it represents power-law distribution of signal. Fig. 4.8 shows the boxplot for *REN* values calculated from non-seizure and seizure EEG signals. Again, on comparing the boxplot shown in Fig. 4.8, it can be illustrated that the boxplot of *REN* is more negatively skewed for seizure EEG signals compared to non-seizure one.



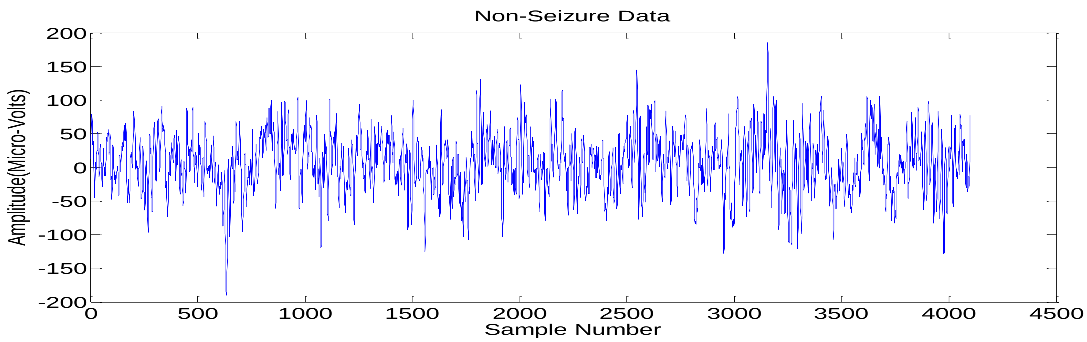
(a) (b)

Figure 4.8 (a) Boxplot of *REN* feature for non-seizure EEG signals (b) Boxplot of *REN* feature for seizure EEG signals

4.4 THREE CLASS CLASSIFICATION PROBLEM

4.4.1 EEG Database

EEG data used in same as used in case of two class problem with the extra pre-seizure data which consist of subset F and subset N. The subset Z and O are acquired from five healthy patients in eyes closed and eyes open condition recorded extracranially. The subset F is recorded from five patients in epileptogenic zone and subset N is recorded from hippocampal formation of the opposite hemisphere of the brain when there was no seizure. The subset S is obtained from same five patients during epileptic seizure from all ictal zones. The subset F, N and S are recorded intracranially. Exemplary EEG time series for normal, pre-ictal and ictal classes are shown in Fig 4.9.



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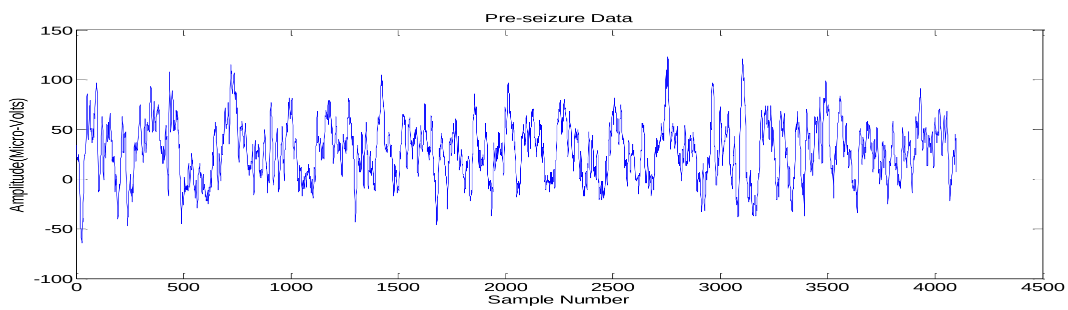

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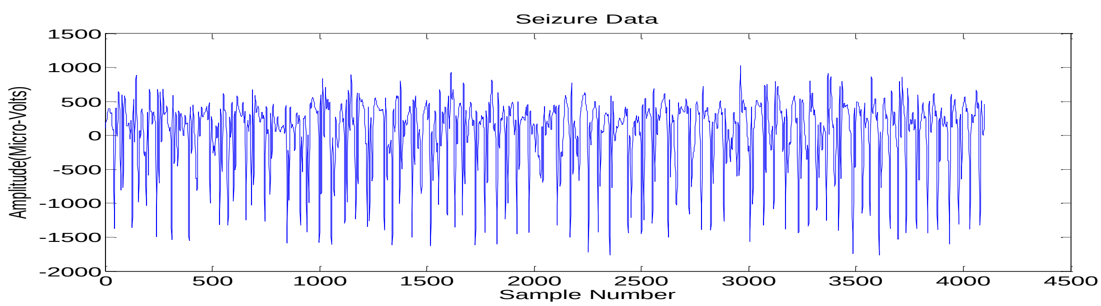
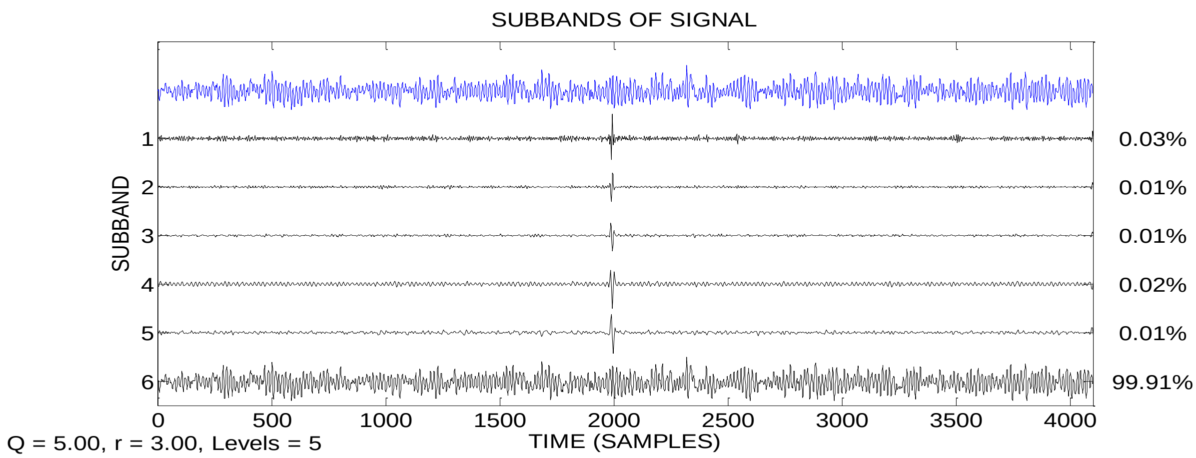


(c)

Figure 4.9 Exemplary EEG time series (a) subset Non-seizure (b) subset Pre-seizure (c) subset Seizure

4.4. 2 Feature Extraction for Three Classes

Tunable Q Wavelet Transform (TQWT) coefficients energy distribution over sample values is presented in Fig. 4.10. However, Fig. 4.11 represents the total energy distribution of non-seizure, pre-seizure and seizure EEG signals. It can be easily deduced from Fig. 4.10 and Fig. 4.11 that low as well as high frequency sub-bands possess significant amount of energy for all the three classes. Therefore, all these frequency sub-bands have been used in calculation of features. After decomposing EEG epochs to TQWT sub-bands, approximate entropy and FD based features are extracted from decomposed sub-bands in this study.



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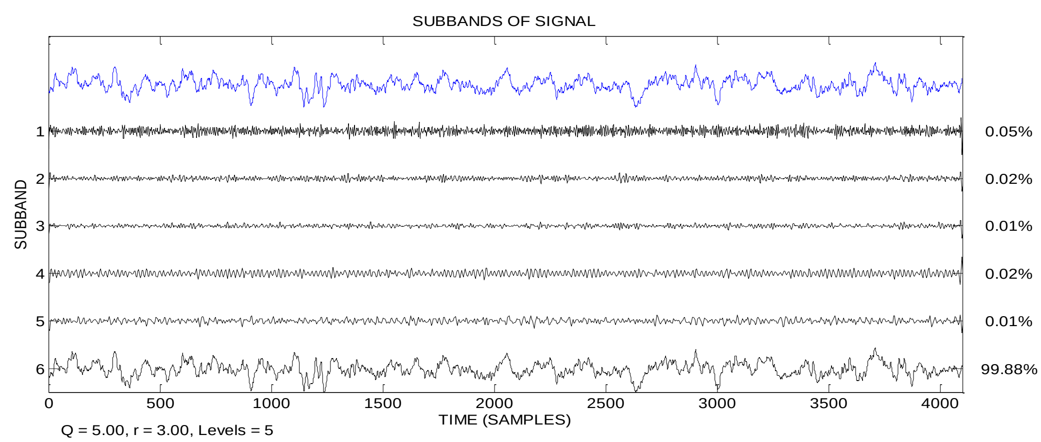

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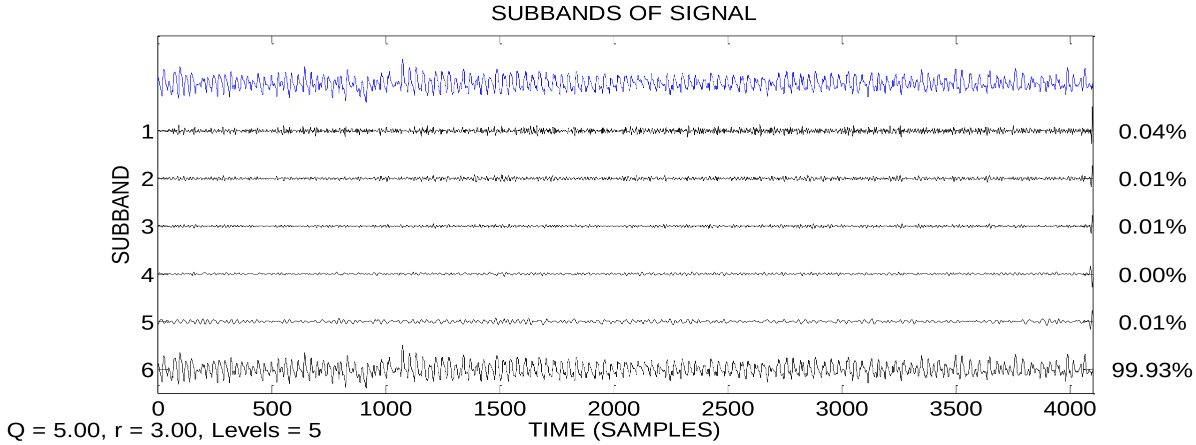

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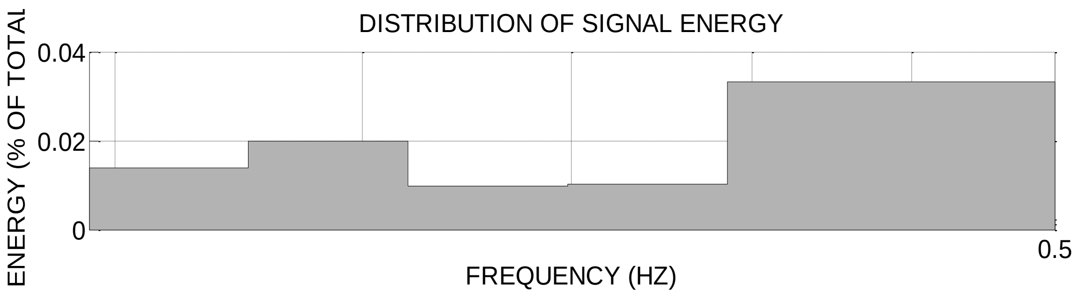
Figure 4.10 TQWT coefficients energy distribution over sample values (a) Non-Seizure (b) Pre-seizure (c) Seizure



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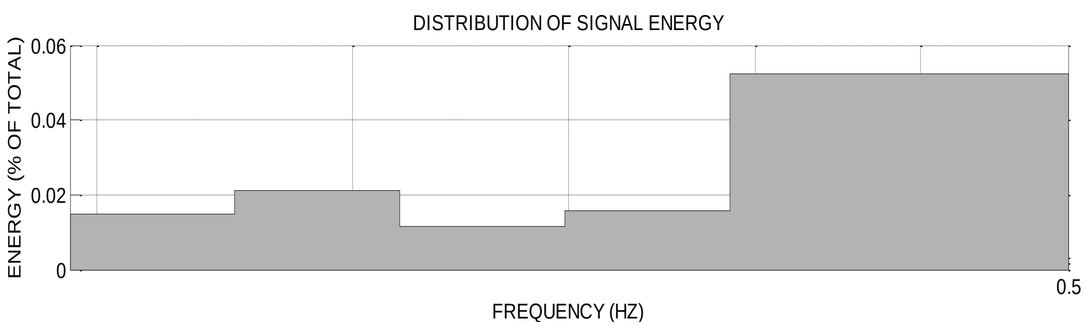
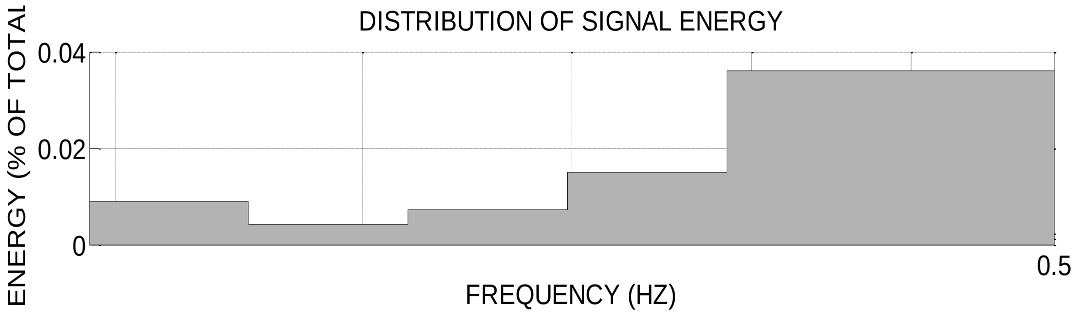


(b)



(c)

Figure 4.11 Total energy distribution (a) Non-Seizure (b) Pre-seizure (c) Seizure

4.4.2.1 Higuchi's Algorithm:

Higuchi's FD estimation algorithm is based on the measurement of curve length. The curve is divided into *k* number of samples and mean length of the curve is calculated. For a time series of finite set $(S(n); n = 1,2 \ldots.\}$; N is number of sample points on the curve, the Higuchi FD estimation can be given by following steps.

Step 1: construct *k* new time series S_{nk} for range of *k* from 1 to k_{max}.

$$S_n^k = \{S(m), S(m+k), S(m+2k), \ldots \ldots S\left(m + int\left(\frac{N-m}{k}\right).k\right)\} \quad \text{Equation (4.6)}$$

where *m* indicates initial time value (m = 1,2,3,….k) and *k* indicates the discrete time interval between points.

Step 2: for each of the curve S_n^k constructed, length $L_m(k)$ is constructed as,

$$L_m(k) = \left[\left(\sum_{i=1}^{int\left(\frac{N-m}{k}\right)} \begin{matrix} |S(m+ik) \\ -S(m+(i-1).k)| \end{matrix} . \frac{N-1}{int\left(\frac{N-m}{k}\right).k}\right)\right].k^{-1}$$

Equation (4.7)

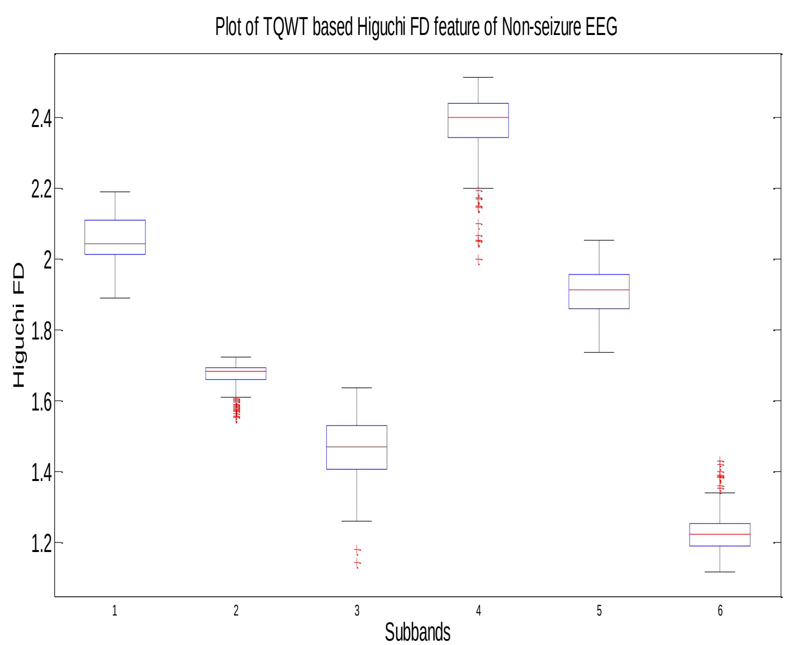
here, *(N-1)*. $(int\left(\frac{N-m}{k}\right).\mathrm{k})^{-1}$ is a normalization factor for length of curve S_n^k.

Step 3: For each value of k, calculate average length of curve of waveform as

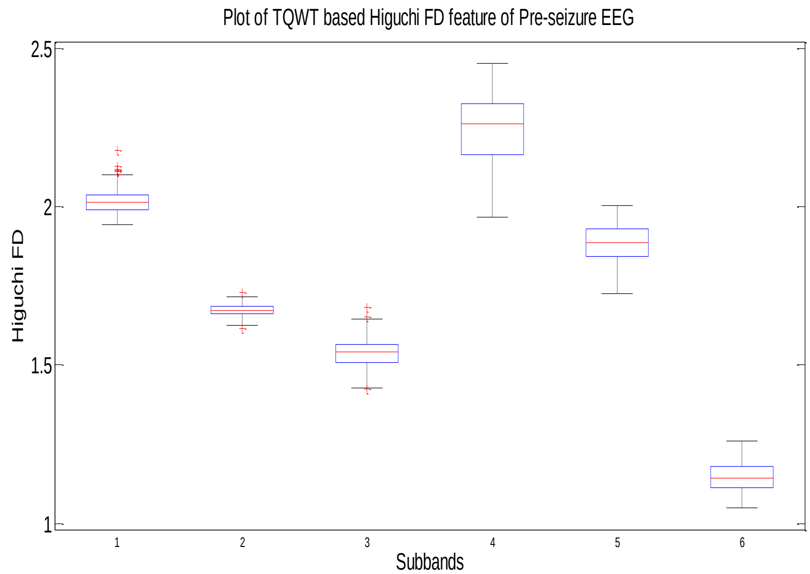
$$L_{avg}(k) = \frac{1}{k}\sum_{m=1}^{k} L_m(k) \qquad \text{Equation (4.8)}$$

The above calculation is repeated for all values of k ranging from 1 to k_{max}.

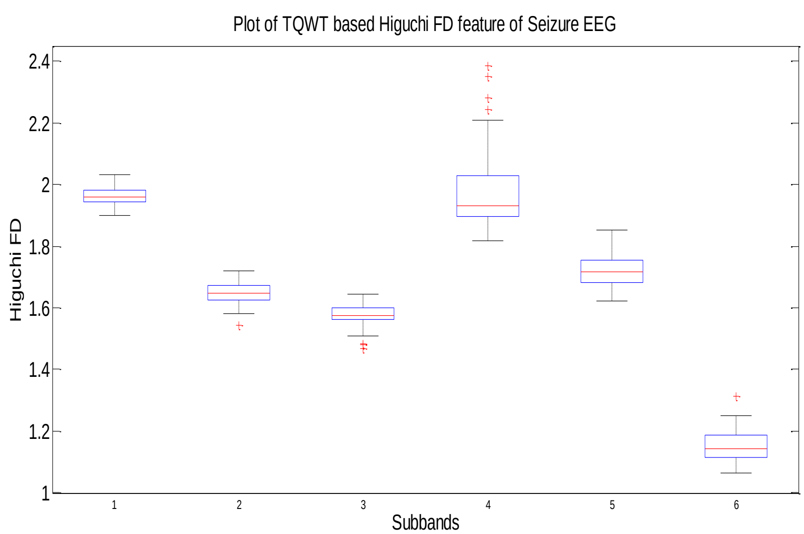
Step 4: the total average length $L_{avg}(k)$ is directly proportional to k^{-D}, where D is higuchi's FD. In the curve of $\ln(L_{avg}(k))$ versus $\ln(\frac{1}{k})$, the slope of least square linear best fit is estimate of higuchi's FD. Fig 4.12 shows the boxplot of TQWT based Higuchi's FD features.



(a)



(b)



(c)

Figure 4.12 (a) Boxplot of *Higuchi's FD* feature for non-seizure EEG signals

(b) Boxplot of *Higuchi's FD* feature for seizure EEG signal

(c) Boxplot of *Higuchi's FD* feature for seizure EEG signals

4.4.2.2 Katz's Algorithm: Mandelbrot gives FD of a planar curve as,

$$FD_{mandelbrot} = \frac{\log(L_t)}{\log(d)} \qquad \text{Equation (4.9)}$$

where L_t is sum of distance between successive points on curve and d is distance calculated as distance between first point and point which is situated at farthest distance from first point. If a point on waveform is $T_i = (x_i, y_i)$ with $x_i < x_{i+1}$, i = *1, 2, 3….,N* (*N*=total number of points). It defines waveform propagating ahead in x-direction. Mathematically, L and d are obtained as

$$L_t = \sum_{i=1}^{N} \|T_{i+1} - T_i\| \qquad \text{Equation (4.10)}$$

$$d = max\|T_i - T\|$$

In equations above ||.|| denotes Euclidean distance. $FD_{mandelbrot}$ depends upon the measurement units.

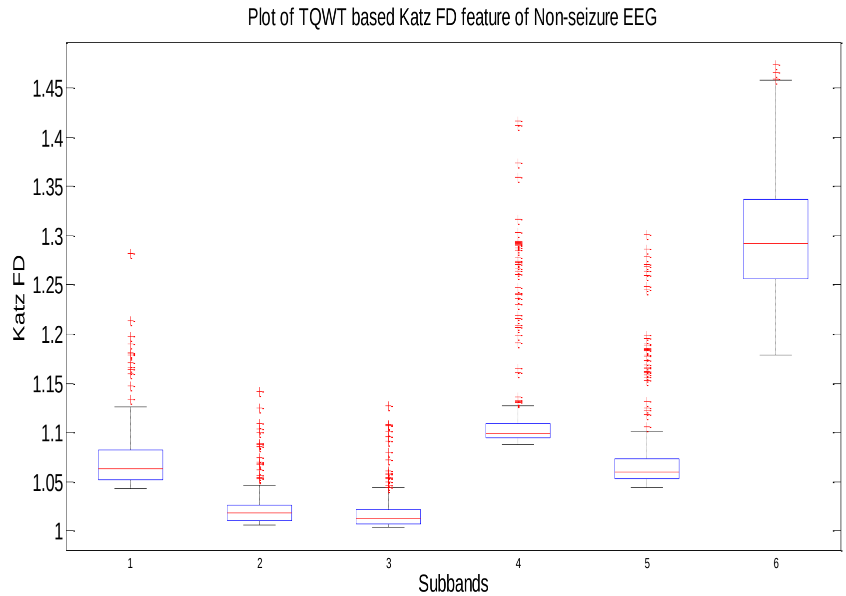
Katz combines a unit of measure or 'Yardstick' definition, along with Mandelbrot's original contribution, and figure out that discretization of space is done to calculate FD. Katz's approach solves the problem of discretization by generalizing unit: the average distance between successive points a. Katz proposed the idea of normalizing distance d by average value a. Katz's FD is given as,

$$FD_{katz} = \frac{\log(L_t/a)}{\log(d/a)} \qquad \text{Equation (4.11)}$$

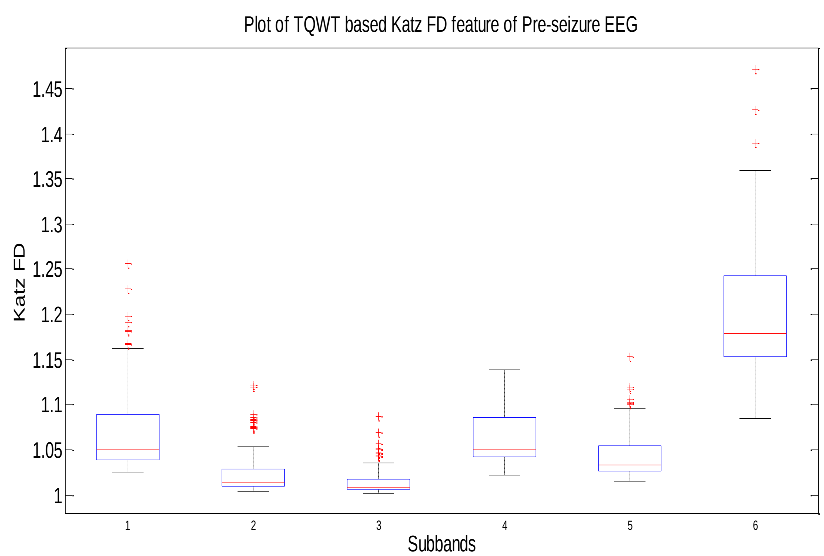
Presenting n as a number of steps in curve $n = L_t/a$ and substituting n, we get

$$FD_{katz} = \frac{\log(n)}{\log(n)+\log(d/n)} \qquad \text{Equation (4.12)}$$

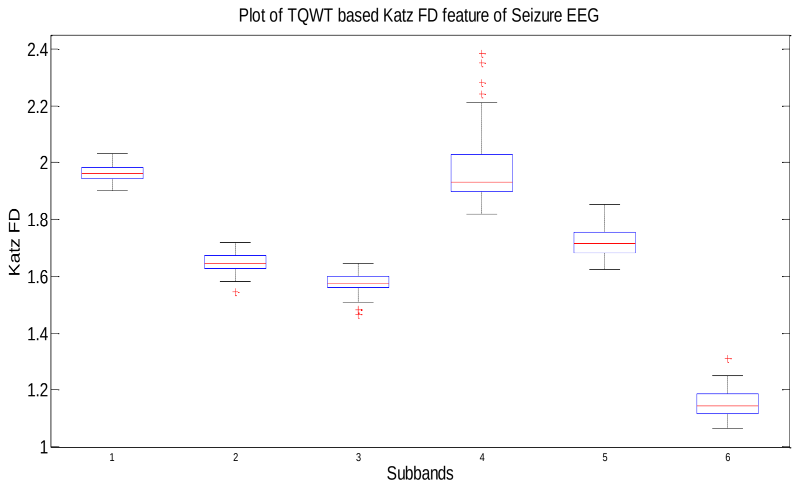
Fig 4.13 represents bloxplot of non-seizure, pre-seizure and seizure EEG signals.


Plot of TQWT based Katz FD feature of Non-seizure EEG
Katz FD
1.45
1.4
1.35
1.3
1.25
1.2
1.15
1.1
1.05
1
1
2
3
4
5
6
Subbands

(a)


Plot of TQWT based Katz FD feature of Pre-seizure EEG
Katz FD
1.45
1.4
1.35
1.3
1.25
1.2
1.15
1.1
1.05
1
1
2
3
4
5
6
Subbands

(b)



(c)

Figure 4.13 (a) Boxplot of *Katz's FD* feature for non-seizure EEG signals

(b) Boxplot of *Katz's FD* feature for seizure EEG signal

(c) Boxplot of *Katz's FD* feature for seizure EEG signals

4.4.2.3 Approximate entropy

Approximate entropy used here is same as that was used in case of two class problem and the plot is also same with addition of pre-seizure approximate entropy plot as shown in fig 4.14.

On comparing the boxplot shown in fig. 4.14 with that of plot of fig. 4.6, it can be illustrated that the boxplot of *ApEn* is more negatively skewed for seizure EEG signals compared to non-seizure one.

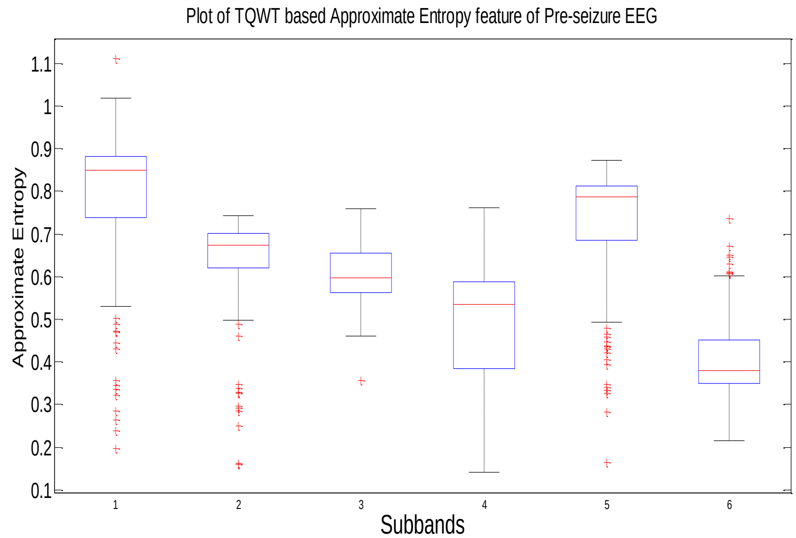


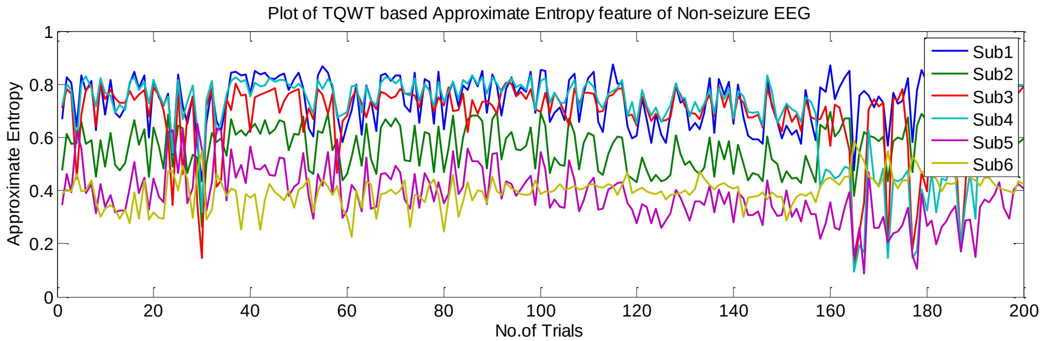
Figure 4.14 Boxplot of *ApEn* feature for pre-seizure EEG signal

4.5 RESULTS AND DISCUSSION

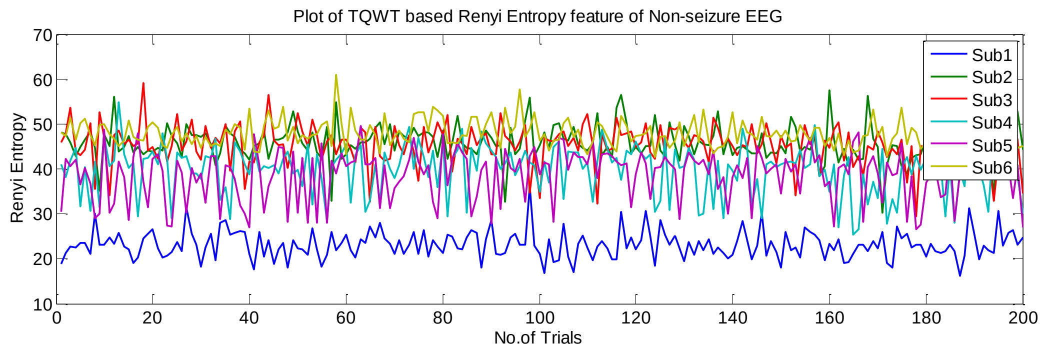
Results for both the two class problem as well as three class problem have been discussed here and compared with previous studies as well.

4.5.1 Results of Two Class Problem

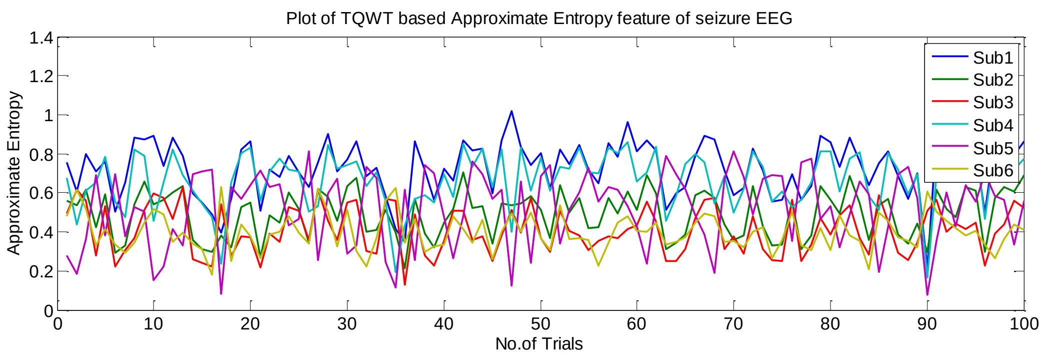
Features are accumulated to form the feature vectors of corresponding non-seizure and seizure classes. The prepared feature vectors are provided as an input to the classifiers for training and validation purposes. The classification of EEG signals for epileptic seizure detection is performed using LS-SVM, ANN and RF classifiers. Total *200* EEG trials corresponding to non-seizure class and *100* EEG trials relating to seizure class are considered in this study. The 10-fold cross validation technique is used for classification here. In 10-fold cross validation technique the data is divided into ten folds and classification is carried out in ten iterations. However, the result is the average of results of all the ten iterations. The 10-fold cross validation technique is preferred to have no statistical biasing present in the results. Fig. 4.15 shows the plots of TQWT based *ApEn* and *REN* features calculated using non-seizure and seizure EEG signals. It is observed from Fig. 4.15 that *REN* coefficients for all sub-bands shows large variation for non-seizure EEG signals and slow variation for seizure EEG signals. Similarly, *ApEn* coefficients of sub-bands vary frequently for non-seizure EEG and not for seizure EEG signals.



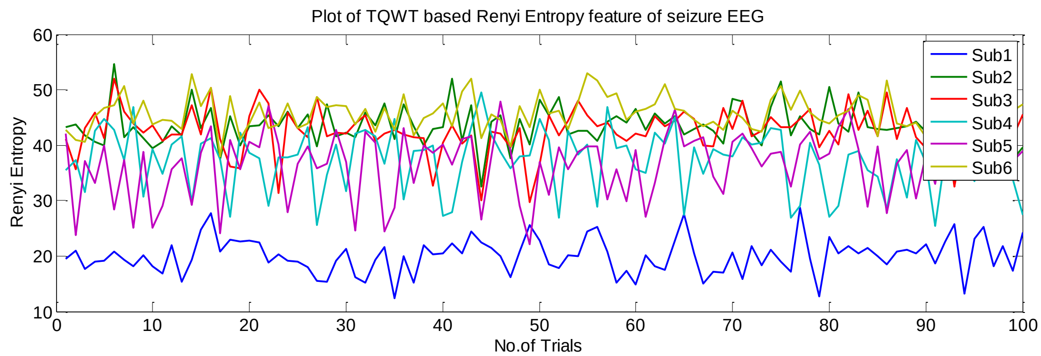
(a)



(b)



(c)



(d)

Figure 4.15 (a-b) Plot of extracted features for non-seizure EEG signals (c-d) Plot of extracted features for seizure EEG signals

Table 4.1. Confusion Matrix of LS-SVM, ANN and RF for 2 classes

Classifier Type	Non-Seizure	Seizure	Classified as
LS-SVM	200	0	**Non-Seizure**
	2	98	**Seizure**
ANN	199	0	**Non-Seizure**
	3	97	**Seizure**
RF	199	1	**Non-Seizure**
	3	97	**Seizure**

Table 4.2. Classification Parameters of LS-SVM, ANN and RF for 2 classes

Classifier Type	Sensitivity	Specificity	F-measure	Precision
LS-SVM	98%	100%	0.993	0.993
ANN	97%	99%	0.987	0.987
RF	97%	99%	0.987	0.987

It is observed from Table 4.1 and Table 4.2 that, LS-SVM classifier efficiently classifies the seizure and non-seizure EEG signals (two class problem) and shows the best classification performance among all three classifiers. The LS-SVM classifier classifies the two classes of EEG signals with highest classification efficiency of 99.40 %. In addition, the specificity parameter for the classification is 100. The classification performance of ANN and RF classifiers is almost comparable with very slight variation. The classification efficiency obtained for ANN and RF classifiers is 98.70 % and 98.67 % respectively. The results of the classification evident the efficacy of proposed feature extraction methodology for binary classification problem of seizure detection. A brief comparison of present methodology of automatic seizure detection and those suggested in past, is presented in Table 4.3. It is evident from Table 4.3 that the proposed technique is more accurate compared to the previously proposed techniques for seizure and non-seizure EEG signal detection.

Table 4.3**.** Comparison of present methodology of automatic seizure detection with previously proposed techniques

Authors	Features/Method	Classifiers	Accuracy%	Sensitivity%	Specificity%
Sharma and Pachori [88]	EMD, confidence area measure	LS-SVM	85-90	NA	NA
Swami et al. [89]	Wavelet packet transform, standard deviation, entropy	SVM	99.33	99.21	99.34
Swami et al. [90]	DTCWT, energy, standard deviation, entropy, etc.	General regression, neural network	99.15	98.32	99.55
Pachori and Patidar [86]	EMD, SODP based-confidence area measure	LS-SVM	97.75	97.68	98.07
The proposed work	**TQWT, Approximate and Renyi's Entropy**	**LS-SVM**	**99.40**	**98.00**	**100**

Table 4.3 shows the comparison of different papers on automated epileptic seizure detection in which accuracy of different techniques proposed by different authors is shown. It is noteworthy that our proposed work is more accurate as compared to other methods as shown in table 3. In some cases proposed method outperforms other techniques. Two entropy based features are calculated from six frequency sub-bands of TQWT coefficients. It is perceived from the results of classification that LS-SVM classifier can recognize two classes of EEG data with

highest classification efficiency of 99.40%. However, the classification performance achieved from ANN and RF classifiers is almost comparable. The proposed automated methodology offers high degree of accuracy in epileptic seizure detection. Complete automation and high degree of classification accuracy make this methodology clinically suitable for the diagnosis of epileptic seizure using EEG signals.

4.5.2 Results for Three Class Problem

Features are accumulated to form the feature vectors of corresponding non-seizure, pre-seizure and seizure classes. Similar to the two class classification task, the prepared feature vectors are provided as an input to the classifiers for training and validation purposes. The classification of EEG signals for epileptic seizure detection is performed using LS-SVM, ANN and RF classifiers. The number of trials for seizure and non-seizure classes are similar to the two class classification problem explained in this chapter. Only the trials for pre-seizure activity are added in this section and in total *200* EEG trials are considered under pre-seizure class of EEG data. Similar to the previous section, 10-fold cross validation technique is used for classification in this section as well. Table 4.4 shows the confusion matrix for three class classification problem using LS-SVM, ANN and RF classifiers. Table 4.5 shows the classification performance obtained using LS-SVM, ANN and RF classifiers.

Table 4.4. Confusion Matrix using LS-SVM, ANN and RF classifier

Classifier Type	**Non-Seizure**	**Pre-seizure**	**Seizure**	**Classified as**
LS-SVM	200	0	0	**Seizure**
	0	200	0	**Pre-seizure**
	0	0	100	**Non-seizure**
ANN	200	0	0	**Seizure**
	0	200	0	**Pre-seizure**
	0	0	100	**Non-seizure**
RF	197	0	3	**Seizure**
	0	200	0	**Pre-seizure**
	3	0	97	**Non-seizure**

Table 4.5. Classification performance obtained using LS-SVM, ANN and RF classifiers

Classifier Type	Sensitivity	Specificity	F-measure	Precision
LS-SVM	100%	100%	1	1
ANN	100%	100%	1	1
RF	98.8%	99.4%	0.988	0.988

It is observed from Table 4.3 and Table 4.4 that, LS-SVM and ANN classifiers efficiently classify the seizure, pre-seizure and non-seizure EEG signals and show the high classification performance for three class classification problem. The LS-SVM, ANN classifiers classifies the three classes of EEG signals with highest classification efficiency of 100 %. Hence, the specificity and sensitivity parameters are having the highest value of 100%. The classification performance of RF classifiers is almost comparable with very slight variation. The classification efficiency obtained for RF classifiers is 98.8 %. The results of the classification evident the efficacy of feature extraction methodology proposed in this section for three class classification problem of epilepsy detection. A brief comparison of present methodology of automatic epilepsy detection and those suggested in past, is presented in Table 4.6. It is evident from Table 4.6 that the proposed technique is more accurate compared to the previously proposed techniques.

Table 4.6. Comparison of present methodology of automatic seizure detection with previously proposed techniques

Authors	Features/Method	Classifiers	Accuracy%
Kousarrizi et. al.[91]	Haar wavelet based features	SVM, NN	94.67
Vyas et. al. [92]	DWT, PCA	SVM	98.33
Pan et. al. [93]	FD features	RF	92.2
Subasi [94]	DWT	ANN	93.33
The proposed work	**TQWT, Approximate Entropy and FD features**	**LS-SVM, ANN**	**100**

Table 4.6 shows the comparison of different papers on automated epileptic seizure detection in which accuracy of different techniques proposed by different authors is shown. It is noteworthy that our proposed work is more accurate as compared to other methods as shown in table 4.6. In some cases proposed method outperforms other techniques. In this work, the features of EEG signals are extracted from decomposed TQWT coefficients. Entropy and FD based features are calculated from six frequency sub-bands of TQWT coefficients. It is perceived from the results of classification that LS-SVM and ANN classifier can recognize three classes of EEG data with highest classification efficiency of 100%. However, the classification performance achieved from RF classifiers is almost comparable. The proposed automated methodology offers high degree of accuracy in epileptic seizure detection. So, our proposed technique is more accurate and reliable yielding significantly higher classification efficiency. Countries with less facilities and experts can use this proposed technique to detect epileptic seizure.

4.6 SUMMARY

In this chapter, two class as well as three class problems are discussed and their comparison with previous studied is carried out. In the two class problem, features are extracted using entropies like approximate entropy and Renyi's entropy whereas in case of three class problem features are extracted using approximate entropy and FD based features. The classification is performed using SVM, ANN and RF in both the cases and results are compared.

CHAPTER 5	CONCLUSIONS

This thesis work had concentrated upon feature extraction and classification of EEG signals to design an efficient automated epileptic seizure detection system. The main objective of this thesis was to detect epileptic seizure with best classification efficiency. Various techniques were available for epilepsy detection as shown in literature survey but to overcome disadvantages of those previous techniques, new techniques were implemented in this thesis work. In this study, it was found that EEG signals recorded for same mental task at two different physiological conditions (Seizure and Non-seizure) are widely different.

Study for two class problem i.e. seizure and non-seizure as well as three class problem i.e seizure, pre-seizure and non-seizure is presented in this thesis work. These EEG signals are classified using SVM, ANN and RF classifiers.

In chapter one, a brief introduction about Epilepsy is given and the outline of the present thesis is provided. In literature review, a study of various researches have been provided and analysis of different steps like pre-processing, feature extraction, selection and classification is performed. A brief introduction of different techniques is also provided in that section.

Flexible Analytical wavelet Transform is used in the chapter 3 for wavelet coefficients calculation and classification efficiency for two classes (Seizure and Non-seizure) is 99.33% using Random Forest classifier, 99% using Artificial Neural Network and 97.33% using Support Vector Machine.

Tunable-Q Wavelet Transform is used to classify two class as well as three class problem. In the two class problem, the non-seizure and seizure EEG signals are used and results obtained are 99.40% classification efficiency with Least Square- Support Vector Machine, 98.70% using Artificial Neural Network and 98.66% using Random Forest classifiers. In three class problem, TQWT is applied on three classes i.e. Normal, Pre-Ictal and Ictal. To extract features of three classes EEG approximate entropy and Fractal dimension is used. Then, these features are used to classify the coefficients using SVM, ANN and RF classifiers. The classification efficiency of SVM and ANN classifiers is 100% whereas for RF classifier efficiency is 98.8%.

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Communicated Journal:

K. Jindal, R. Upadhyay, “Epileptic Seizure Detection Using Tunable-Q Wavelet Transform Based Entropy Features” International Journal of Biomedical Engineering and Technology, Inderscience, 2017.

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ORIGINALITY REPORT

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PRIMARY SOURCES

1	Submitted to Thapar University, Patiala Student Paper	%16
2	Submitted to University of North Texas Student Paper	%2
3	Upadhyay, Rahul, Swati Jharia, Prabin Kumar Padhy, and Pavan Kumar Kankar. "Application of wavelet fractal features for the automated detection of epileptic seizure using electroencephalogram signals", International Journal of Biomedical Engineering and Technology, 2015. Publication	%2
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7	Acharya, U. Rajendra, H. Fujita, Vidya K. Sudarshan, Shreya Bhat, and Joel E.W. Koh. "Application of entropies for automated diagnosis of epilepsy using EEG signals: A review", Knowledge-Based Systems, 2015. Publication	<%1
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21	Chongchong Tang, Michael Stueber, Hans Juergen Seifert, Martin Steinbrueck. "Protective coatings on zirconium-based alloys as accident-tolerant fuel (ATF) claddings",	<%1