

A NOVEL APPROACH FOR IDENTIFYING EPILEPTIC SIGNALS USING SIGNAL PROCESSING

*Dissertation submitted in the partial fulfillment of
requirements for the award of degree
of*

**Master of Engineering
in
Wireless Communications**

Submitted by
Jasjeet Kaur
Roll No. 801363015

Under guidance of
Ms. Amanpreet Kaur
Professor, ECED



Electronics and Communication Engineering Department

THAPAR UNIVERSITY

(Established under the section 3 of UGC Act, 1956)

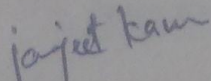
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I hereby declare that the seminar report entitled "A novel approach for identifying Epileptic Signals using Signal Processing" is an authentic record of my study carried out as requirement for the award of degree of Master of Engineering in (Wireless Communication Engineering) at Thapar University, Patiala, under the supervision of Ms. Amanpreet Kaur (Assistant Professor), Electronics and Communication Engineering Department (ECED). The matter presented in this dissertation has not been submitted in any other University/Institute for the award of degree.

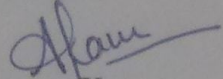
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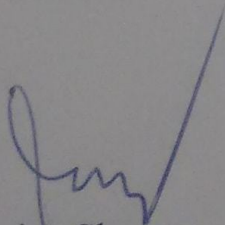
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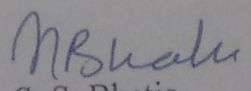
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Date: 14/7/15


Amanpreet Kaur
Asst. Professor, ECED
Thapar University

Countersigned by


Dr. Sanjay Sharma
Professor and Head (ECED)
Thapar University, Patiala


Dr. S. S. Bhatia
Dean, Academic Affairs
Thapar University, Patiala

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Roll no. 801363015

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Amanpreet Kaur

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Thapar University

Countersigned by

Dr. Sanjay Sharma
Professor and Head (ECED)
Thapar University, Patiala

Dr. S. S. Bhatia
Dean, Academic Affairs
Thapar University, Patiala

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Date: _____

Jasjeet Kaur

Place: Patiala

(801363015)

Abstract

Electroencephalography is a technical method known to analyse the behavior of human brain. The record of neurological activity is highly effective when neuronal diseases like epilepsy are to be studied. Although, the biochemical or neuro-physical causes of epilepsy remain unknown but its detection and diagnosis is no more a mystery because of EEG records. The precise and timely diagnosis of disease prevents a lot of trouble. It is challenging to handle large and bulky EEG records. This research work aims at developing an automated method to differentiate the EEG records during an epileptic seizure from the normal EEG records. The wavelet transform has an ability to zoom in the signal to its most resourceful parts and thus remove any ambiguous information from the signal. Further, the generation of useful feature set helps in setting up differentiation criteria between two types of signals. Next, the classification using neural network and support vector machine completes the process to identify the diseased signals. Also, this study contemplates the dissimilarity between two classifying techniques in order to determine the most efficient method for rational classification. The method proves to be very efficient on the pre-recorded data. The data has been acquired from universally available source mentioned in the references. The work can be extended further on simultaneous monitoring of EEG records. Also, this work can be applied to determine other neurological disorders, such as schizophrenia.

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List of Abbreviations and Symbols

Abbreviations

ANN: Artificial Neural Network

ARMA: Autoregressive Moving Average

BCI: Brain Computer Interface

CDF: Cumulative Distribution Function

CWT: Continuous Wavelet Transform

DB: Daubechies

DFT: Discrete Fourier Transform

DWT: Discrete Wavelet Transform

EEG: Electro-encephalo-graph

EMG: Electro-musculo-graph

ENT, E: Entropy

EOG: Elector-oculo-graph

FFT: Fast Fourier Transform

GARCH: Generalised Autoregressive Conditional Heteroskedacity

LORETA: Low Resolution Electromagnetic Tomography Algorithm

LS-SVM: Linear State Support Vector Machine

L1N, L: L1 Norm

ICA: Independent Component Analysis

MAX, M: Maximal Point

MLPNN: Multi-layered Perceptron Neural Network

MMH: Maximal-margin Hyper-plane

OSH: Optimal Separating Hyper-plane

PCA: Principal Component Analysis

PSD: Power Spectral Density

Q3, Q: Third Quantile (or Tertile)

SD, S: Standard Deviation

STFT: Short Time Fourier Transform

SRM: Structural Risk Minimization

SVC: Support Vector Classifier

SVM: Support Vector Machine

VEP: Visually Evoked Potentials

WHO: World Health Organization

WT: Wavelet Transform

Symbols

μV : Microvolts

$C_a^\psi(\tau, k)$: Continuous Wavelet Transform

$\psi_{\tau,k}(t)$: Basis Function

$y[n]$: Convolution of signals

y_{low} : Low Pass Filter Response

y_{high} : High Pass Filter Response

$x[n]$: Reconstructed Signal from WT

ρ : Standard Deviation

$H(X)$: Entropy of a random signal X

O_n : Output to Neural Network

Chapter 1

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Chapter 1 – Introduction

1.1 Motivation

The modern era is the era of technology and advancements. There is an enormous raise in interest as well as necessity in studying the medical conditions that a human body undergoes in the past few decades. The roots of studying these medical conditions of human body penetrate towards the field of engineering. Biomedical engineering deals with the clinical aspects of human body. The electrical activity in the brain is held responsible to symbolize the status of brain as well as whole body. These two factors of biomedical advancements and significance of electrical activity in brain provide impulse to study and analyse EEG signals.

Epilepsy is one of the most common chronological disorders found in both men and women. According WHO report, more than 50 million people in the world are affected by epilepsy. It is one of the costliest disorders to be treated but generally found in economically weaker sections of society as awareness is less among such people [1]. The timely and precise analysis is a challenge in front of both a medical practitioner and an engineer.

This study has been motivated by the need of tailoring a lesser complex, and still cheaper method to detect epilepsy, using signal processing, which can be further useful in developing BCI systems to treat epilepsy. Differentiation between epileptic and non-epileptic EEG signals will give rise to neural-ergonomic approach for disorder detection system. Wavelet transform has an ability to act like a mathematical microscope that zooms in the complex non-stationary signal like an EEG to smaller components by eliminating the redundant information. The comparison between the classification methods provides a platform to envisage the efficient technique for further work.

1.2 Objective

The present work entails a method for offline analysis of EEG signal during the condition of epileptic seizure. The key objective is to project an automatic approach for identification of epileptic seizure in EEG signal. Practical implementation of BCI system will become possible as signals will be accurately and timely identified. Offline analysis of seizure affected signals will serve as pre-requisite for the real-

time BCI application. Thus, the goal is to ascertain signal processing methods adept to precise identification of epilepsy affected EEG signals. The study also targets:

- i) to ascertain the beneficial features for accurate differentiation between seizures;
- ii) to compare the classification methods in terms of trade-off between accuracy and user training.

1.3 Thesis Orientation

This work has been organised in six chapters. The first chapter outlines the motivation and objective behind the proposed work. The second chapter gives the review of relevant literature about the work done. The third chapter deals with diverse areas of brain and basic EEG terminology. Fourth chapter discusses the different methods used for processing and classifying the EEG signals. Fifth chapter describes the experimental protocol for carrying out the study. The sixth chapter provides the results achieved for every experimental stage and compares the precision achieved through different methods. The seventh chapter concludes the work and discusses the future scope for the work.

Chapter 2

Chapter 2 – Literature Review

Epilepsy is the condition when the brain acts as an abrupt machine. This abnormal behaviour occurs due to the bursting of electrical discharges at unusual rates. The following section summarizes the relevant literature regarding the detection of epileptic activity using various techniques on EEG. Conventionally, statistical linear and non-linear methods are used for analysis of EEG signals. These methods are enhanced using techniques like autoregressive modelling, autoregressive moving average (ARMA), generalised autoregressive conditional heteroskedacity (GARCH) and low resolution electromagnetic tomography algorithm (LORETA). Later, Fourier Transform was widely developed for detection of epilepsy using the frequency domain of EEG signal. It was dependent upon four characteristic EEG waveforms. But the method was inadequate. However, the method was replaced with fast Fourier transform, but it also as it was highly sensitive to noise. Also, it was not very suitable to be used on non-stationary signals such as EEG. As a result, another method called Short Time Fourier Transform (STFT) was developed. Now, in this method the window function was fixed. So a trade-off had to be developed in order to compensate between the frequency and time resolution of the signal.

[2] N. Ahammad et al. [2014] proposed a method for the automatic detection of epileptic seizure. The features based on statistical methods and wavelet transformed was employed to carry out the research. The signals consist of three classes. The first were signals from a healthy volunteer with eyes kept open. Second category contained epilepsy affected signal. And the third category consisted of signals occurring in epileptic-form zone. The neural classifier was used to classify the signals. Its efficiency came out to be around 98 per cent.

[3] R. Sharma et al. [2014] differentiated between the focal and non-focal EEG signals of epileptic origin based on empirical mode decomposition. This method calculates a simpler form of the signal in the form of intrinsic mode functions. The sample entropies and variances are extracted as features from the intrinsic mode functions. The resultant features are classified using least square support vector machine. The LS-SVM classifier here utilises radial basis function to act as a kernel.

[4] S. Xie et al. [2014] proposed a method using dynamic principal component analysis. It also use non-overlapping window along with dynamic PCA. The signal classification is done by employing two different methods for detection of sparse features. Based on this method the ictal and inter-ictal seizures are detected. The study is tested on single-channel short term EEG data as well as multi-channel long term EEG data. For the purpose of making the signal features more interpretable, only 3-dimensional feature vector is considered as data input. The classification performance was also compared with other existing techniques.

[5] Y. Kumar et al. [2014] came up with a method for detection of epilepsy using DWT analysis and approximate entropy. The analysis is done on two stages. The first stage performs DWT on the signal and in the second stage the entropy is calculated. Both the stages are performed on approximation as well as detailed coefficients. The signals are classified using SVM classification and k-fold cross validation is calculated. And then the signals are classified using neural network to determine the seizure free signals and the signals during seizure activity.

[6] A.H. Siddiqi et al. [2013] investigated the usability of FFT and wavelet transform for the analysis of EEG data. For the spectral analysis the harmonic transform of first-sixth order harmonic amplitude and phase are determined. The variations in temporal and frequency domain are determined with the help of WT. The method was used to detect epilepsy in the patients based on the relative energy of the analysed signal.

[7] M. Sharanreddy et al. [2013] proposed a method of multi-wavelet transform to access features necessary for detection of epileptic signals. The technique focussed in gathering features from various sub-bands after application of multi-wavelet transform. And the abruptions in the EEG signal were determined through entropy. The system was classified using feed-forward neural network. Only the first level epilepsy signals were determined and the method gave promising results. The overall accuracy achieved came out to be 93 per cent.

[8] P. Bhuvaneshwari et al. [2013] show the use of support vector machines for EEG signal classification. Linearly separable and non-linearly separable data are

classified using SVM. This paper concludes that the feature space of large EEG data is reduced using different statistical methods like ICA and PCA and many more. The extracted feature space is classified employed different kernel functions in support vector machine.

[9] S. Garg et al. [2013] utilised the fact that wavelet transform has exclusive benefit of nullifying the undesired frequencies and allowing only the filtered EEG waves. The main concentration is to obtain the delta band. Simple features such as mean, median for this delta band are determined. The epileptic and non-epileptic data are then classified based on these values using the ANN classifier.

[10] Zarita Zainudin et al. [2013] proposed a reliable approach for seizure detection using wavelet neural network. The predictive ability of the system was calculated and classification accuracy of the network determined. The 10th and 90th percentile values are determined to examine the presence of seizure. The benefit of using Type-2 Fuzzy Means algorithm alongwith k-fold clustering is to handle noise and uncertainty in the signal. The method claimed to give a fast and accurate response to a bulky EEG signal.

[11] A.F. Hassoney et al. [2012] compared the performance of orthogonal and bi-orthogonal wavelet transform to filter the visual evoked potentials (VEPs). A range of noisy signals based on altering SNR values was selected. Then using the longest subsequence and BLAS tool the performance of visual quality was measured subjectively as well as objectively. The results of Bi-orthogonal, Daubechies, Symlet and Coiflet transforms were compared. In this study, the Coiflet -5 transform outperformed the other transforms.

[12] A. Madhu et al. [2012] followed a probabilistic approach of neural network to differentiate epilepsy affected EEG signals from the non-epileptic ones. The time-frequency domain of the signals was considered. The performance of various time frequency techniques for differentiating between two types of signals was evaluated. It was found that most techniques show about 83-97% accuracy when combined with neural network.

[13] L. I. Kuncheva et al. [2012] compared the results of various feature extraction methods such as ICA, WT and PCA. The extracted features were differentiated by employing a number of classifiers and results were further verified. The data used for the analysis was event-related potential data. The ERP data in raw form has very high dimensionality and is highly contaminated with noise. The classification of such a complex data is thus very difficult. The linear state and perceptron kernel based SVM, neural network and a random forest classifier were used. It was incurred that resultant feature sets performed well with each of the classifiers.

[14] M. Nandish et al. [2012] evaluated the performance of two features *viz.* average and max_min for different frequency bands of the EEG signal. The pattern recognition technique was employed to test the performance. The accuracy of average method was found to be comparatively lesser than the other method.

[15] A.S.M. Murugavel et al. [2011] proposed a method for automatic detection of epilepsy based on approximate entropy and probabilistic neural network. The approximate entropy predicts the present values of the EEG signal by utilising the previous values. Then two main features *viz.* maximum absolute difference between two classes and minimal variance inside the class are extracted using the wavelet thresholding techniques. The system is classified using PNN to detect the epileptogenic signals.

[16] Orhan et al. [2011] used a method to find probability density of EEG signals based on equal frequency discretisation. Firstly, the DWT is applied to segregate the signal into sub-bands. In the next step the probability density functions for the coefficients of sub-bands are calculated. Based on epileptic and non-epileptic values two types of probability density functions are identified through their curve fitting. These values are classified with the help of mean square error and then classified results are evaluated for the epileptic EEG.

[17] Mirzaei et al. [2010] presented a wavelet spectral entropy based method. In this method the sub-bands of EEG signal are determined using Discrete Wavelet Transform (DWT) as various high pass and low pass filtered values. The entropy is based on the amplitude of source signal. The three types of signals *viz.* normal,

epileptic during seizure and epileptic without seizure are distinguished using this technique. The results are then classified using neural network.

[18] A.T. Tzallas et al. [2009] came up with the analysis of EEG signals in spectral using the method Short Time Fourier Transform. The signal is divided into small segments and the signal within this segment is assumed to be stationary. The segmentation of signal is done using the window function that has equal width as the segment of the signal. The choice of window function depends upon the minimum frequency separation required to resolve two amplitude frequency components. However, the size of window function also require a good trade-off between the frequency and time resolution as wider window function results in good frequency but poor time resolution and vice-versa. Using this method, PSD of signal is calculated and energy distribution on the overall signal is determined.

[19] E. D. Ubeli [2009] presented a method that combined the wavelet coefficients with the neural network to classify the EEG signals. The statistical features from the wavelet coefficients are extracted and given as input to the neural network. The results were compared to the MLPNN trained network and found to be better than those. The classification of Symlet, Coiflet and Daubechies wavelet transform were compared. Daubechies transform was ratified as having best accuracy.

[20] Ocak [2009] presented the analysis of EEG signals when done in both time and frequency domain provides considerable results. If the analysis is followed by some kind of classifier, then the results get enhanced. Although, when features in either of the time or frequency domain are extracted, the results are noteworthy, but success rate becomes comparatively higher if the time-frequency domain of signal is analysed. However, the role of features to be selected as well as the type of classifier used cannot be neglected.

[21] A. Prochazka et al. [2008] used DWT as an alternative approach for DFT. The DWT coefficients are determined using the popular Bayesian approach. The simple method of cluster analysis followed by pre-processing is applied on the extracted set of features. The issues regarding multichannel segmentation were also considered regarding this context. The given study although assumed that the range of number

of classes was sufficient to create a self-dependent and optimised classification method and eliminate the prospect of dead neurons.

[22] Mousavi et al. [2008] developed autoregressive estimation of EEG signals to detect epilepsy in patients. The AR model based on Bayesian Information Criterion for determination of optimum order and the AR parameters of EEG signals. The method is combined with discrete wavelet transform to obtain a subset of features. These features are fed to multilayer perceptron classifier to differentiate between the epileptic and the non-epileptic data.

[23] Y.P. Lin et al. [2008] proposed a method to classify EEG signals as a response to emotional music with the help of support vector machine. The artifacts from the raw EEG signal were removed by visual inspection and STFT was utilised for extraction of power spectral density of signal. The main domains that were analysed were the types of features used, temporal resolution of the features and the constituents of EEG. However, the results of classifier were different for different kinds of features but an overall efficiency of about 92% was achieved using SVM.

[24] A. Subasi [2007] developed a method using mixture expert model for the classification of EEG Signals. The features were extracted using wavelet transform of signals and were taken as input for mixture expert model. The mixture expert model gave two discrete outputs i.e. epileptic and non-epileptic. To improve the accuracy of the system, local weights were set for the outputs and were called 'gating functions'. The accuracy rate was higher as compared to that of neural network alone.

[25] K. Polat et al. [2007] presented a decision tree classifier and FFT based hybrid system to detect the epileptic seizures. The hybrid system consists of two steps. First, the useful features are extracted using fast Fourier Transform. And in the second step, a decision with the help of decision tree is finalised. The method was enhanced using k-fold cross-validation and determining the classification accuracy. The focal epileptic and scalp EEG are taken for the purpose of the study.

[26] T. P. Exarchos et al. [2006] presented a simple approach which depends upon the classification on transient events of EEG recordings. Based on these recordings association rule is created that differentiates the epilepsy effected EEG signal from a non-affected EEG signal. The transient events are clustered to extract some beneficial features and a subset of discretised features is created for the selection purposes. The transient events are taken in the form of eye blinks, muscular activity, sharp alpha activity and epileptic spikes. This method on the whole was called Association Rule.

[27] A. Subasi et al. [2005] applied artificial neural network for the optimization of epileptic and non-epileptic EEG signals. The parameters used for differentiation were the auto-regressive model parameters and maximum likelihood estimation. For more processing speed FFT was considered. In this automatic classification of seizures 92% accuracy was achieved. The study also suggested that system performance can be improved by using non-linear AR model parameters for signal representation.

[28] A. Subasi et al. [2005] proposed a method using lifting based DWT for the pre-processing of epileptic EEG signal. The classification technique employed the use of ANN accompanied with logistic regression. The logistic regression method promotes classification on the basis of traditional mathematics whereas ANN is programming based technique. The results of two types of classifiers were classified using receiver operating characteristics and scalar performance measures of the classifiers. The classification efficiency of ANN came out to be better than that of logistic regression.

[29] N. Hazarika et al. [1997] classified three types of EEG signals by utilising wavelet transform. The three types of signal taken were normal, schizophrenic and obsessive-compulsive disorder. It has been emphasised that wavelet transform is suitable of pre-processing of EEG signals having non-linear nature. However, the scope of improvement in the performance of method has been indicated using some classifying techniques.

Chapter 3

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Chapter 3 – EEG Background

3.1 EEG Signals

Human Brain is responsible for carrying out various activities in the body. It carries out such activities by directing electrical signals all the way through neurons present in the body. A neuron (or nerve cell) is the elementary functional unit of the nervous system. Neurons carry the message from and to the brain in the form of electric signals. The voltage by a single neuron is too small to detect. So a sum of synchronous activity of the neurons is taken. In anatomy such electrical signals are termed as ELECROENCEPHALOGRAPH (EEG) and the brain is termed as encephalon (it is brain in layman terms). A basic structure of neuron has been depicted in the figure 3.1.

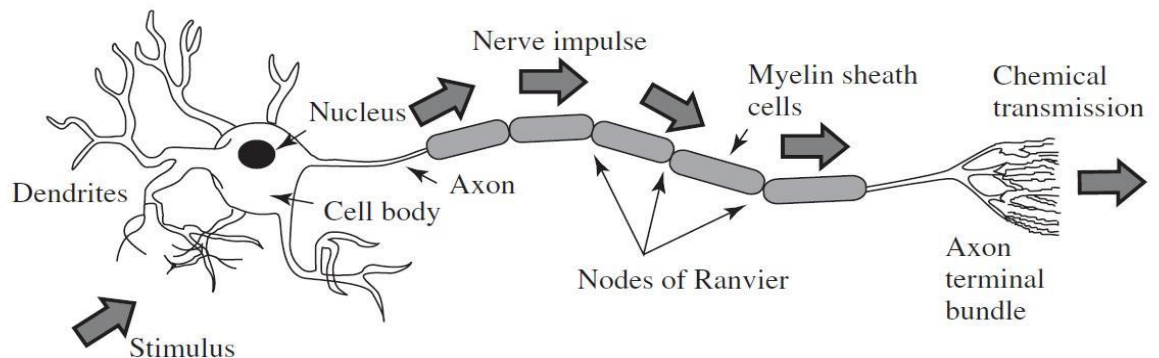


Figure 3.1: Typical Neuron Structure [30]

The encephalon has three major parts, viz., cerebrum (forebrain), cerebellum (hindbrain) and brain stem. The responsibility of cerebrum is to manage higher mental as well as emotive functions such as vision, taste, control and coordination, emotional familiarity and judgement ability. It has further divisions called frontal (F) lobe, occipital (O) lobe, parietal (P) lobe and temporal (T) lobe. The hindbrain i.e. cerebellum handles the responsibility to manage voluntary movements of muscles and maintain balance and equilibrium in the posture. The brain stem located in the middle of the brain is concerned about the involuntary movements like eye blinks, heartbeat, respiratory movements, movements of other internal organs and response to sudden light or heat etc. EEG thus, has a vital role in identifying various neurological disorders and their rectification. The following diagram (figure 3.2)

gives the diagrammatical representation of a human brain. The frontal, parietal, temporal and cerebral lobes and the brain stem are clearly visible as mentioned above.

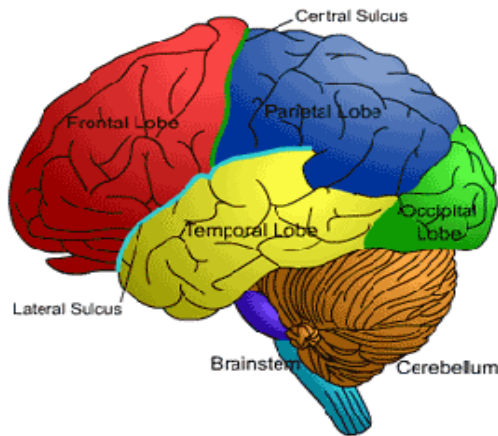


Figure 3.2: Human Brain (the Brain-www)

However, the magnitude of an EEG signal is extremely small, i.e. around 0.5-100 μV only. So the signal is generally taken in bulk to extract some useful information. Thus, the continuous recording of signal is taken for more than 20 minutes to extract some useful information. The frequency range may vary from 0.5-100 Hz. On the basis of frequency range and occurrence stages EEG signals are categorised into five major types of waves called alpha, beta, theta, gamma and delta waves. These waves have fixed frequency ranges and occur only when the brain is performing specific task in particular age. The recording of EEG signals is simply done by placing electrodes on the scalp of the subject. The signal extracted from electrodes is called raw EEG signal.

3.2 EEG Recording

The EEG signal is recorded by employing electrodes on the scalp of the patient. The method may include monopolar or bipolar recordings. The monopolar recording is measured by taking the electrode potential at an active electrode w.r.t a reference point. Generally, the earlobe is taken as reference point. So it is also called referential recording. The bipolar record is measured as the voltage difference between two neighbouring active electrodes. This method is solely known as derivation. It is generally employed when the EEG is assumed to be clean and the

signal is visually interpreted. The mono polar recording is a pervasive method and is broadly employed in this purpose.

The site of electrodes is grounded to a standard called 10-20 system and may contain 21 to 64 electrodes based upon the requirement. The values '10' and '20' in the method denote the real space between neighbouring electrodes. This is merely 10/20 % of the front-back (nasion-inion) or right-left distance of the encephalon. The electrodes are named according to the portion of brain in which they lie. For example, if an electrode lies in frontal region in left side then it will be named as F1, F2, F3 and so on. Similarly, T means temporal, C stands for cerebral, P and O characterize parietal and occipital lobes, respectively. The odd numbers are for the left hemisphere whereas the even ones represent the right hemisphere of brain. In standard reading, nasion represents the front (it is generally the region immediately below the eyes) and inion (extreme end of the skull) represents the back of the skull. A1 and A2 represent left and right earlobes.

The figure shown represents the basic 10/20 system and has been taken from McGill Physiology Virtual lab. It is shown in the figure 3.2.1. This system is actually the measurement system in which the distance of electrodes from one another is calculated to be 10% or more, as per the requirement.

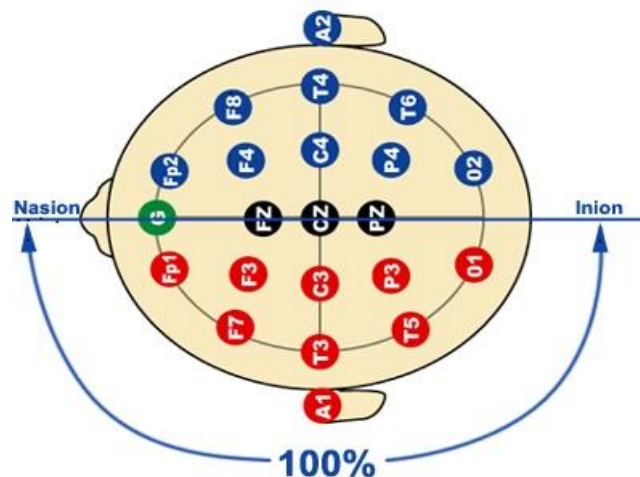


Figure 3.2.1: 10/20 system

The electrodes consist of noble metal like tin, gold or silver and covered with AgCl. Material like glue or electrode gel or some metallic clips are used to hold them

properly on the scalp for the duration of recording. These adhesives do not intrude the nature of the signal and are safe to be used on human brain.

This signal extracted from the electrodes may consist of various contaminations and is not fully suitable for accurate diagnosis. Any kind of contamination may lead to misinterpretation of the signal and diagnosis may suffer. These contaminations are called artifacts (which are discussed later) and the signal is termed as raw EEG signal (as revealed above). The raw EEG signal endures several routes in order to become legible. These processes include pre-processing of the signal which consists of filtration or noise removal. The statistical methods are generally employed to clean the EEG signal, so that it is presentable and readable in clinical terms.

3.3 Characteristics of EEG

Every signal has its own characteristic properties which cannot be neglected. Some of the important characteristics have been conversed as under.

- **Frequency**

Frequency represents the rhythmic repetitive activity. In simple terms, it is the number of times a waveform of specific pattern repeats itself in a single second. The frequency of EEG activity may bear altered properties including rhythmic (the signal with stable frequency), arrhythmic (the signal with unstable frequency) and dys-rhythmic (the signal which has stable frequency at some instants and unstable frequency at other instants). Although dys-rhythmic frequency EEG waves rarely exist. The given figure (figure 3.3.1) shows rhythmic and arrhythmic EEG signals.

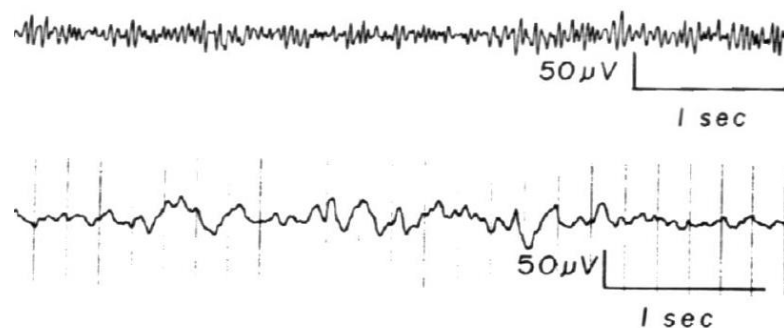


Figure 3.3.1: Rhythmic wave (above) arrhythmic wave (below)

- **Voltage or Amplitude**

It is the average or peak voltage at which EEG activity is observed. These values are somewhat reliant on the recording system. The magnitude is only a few microvolts for EEG signals.

- **Localisation**

It refers to the portion of head where the EEG activity is observed. For example, if it is observed only in particular part, like only in occipital lobe, then it is called focal activity, and if it is distributed in all parts of brain then it is called generalised activity. Also, if frequency, amplitude and morphology on left part of brain are same as right part of brain, it is called symmetric EEG, and otherwise it is asymmetric EEG.

- **Morphology**

It depicts the outline of the waveform. The shape of an EEG pattern is confirmed by the frequencies which conglomerate to make up the waveform and phase and voltage interactions of its constituent components. If the EEG signal is found to have only one component, then it is call monomorphic. Otherwise, it is termed as polymorphic. And when a there are different morphologies present in records of same EEG waveform, and then they are called complexes. The different morphological patterns are presented in figure 3.3.2

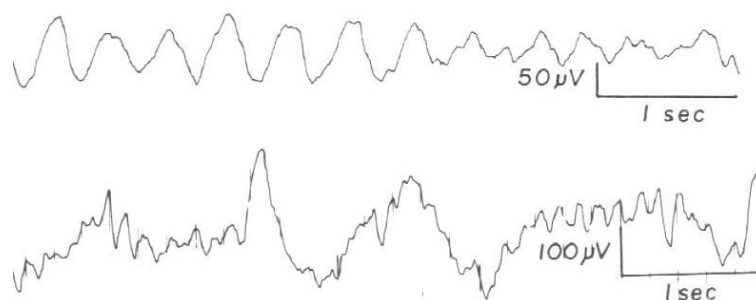


Figure 3.3.2: Monomorphic Pattern (above) Polymorphic Pattern (below)

- **Synchrony**

It is the measure of order of synchronous activity in the brain. It is generally seen in normal adults and children.

- **Reactivity**

It is the degree of change in any of the characteristics due to some kind of stimulus. The figure 3.3.3 shows reactivity due to opening of eyes. There is a shift in amplitude and frequency when eyes are opened or closed.

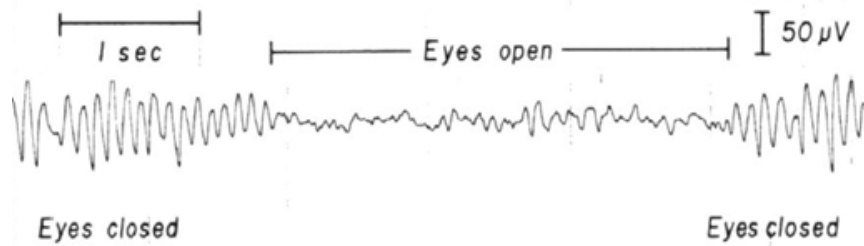


Figure 3.3.3: Reactivity of EEG Waveforms

- **Periodicity**

It refers to the dispersal of configurations in time. The EEG activity may be generalised, focal or lateral based on its periodicity.

3.4 EEG Waves

There are various sorts of EEG rhythms or waves that indicate different conditions of the encephalon. Study of such waves is becomes necessary as each kind of wave is generated due to some specific kind of condition or behaviour. Some the main waves of EEG signal are discussed below.

- **Delta Waves**

The delta waves have the lowest frequency band (0.5-3.5 Hz) and high amplitude of about 20-200 μ Vs. A short sample of delta waveform is shown in the figure 3.4.1. These waves are dominant in frontal regions of adult brain and posterior region of child brain. They originate during the state of sound sleep in children or in the state of anaesthesia in adults. It has quiet an irregular and slow wave pattern.



Figure 3.4.1: Delta Wave

- **Theta Waves**

The theta waves having frequency range 3.5-7 Hz and amplitude of about 20-100 μ Vs, indicate little drowsiness. So, these are also called ‘slow activity waves’. These are mainly observed in left hemisphere of the brain. If large amount of theta waves are seen in EEG of an adult while he is awake, then it is possible that he might be suffering from some serious pathological disorder. Contrarily, these waves also exist during relaxed and meditative stage. A theta wave is presented below in figure 3.4.2.

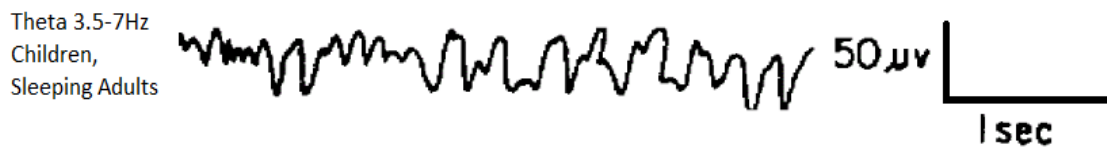


Figure 3.4.2: Theta Wave

- **Alpha Waves**

Alpha waves have the frequency of 7-13 Hz and amplitude varies between 20-60 μ Vs. These are the most prevalent in normal and healthy human beings. These indicate the relaxed state of mind. With the increase in alertness the alpha wave is diminished. Figure 3.4.3 depicts a standard alpha wave pattern.



Figure 3.4.3: Alpha Wave

- **Beta Waves**

Beta waves have frequency greater than 14 Hz and less than 30 Hz with amplitude range of about 2-20 μ V. Basic beta wave pattern is shown in figure 3.4.4. Beta waves are associated with ‘fast activity’. These are found in normal adults performing some active task such as reading, problem solving etc. Too much of beta activity indicates the anxiety in the patient.



Figure 3.4.4: Beta Wave

- **Gamma Waves**

The gamma waves have the frequency more than 30 Hz and are the least occurring waves. One more category of waves that occur in the brain is the mu rhythms. These are predominant in the central region of the brain and have frequency of about 7-11 Hz. The typical gamma wave pattern is shown in figure 3.4.5

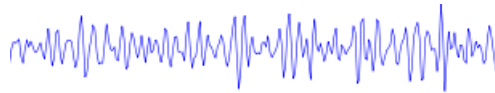


Figure 3.4.5: Gamma Wave

- **Mu Waves**

Mu waves are observed during imagined movement and elapse with immobility. Although, the frequency range of mu waves is similar to those of alpha waves, but these can be differentiated from alpha waves based on their morphology and localisation. So these are also called arcade, comb or wicket waves depending upon their morphology. Figure 3.4.6 shows mu wave pattern.



Figure 3.4.6: Mu Waves (left) Lambda Waves (right)

- **Lambda Waves**

Lambda waves are observed during horizontal movement of adult retina in the occipital region. These last for about 0.25 seconds only and are vanish when eyes are closed. Figure 3.4.6 shows lambda wave pattern.

3.5 Abnormalities in EEG Activity

Patients suffering from some neurological, pathological or any other brain related diseases tend to exhibit various abnormalities in their EEG. These abnormalities may be in their EEG pattern displaying unusual frequency, amplitude, morphology, reactivity or localisation. Although, these abnormalities may be seen due to machine or human error but care is taken so that actual signal does not escape the eye of the medical practitioner. For instance, a few of such abnormalities are discussed below.

- **Spikes and Sharp Waves**

Sometimes sharply contoured waves of time duration 20-70ms or 70-200ms may occur in EEG pattern. These are respectively called spikes and sharp waves and may be indicative of some epileptic seizure. The figure 3.5.1 depicts an example of spikes and sharp waves.

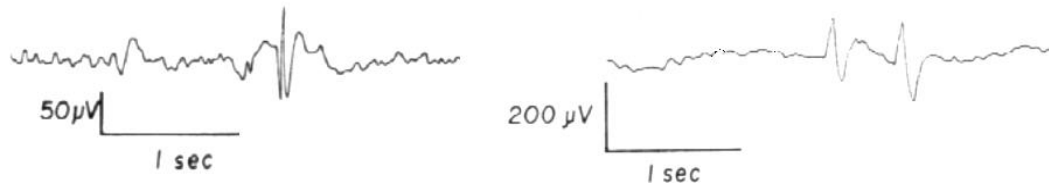


Figure 3.5.1: Spike (left) Sharp Wave (right)

- **Spike-Slow-wave Complex and Sharp-Slow-wave Complex**

A slow wave of a very long duration wave following a spike or sharp wave creates a complex that may repeat at the rate of 3-6 Hz or 1-2 Hz respectively. Generally, such signals are witnessed in case of severe epileptic conditions and indecisiveness during critical situations.

- **Burst-Suppression Activity**

It refers to the time related bursts that repeatedly occur after a certain time period and are also known as periodic discharges. It may exhibit different morphology amplitude and frequency as shown in figure 3.5.2.



Figure 3.5.2: Burst-Suppression Activity

- **Electro-Cerebral Inactivity**

In such a signal EEG signal ceases to extreme attenuation and this continues for variable durations. As the figure 3.5.3 shows, the scale is reduced to 10 microvolts as compared to 50 microvolt scale that is considered normally and the transients in this figure are also a result of ECG artefact.



Figure 3.5.3: Electro-Cerebral Inactivity

3.6 Artifacts in EEG

Artifacts in EEG signals may be of two types i.e. physiological and non-physiological artifacts. The physiological artifacts (also called biological artifacts) are caused due to contamination due to other types of signals running through the body.

The other types of signals are electrocardiographs, muscular potentials (EMG) etc. The blinking of eyes also causes certain contaminations in the signal which can be visually detected and corrected. The potentials produced due to movement of eyeballs (recorded as EOG – electrooculogram) may cause the EEG signal look like transient slow wave EEG rhythm. The skin potential that may vary due to sweat and electrolyte concentration of skin may produce low frequency baseline changes in EEG.

Then there are glosso-kinetic potentials generated by the movement of tongue that produce spike activity in the EEG. The other category of artifacts i.e. the non-physiological artifacts are caused due to poor mechanical and electrical coupling of electrodes. Line noise, electrode stabilization, and electric pulse cause these type of artifacts. They are sometimes called environmental artifacts because they are caused due to environmental changes in the EEG.

The elimination of these artifacts is very important from the clinical point of view as minute mistake in the interpretation of the signal may turn fatal to the patient. Environmental artifacts are decreased with the help of advancements in technology and by taking care of the surroundings where experiment is being done. But the biological artifacts signal need to be observed simultaneously and removed immediately after the recording process. This problem can be solved with the help of signal processing.

3.7 Epilepsy

Epilepsy is neurological disorder where there is abrupt discharge of electrical signal in the brain. In the ancient period of human history, this disease was considered to be “given by Gods”. The word ‘epilepsy’ originated from Greek word *epilambanein*, meaning ‘to attack’ [30]. In India also it was thought to be as an attack by some evil soul or Goddesses. It was also considered to be a curse in many regions.

Nowadays, scientists and medical practitioners have established that it is a condition of central nervous system where there subject experiences repeated seizures. The Oxford English Dictionary describes Epilepsy in layman terms as “a disease of the nervous system, characterized by violent paroxysms, in which the patient falls to the ground in a state of unconsciousness, with general spasm of the muscles and foaming at the mouth”. It affects about 50 million population of the world making it a second most common brain disorder (first being stroke) [31, 32].

Epileptic attacks are generally classified on the basis of it origin and localisation in the brain. The generalised seizure may occur in entire brain and partial seizure occurs only in some part of the brain.

The actual principle of the epileptic disorder remains unidentified, but as it is very common problem in the ones whom brain has been conceded by some sort of commotion. While, in children and adolescents the genetic disorders or some birth trauma might be the cause, but in later ages strokes, tumours, cerebrovascular disease or some sort of accident might be the culprits.

Although, the career and family life of people affected by epileptic disorder seem to be very normal, but they are forbidden to involve in some simple activities, such as driving etc., because attack during such activities may prove to be fatal to their life. Patients also struggle with challenging psychological and clinical issues due to the side-effects of curing drugs, the nature of seizures, their tendency to occur suddenly and public perspective about the disorder.

Medical practitioners classify seizures into different types depending upon the way the brain gets affected. Different sort of epileptic attacks have distinctive set of symptoms.

3.7.1 Classification of Epilepsy

Epilepsy is classified in five different ways. The mode of classification is by:

- i. Etiology (cause of origination)
- ii. Semiology (observable manifestations of seizures)
- iii. location of seizure origination
- iv. Discrete, identifiable medical syndromes
- v. events that trigger seizures such as reading or music

3.7.2 The Neurophysiology

Although, the underlying biochemical and genetic mechanism is still a sort of mystery, but some specific electrical phenomena are witnessed during seizures. Intercellular measurements at epileptic loci display an unusual persistent, large amplitude membrane depolarization complemented with trains of spikes. It is known as Paroxysmal Depolarization Shift (PDS). A prolonged depolarization may correspond to observe epileptic discharge at surface electrodes. This might be an outcome of various mechanisms or combinations of different mechanisms such as alterations in concentrations of sodium potassium and calcium ions, increased excitation and decreased inhibition (inadequate GABA). Mechanisms of abrupt movements (persistent primary and secondary loci due to prolonged threshold stimulation) and prolonged potentiating (alteration of synaptic activity during synchronous erratic firing), which are associated to memory and learning processes in the standard encephalon operation; also mirror their participation in epileptogenesis [33].

3.8 EEG in Epilepsy

The EEG is generally examined to hook the epileptic grapho-elements occurring during inter-ictal period. The inter-ictal period is the interval between the seizures. The epileptic grapho-elements are associated with the short duration EEG abruptions such as spikes, sharp-waves and various sorts of complexes [33]. The topography and time characteristics of grapho-elements play a major role in the diagnosis of epileptic condition. Also, the ictal archives, during the outbreak, are important for the correct diagnosis. But, the peculiar EEG rhythm occasionally collected with some alterations may be observed. The alterations in the background

activity may also be caused from the medication. The typical EEG record has the duration of 20 to 30 minutes. But this is sometimes inadequate to detect the presence of seizures. And the presence of epileptic-form discharge may not always point towards presence of epileptic seizure in medical terms. Thus, abiding EEG nursing for more than 24 hours, occasionally singular or shared with video monitoring is stressed as the mode of differential diagnosis of epilepsy [34]. Sometimes, epileptic discharge is triggered manually to diagnose the intensity of the problem. The methods utilised for this purpose are called activation methods. So, in such cases EEG data needs a very efficient visual analysis and evaluation. It greatly depends upon the clinical expertise.

3.9 Seizures

The abrupt neurological activity in the brain leads to unconscious behaviour in the movement or sensation of the body. This situation is called seizure. An epileptic patient suffers the abnormal functioning of brain due to malfunction in some region of brain or some sort of transgression in biochemical mechanism [35]. Contrary to this, the non-epileptic seizures are a result of external commotion in the nervous system caused due to sleep deprivation, drug abuse, external injury etc. Seizures may be of different types like partial, generalised, simple, complex, convulsive, non-convulsive and many more. Each type of seizure is treated with a different manner, so the need to be examined very cautiously. Partial and generalised seizures are considered the broader divisions of seizures as partial seizures occur in some region of the brain and remain restricted to that limited area only and the generalised ones affect the entire brain from the inception. In the next section, various characteristics of the seizures are given.

3.9.1 Partial Seizures

As described above, the partial seizures involve only some region of the brain, so they are named partial (i.e. localised to some part). These are further categorised as simple and complex partial seizures. The difference between simple and partial seizures is that the former does not affect the consciousness, whereas the latter does. In the epileptic framework, the individuals lack the understanding and recollection

of the events occurring during a seizure but nothing leads to a situation like coma. Sometimes, a partial seizure may mark the inception of more intense generalised seizures, which cannot and should not be ignored at all.

- **Simple Partial Seizure**

As stated above, the consciousness is not altered during a simple partial seizure but there is a momentary weakening in the subject's sensor and motor system. Sensory seizure occurs in the somatosensory region of the brain and motor seizure affects the motor cortex. During sensory seizure there may be some sort of hallucination of some sort of sound, smell or vision. Or extreme sweating and capillary dilation may be caused. Or some sort of psychic symptoms such as dreamy states, sudden fear sensation and anger may happen. The duration of such a seizure is less than a minute and the patient is able to remember the events happening during such an episode. These medical demonstrations may be very delicate to understand and are sometimes challenging to extricate from emotional phenomena. If considered medically, sudden muscular jerks and postural movements are observed.

- **Complex Partial Seizure**

There is loss of consciousness in a complex partial feature. These are also accompanied by hallucinations like smell or touch illusion along with autonomous behaviour of snapping fingers, walking aimlessly, mumbling and so on. The seizure of duration about 2-3 minutes leaves the patient in the confusion for few minutes.

3.9.2 Generalised Seizures

The generalised seizure disturbs the entire encephalon. These are sometimes associated with intense muscle activity and are termed as generalised convulsive seizures.

- **Generalised Convulsive Seizures**

The nature of spastic muscle activity and state of consciousness in the course of convulsive seizures further subdivides this field into four types *viz.* clonic, myoclonic, tonic and tonic-clonic. In a myoclonic seizure the state of consciousness is not affected but rapid muscular movements are observed. It is also allied with

some neurological disorders. During a clonic seizure also an abrupt muscular movement occur but at a slower rate and the consciousness is lost. The tonic seizures witness a swift shrivelling of facial and trunk muscles and are commonly experiences in childhood. Tonic-clonic seizures witness the characteristics of both clonic and tonic types, making it most unfortunate type of seizure. They go unnoticed in the beginning as the contraction of muscles is disturbed by short periods of relaxation. Steadily, frequencies of relaxation periods increase become recurrent resulting in vigorous muscular activity. This may last for 2-3 minutes only, but the period of lost consciousness may be more than fifteen minutes. Also, fatigue and tiredness may be experienced for hours or a couple of days. The partial signals that mark the inception of such generalised seizures are termed as secondarily generalised seizures. During the generalised seizures sensory or motor auras are not experienced by patient.

- **Generalised Non-convulsive Seizures**

Loss of consciousness, staring, eye blinking etc. mark the symptoms of this type of seizures. Although the duration is just a few seconds, these seizures have the tendency to occur quiet frequently. Generally, these are termed as absence seizures and most commonly witnessed in childhood. And then, the other type of generalised non-convulsive seizure called the atonic seizure lead to impulsive loss in tenor of postural muscles. The consciousness is not affected. It may lead to dangerous falls resulting in serious head injuries or fractures.

3.9.3 Status Epilepticus

It is the critical situation of epilepsy where the patient remains in continuous state of epileptic attack. The above mentioned seizures may occur so frequently that it almost seems to be continuous. The patient either appears to be in the state of coma or the consciousness is not recovered for long durations during status epilepticus.

3.10 Treatment of Epilepsy

People suffering from epilepsy may experience varying degrees of severity. In around 4/5th of the cases, it can be controlled using anti-epileptic drugs that curb the capability of the neurons to fire at excessive rates. It is of utmost importance that the

type of seizure is identified accurately. This is so because each drug will have different impact depending upon the nature of the seizure. The wrong medication may exacerbate the intensity of the seizures and may also introduce some new problems. For the remaining 1/5th of the patients, treatments like surgery, ketogenic diets and vagus stimulation come for rescue.

- **Surgery:**

Surgery becomes a practicable option if the precise region of the occurrence of seizure is identified accurately. To accomplish this, amalgamated medical and electrographic confirmation through long-term video and EEG records; MRIs indicating anatomy of brain and body; PETs scans confirming metabolic evidences; and neuropsychological testing are required. There are four types of surgery offering removal of temporal lobe, cortex or hemisphere and separation of hemispheres.

- **Vagus Nerve Stimulation**

This is the method in which an electronic device is fixed on the left side of neck to kindle the vagus nerve occasionally. The device is called Vagus Nerve Stimulator. The optimal time periods and intensity of stimulation cannot be determined as the root cause of epilepsy remains unknown. But the seizure frequency and severity is considerably reduced using vagus nerve stimulators. So it is also entitled “pacemaker” of the brain. Physically, it consists of a small device that directs electrical pulses to encephalon through the vagus nerve. The device needs to be pre-settled depending upon the condition of patient (the severity of attacks he/she experiences). It is a great alternative for the ones who cannot cope with medicines or undergo surgery due to any other side-effect dangers.

- **Ketogenic Diet**

The foods containing high ketosis amounts rather than glucose have proved to be beneficial in controlling epileptic behaviour of the brain. Such a diet comprises higher content of fat and lower content of proteins and carbs. This diet influences the encephalon to function on ketones instead of glucose. The state of body during ketone functioning is called ketosis. Although, the mechanism behind this kind of behaviour of brain remains mystery, just like the cause of epilepsy, but the clinical demonstrations have found that it is an effective method of reducing the intensity and frequency of the seizure.

Chapter 4

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4.1 Wavelet Transform

Analysis of EEG signals can be done by a large number of methods. Conventionally, time domain methods were used for this purpose. With the advancement in technology various frequency and t-f based methods were introduced. Generally, the EEG signal during analysis is assumed to be Gaussian random process and thus probability distributions and few moments were considered to be enough for the purpose. Thus, statistical model recognized success but the biophysical model was not as successfully apprehended. The methods that were dependent on either on time or frequency domain were more suitable for non-stationary signals. The wavelet transforms are modified to yield results in both time and frequency domains. This characteristic of time-frequency analysis provides compact-support. It is thus one of the best tools to analyse signal in time-frequency domain for a bulky and non-stationary EEG signal. The signal is resolved to least amount such that it contains the maximum information by scaling the signal. Subsampling of signal is done for this purpose by dropping at the rate of n i.e. reducing n samples of the signal at every level. Two individual sets of up sampled and down sampled values are obtained. It is generally a linear combination of prototype functions called mother wavelets. The signal can be decomposed to a very simplified version and then reconstructed to the desired level. It helps in ignoring the redundant portion of the signal and obtains the localized form of the signal. Wavelet Transform can be applied in two ways i.e. Continuous Wavelet Transform and Discrete Wavelet Transform. The difference between the two is that the latter consists of lesser redundancy and comparatively easier to implement. Thus, it provides adequate information for analysis as well as synthesis of original signal along with reduced computation time.

The CWT (continuous wavelet transform) is calculated as an integral of signal multiplied to the wavelet function,

$$C_a^\psi(\tau, k) = \int a(t) \cdot \psi_{\tau, k}^*(t) dt \quad (4.1)$$

Where,

$$\psi_{\tau,k}(t) = \frac{1}{\sqrt{k}} \psi\left(\frac{t-\tau}{k}\right) \quad (4.1.1)$$

represents the basis function. This method is however quite expensive and computationally complex. By using DWT, the complexity is reduced as the shifts and scales are based on power of 2. And thus efficiency also increases. Introduced in 1976 for decomposition of discrete time signals, it was called sub-band coding. DWT is basically to calculate correlation of wavelet with the signal at a scale used as measure of similarity. Figure 4.1.1 shows a typical structure for DWT.

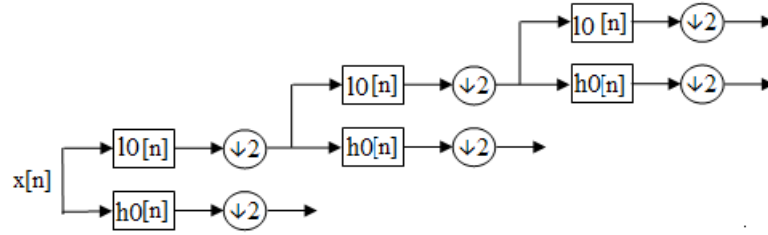


Figure 4.1.1: DWT representation

Mathematically, for a signal x , the first samples are convoluted to the impulse response of low pass filter l

$$y[n] = (x * l)[n] = \sum_{-\infty}^{\infty} x[m]l[n - m] \quad (4.2)$$

And simultaneously through high pass filter impulse response h

$$y[n] = (x * h)[n] = \sum_{-\infty}^{\infty} x[m]h[n - m] \quad (4.3)$$

First of all, the high pass and low pass filter of cut-off frequency nearly $1/4^{\text{th}}$ of the sampling frequency is applied on the original signal. The resultant signals can be further down-sampled using Nyquist criterion, and the procedure may be continued till the desired level of decomposition and is given as Mallet's notation:

$$y_{low} = \sum_{-\infty}^{\infty} x[m]l[n - m] \quad (4.4)$$

$$y_{high} = \sum_{-\infty}^{\infty} x[m]h[n - m] \quad (4.5)$$

DWT is applied on the original EEG signals to extract lower sub-bands. The signal is decomposed using Daubechies Wavelet and sixth level of the signal is extracted.

The Db4 wavelet is used as it provides the best resultant signal and has appropriate length. The detailed and approximation coefficients for level six are obtained and features for the approximation coefficients are calculated. The original signal can be reconstructed using the reconstruction formula as given below:-

$$x[n] = \sum_{-\infty}^{\infty} (y_{high}(m) \cdot h[-n + 2m]) + (y_{low}(m) \cdot h[-n + 2m]) \quad (4.6)$$

The EEG signals are generally restrained to the superposition of unlike structures occurring on various time scales at different times. WT is quiet efficient in differentiating and sorting of those underlying time-scale structures. In the study carried out here, the selection of appropriate mother wavelet and levels required for decomposition was considered of utmost importance. The t-f signal processing algorithms such as DWT are essential to report altered behaviour of EEG. It appropriately determines the localisation of transient events (behaviour like occurrence of spikes or sharp waves). Also, DWT has great plus over spectral analysis.

4.2 Features Extraction

The wavelet transform provides a squeezed distribution of signals in t-f domain. It is important to appropriately determine the inputs for the neural network. So, the features are calculated to be given as inputs to the network. The following set features has been extracted to perform the further analysis

- i. Standard Deviation for approximate values of decomposed signal.
- ii. Shannon Entropy of wavelet decomposed signal at level 1.
- iii. L1 norm of the wavelet decomposed signal.
- iv. Maximum values of the decomposed signal at level 6.
- v. First quantile of the signal at sixth decomposition level.

Standard Deviation: It is the simplest way to pull out the dispersion of the signal from its mean value. For, two different types of signals, the mean may appear to be the same. But standard deviation will vary according to the distribution of the signal. Statistically, it can be given as follows

$$\rho = \sqrt{\frac{\sum f(x-\bar{x})^2}{\sum f}} \quad (4.7)$$

Where, \bar{x} represents mean of the function x .

Shannon Entropy: It depends upon the power obtained by the FT of the signal. Shannon entropy is the simplest form of entropy employed for analyzing spectral entropy. It is obtained by summing the product of power level of each frequency to the logarithm of negative of that power level. Mathematically,

$$H(X) = \sum p(x) \log \frac{1}{p(x)} \quad (4.8)$$

Where, $p(x)$ denotes the power level of frequency.

L1 norm: It gives the least absolute errors (or deviations) between the estimated value and the target value of the component. This method is computationally efficient as it provides a single solution to the problem. Mathematically, it can be defined as:-

$$S = \sum_{i=1}^k |a_i - f(b_i)| \quad (4.9)$$

Where, S is the sum of absolute differences of estimated value b_i and targeted value A_i

Maxima: As the name suggests the maxima is the highest possible outcome or the value a signal can achieve. Here, in this work, maxima were calculated directly by using a MATLAB command.

Quantile: It is termed as the inverse of CDF for a random variable taken at regular intervals. The data is equally divided into q -sized subsets, and the values at the boundaries are considered as quantiles. The p^{th} quantile represents the CDF of p^{th} portion of the complete signal. The 3rd quantiles of the signal decomposed at level six were calculated in this study. The third quantiles are also called terciles or tertiles. In some cases, the values generated through quantile are not unique.

4.3 Classification

A major role is played by classification of signals in the research work of biomedical interests. A proficient classification scheme contributes to discriminate between the EEG segments and thus in making the decision regarding the subject's health. The concept of classification is based on the decision-making ability from the presently available information. For instance, assigning a credit status to

individuals depending upon their personal and financial information, issuing of identity cards in study institutions and organisations are some day-to-day classification procedures which we use inevitably. Classification may be supervised or unsupervised. In supervised classification, some kinds of data set are associated with specific class. In the unsupervised classification, nothing is pre-classified. In this work, we use two supervised methods for classification *viz.* neural networks and support vector machine.

4.3.1 Classification using Neural Networks

The neural network consists of artificial neurons working similar to the neurons as in human brain. Similar to the learning pattern of an average human brain to recognize a pattern as it becomes more familiar with it, the neural network also gets trained according to a given pattern and learns to recognize it gradually. The figure below depicts basic block diagram of neural network. In this study the artificial neural network has been utilised to classify the two kinds of signals. An ANN is a simple computation tool consisting of interconnected processing elements termed as artificial neurons much similar to human brain. Special training algorithms are developed to facilitate efficient learning process. These algorithms are based on learning rules assumed to imitate the learning contrivances of biotic processes. Availability of numerous architectures of neural networks to choose from, depending upon the suitability of the job makes this tool more attractive.

The Artificial Neural Network is expressed as a problem of non-linear least squares. In general, artificial neural network is considered as an operation of mapping from an m-dimensional input vector region to an n-dimensional output region. Based on maximum-neighbourhood method, the maximum-likelihood algorithm is employed in this work. The process consists of i) input variables for the knowledge of problem; ii) output variables to represent the dependent variable; and iii) a number of hidden layers to apprehend the non-linearity in the data. In all input, output and hidden layer portion, the key module is the neuron. This is shown in the figure 4.3.1. However, the number of inputs, outputs and the hidden layers may vary according to the requirement of the work.

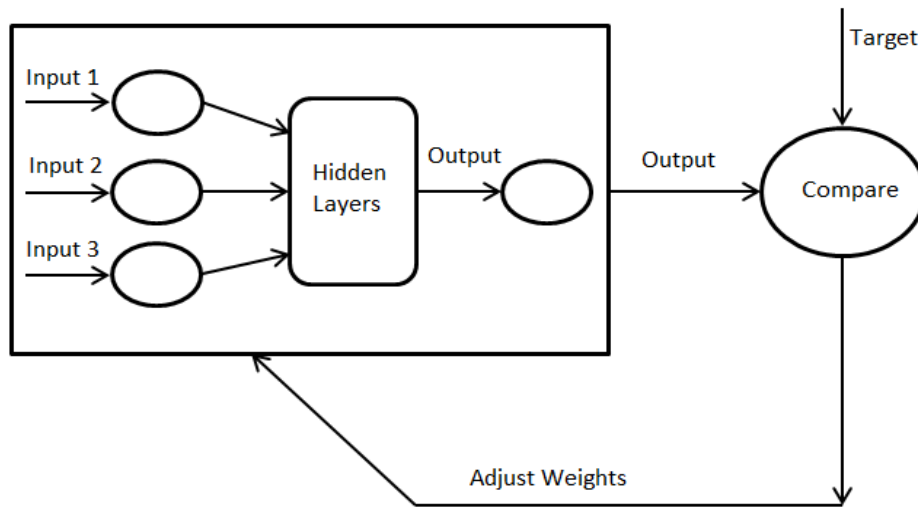


Figure 4.3.1: Basic Neural Network

In the present work, feed forward neural network with a range of number of neurons has been utilized. The result with each count of neurons has been measured and performance has been compared (the results are shown in the next section). Figure depicts the general structure of a neural network. The input and the output are allotted some weight depending upon the prerequisite of the output. The output is given as:

$$O_n = \sum_{k=l=1}^n W_{kl}AD \quad (4.10)$$

Where,

W_{kl} - Weight adjustment for k^{th} input and j^{th} output

AD – neural input

The MLPNN architecture consists of more than one layer. The concept of multilayer perceptron (MLP) is employed for the kind of neural network discussed earlier. It consists of many hidden layers for a single input. The layer is made up of unified muster of processing elements termed as neurons. The interconnections concerning the layers are known as weights. The weights are associated with some numerical values known as bias. The output of each neuron is a function of bias summed with the output of weighted sum of every input. For the neural models employed in

engineering purposes the knowledge of internal parameters is essential to meet the required performance norms. The determination of appropriate architecture and weights is quite a complex task. Theoretical tools are not sufficient to choose optimal values of such features. As a result, MLPNN needs to be trained several times. This is based on the experience and intuition of the practitioner, so there is no guarantee about the optimality of selected features. So, there are number of topologies for an MLP model to progress effectively. In this study, considering the requirement of our work (i.e. classifying EEG), the multi-layer perceptron neural network has been utilised. In the basic, two-layer architecture, only the input and output layers are present. No hidden layer provides any relationship between the input and output. Such a network is suitable for linear problems. For a non-linear signal like EEG, additional processing layers called hidden layers are utilised. However, single hidden layer may be adequate to plot an indiscriminate function to any point of complexity, depending upon the complexity of the function.

4.3.2 Classification using SVM

Support Vector Machines are one the best learning algorithms that can be used for classification of more than one kind of signals. In this section, a brief account of SVMs for classification purposes is given.

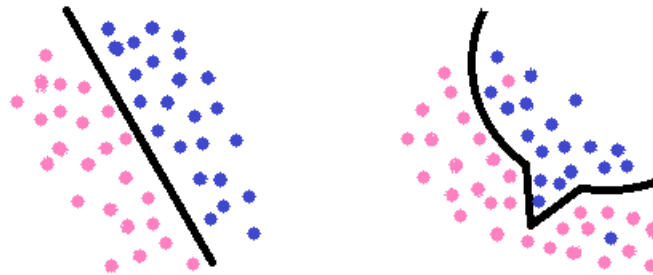


Figure 4.3.2: Simple boundary (left); Complex boundary (right) for SVM

The main chore of SVM is to provide a separation boundary (which may be linear or non-linear) in the feature cosmos. The boundary is defined in a manner that the following observations can automatically be categorized into distinct groups. The concept of support vector machines is based upon the underlying principle of optimal separating hyper-planes (i.e. OSHs). An OSH splits an m-dimensional space into two distinct parts that divides the space optimally. So, we may say that this OSH is a decision plane that outlines decision boundaries on the basis of which the

classification is carried out. The decision plane differentiates between the set of objects containing distinct class connections. A general example is shown in the given figure where the objects are either defined by pink or by blue dots. The separating line defines a boundary that describes pink data on one side and blue on the other. But, this is doesn't work for complex cases, when a non-linear boundary for separation is required. The illustration for simple and complex boundaries this is shown in figure 4.3.2.

To understand an OSH statistically, we assume a real-valued m -dimensional space described in the region \mathbb{R}^m . So, the OSH will be an affine m , such that 1-dimensional space is contained in the larger m -dimensional space. The value of $m=1$ implies that the affine is 1-D area, $m=2$ implies that it is 2-D area and $m>4$ means that it is a hyper-plane. This m -dimensional space optimally separates the space.

For the purpose of classification, a maximal margin classifier, a separating hyper-plane is outer most point from any training observation. For the purpose of classification, a maximal margin classifier, i.e. separating hyper-plane is outer most point from any training observation. It is utilised by computing the perpendicular distance from each training observation, say x_i for a given separating hyper-plane. The minimum perpendicular distance to a training observation from hyper-plane is known as margin.

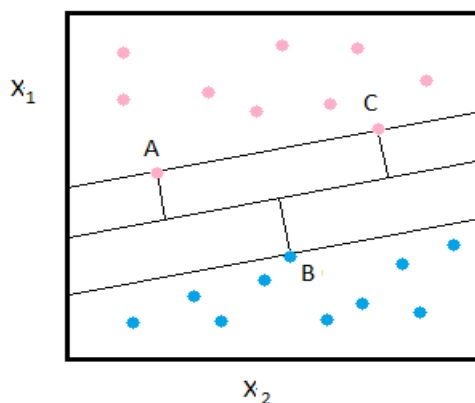


Figure 4.3.3: MMH with support vectors A, B and C

The maximal margin hyper-plane (MMH) is the hyper-plane where the margin is largest. In the classification, the side on which the test of observation falls is determined. Although, it is a good method for classification of data but its performance can be affected when exposed to large amount of test data. Such a

situation is known as over-fitting. The over-fit may occur when data is too closely clustered, and thus differentiating becomes difficult.

So, the optimal hyper-plane would be the one which if doesn't separate the two classes perfectly, is still robust if new separable observations are added and has enhanced grouping on the most of the training observations. To attain this, some of the training data is misclassified. This is the principle of support vector classifier of the soft margin classifier. This means that in an SVC, some of the observations are taken in the wrong side of hyper-plane (as shown in second part of figure 4.3.2). This phenomenon is known as structural risk minimisation (SRM).

Support Vector Machine is a generalised tool to obtain the enhanced generalization due to structural risk minimisation. For non-linear data SVM is used with the help of kernel function. Generally, it is a 2-class classifier. In this work, 160 sets of each type of data were used for training purpose and remaining 40 as test sets. The method employed was simple random sampling (SRS) for two groups of data. A random sample is taken at the time of training and classified into one of the two categories. The ability to allow non-linear enlargement of feature space simultaneously with the retention of computational efficiency, using the 'kernel function' makes this tool a desirable one for classification. Although SVM provides good generalisation characteristics the system offers low speed as a drawback.

4.3.3 Comparison of Neural Network and SVM

Every process has its pros and cons over the other. The two methods applied for classification are different from each other in the following sense.

- i. The neural network is based on the local minima, rather than global minima. This limits the ability of network to concentrate over the bigger picture.
- ii. The neural network may consider noise as a part of data in case of over-fitting. This would make its decision ability weak.
- iii. The SVM is dependent only on the support vectors. Therefore, the results are not affected by whole data set as in case of neural networks.
- iv. The set of features required to train an SVM is comparatively lesser than neural network.
- v. The execution time of neural networks is comparatively lesser than SVMs.

The classifying methods were compared on the basis of following three parameters:

Specificity: It is the percentage of correctly classified negative cases to actual number of negative cases. Total negative cases are the sum of correctly classified negative to misclassified positive cases. It is also termed as true negative ratio. It is mathematically defined as following:-

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (4.11)$$

Sensitivity: It is the percentage of correctly classified positive cases to actual number of positive cases. Total positive cases are the sum of correctly classified positive to misclassified negative cases. It is also termed as true positive ratio. It is mathematically defined as following:-

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (4.12)$$

Accuracy: Ratio of total percentage of correctly classified cases to actual number of cases.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4.13)$$

Chapter 5

CHAPTER 5 – EXPERIMENTAL SETUP

40-42

5.1 Dataset

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5.2 Basic Algorithm of Proposed Work

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Chapter 5 – Experiment Design

5.1 Dataset

The database has been derived from the online available data provided by reference [36]. It consists of five sets of EEG signals with 100 files of EEG recordings from five different patients suffering from temporal lobe epilepsy. 10/20 electrode system was employed to take the records and signals were recorded for 23.6 seconds. Each EEG signal has 4096 samples. The sampling rate of signals is fixed at 173.6 Hz. No further operations such as noise removal are performed on the signal. Set A and Set Z files have been used to perform analysis as well as testing. Sets A contains surface recording of healthy subjects and the latter set consists of seizure activity occurring in the epileptogenic zone prior to any sort of surgical diagnosis. The recordings for each subject involved a different zone part of hemisphere of brain. Further information about the datasets can be obtained from the reference [36].

5.5 Basic Algorithm for Proposed Work

Every system follows a set of protocols in order to operate in a proper manner and generate some sort of results. The two types of classifiers using in this work were applied in a proper manner to determine the feasible results. This section consists of explanation of steps carried out to fulfil the demands of the study.

As seen in the flowchart, the steps for execution are given below:-

- i. Step 1: the signal is taken as input, without knowing the nature of the signal
- ii. (epileptic or non-epileptic)
- iii. Step 2: the signal is pre-processed using wavelet transform. The coefficients for first to sixth decomposition levels are determined.
- iv. Step 3: features for different levels of decomposition are calculated.
- v. Step 4: the ANN was trained.
- vi. Step 5: the result of ANN classifier analysed on test signal.

Following is the flow chart showing the utilisation Neural Network on two types of signals.

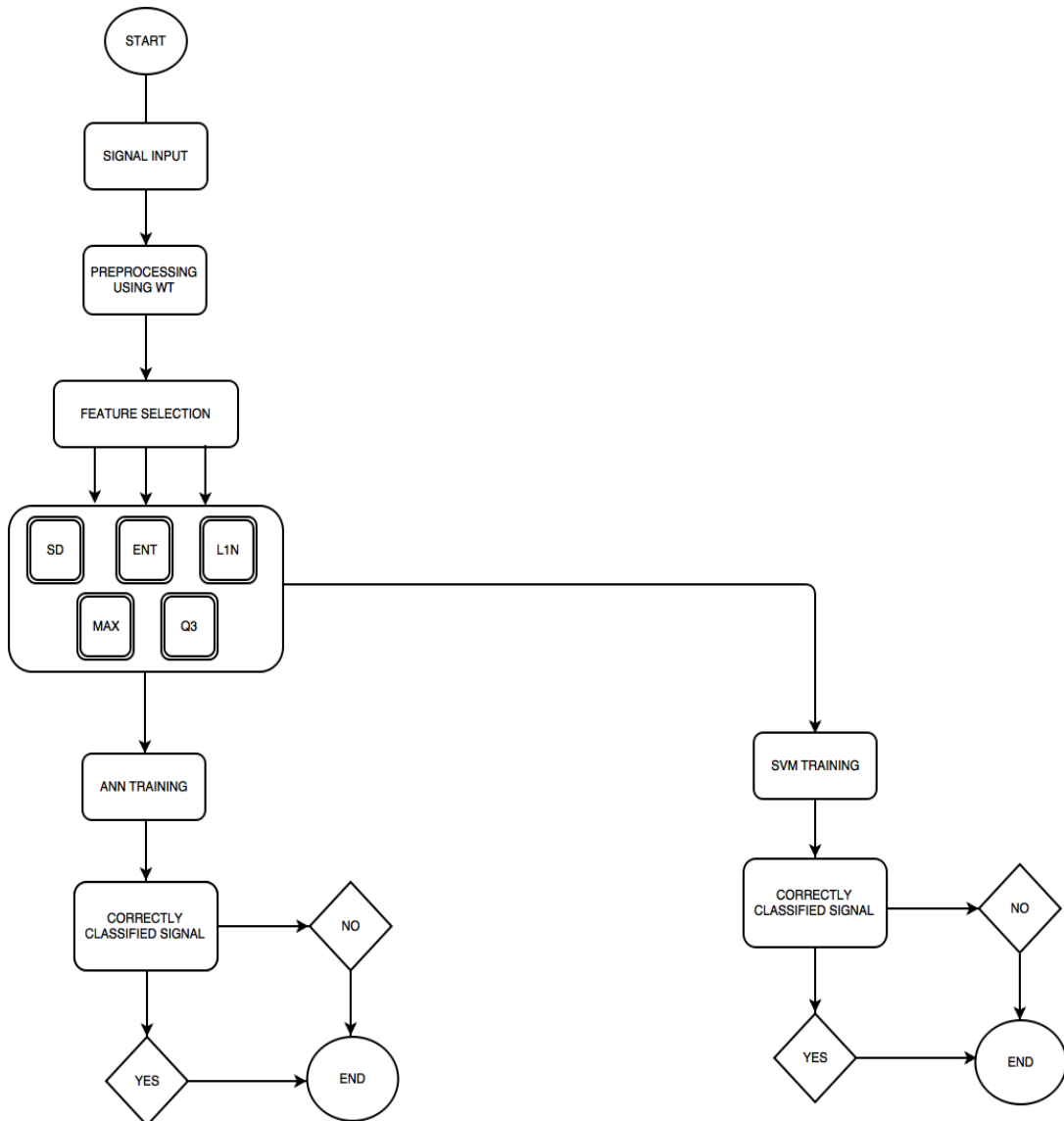


Figure 5.5.1: Flow-chart of proposed algorithm

For the classification using support vector machine same procedure was followed. The LS-SVM classifier was utilised in step 4 and step 5. The feature set for test data and training data were also taken same as in neural network classifier.

Chapter 6

CHAPTER 6- RESULTS AND DISCUSSION

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Chapter 6 – Results and Discussion

The EEG signals of epileptic and healthy subjects are taken using 10/20 electrode system. Existence of abruptions like spikes and complexes may be cause of an epileptic seizure. Sometimes, these seizures may have very small variations and might get neglected. Also, these may go unnoticed, as sometimes they resemble normal signals. Even if the signal is analyzed and functions like noise removal are performed, the by-product may not be easy to distinguish. This can be very well shown in the following figure, where the actual EEG plots of normal and the epilepsy affected signals are shown. Both the signals in the given figure show 4097 samples but the ranges vary from -200 to 200 μV for normal signal and -1000 to 1000 μV when there is an epileptic attack.

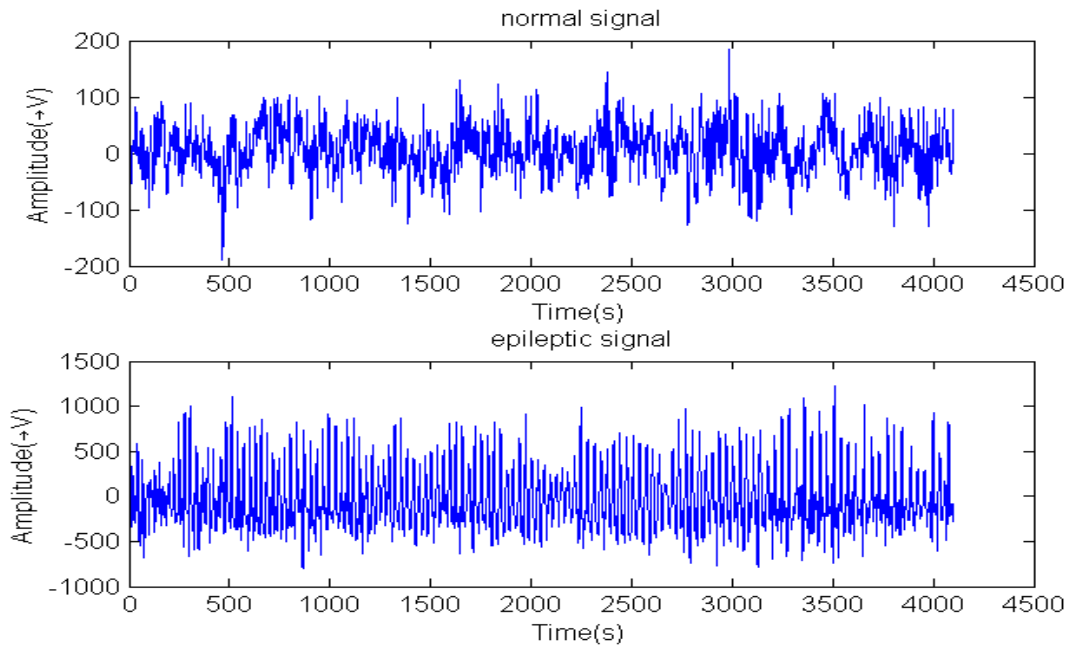


Figure 6.1: Original normal signal (above) epileptic signal (below)

The figure 6.1 shows an EEG signals during an epileptic seizure and during normal brain functioning. For a large EEG data, it is a tedious task to distinguish between two types of signals. Also some discrepancies may get introduced as a long range signal can be itself deceptive to the eye. Then, we apply DB-4 Discrete Wavelet Transform up to the sixth level of decomposition. The coefficients achieved at the sixth level are depicted in the figure 6.2. Here, we can see that the signal is now reduced to only less than 70 values. That means it is now easier to analyse.

However, the redundancy in the signal has been scaled down to a large extent. But the problematic situation persists, as the distinction of two kinds of signals has now become even more difficult with lesser values. This situation is dealt by extraction of significant features *viz.* entropy, standard deviation and L1 norm calculations of the sixth sub-band of discrete WT. The given figure shows the approximate coefficients for the Daubechies 4 at sixth decomposition.

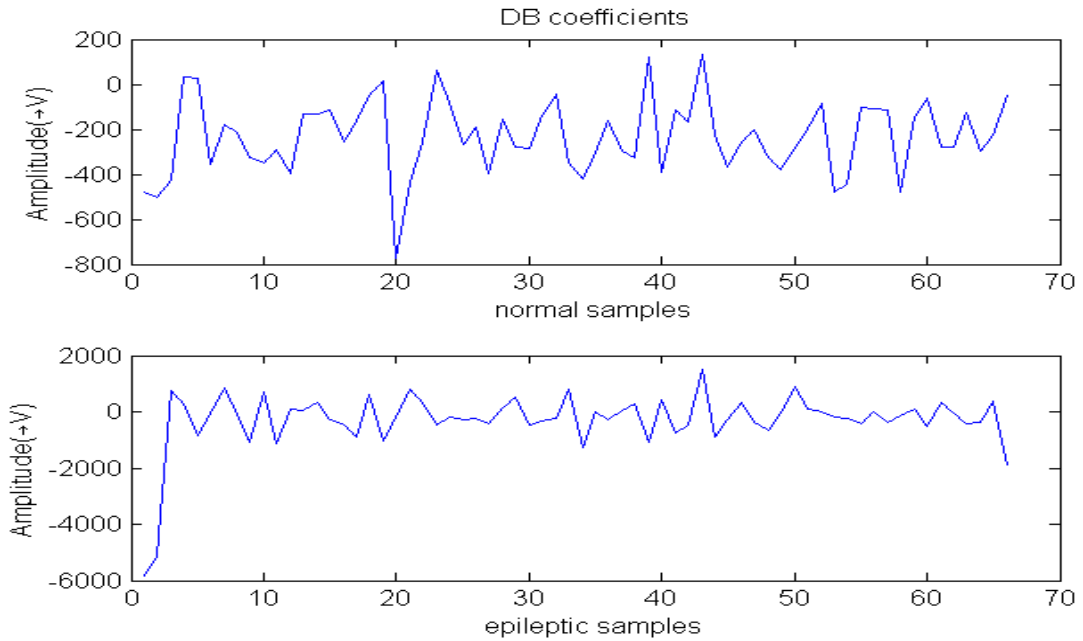


Figure 6.2: DB affected normal signal (above) epileptic signal (below)

The standard deviation values show a set of variations for many signals. This can be assumed from the scatter plot given in figure 6.3.

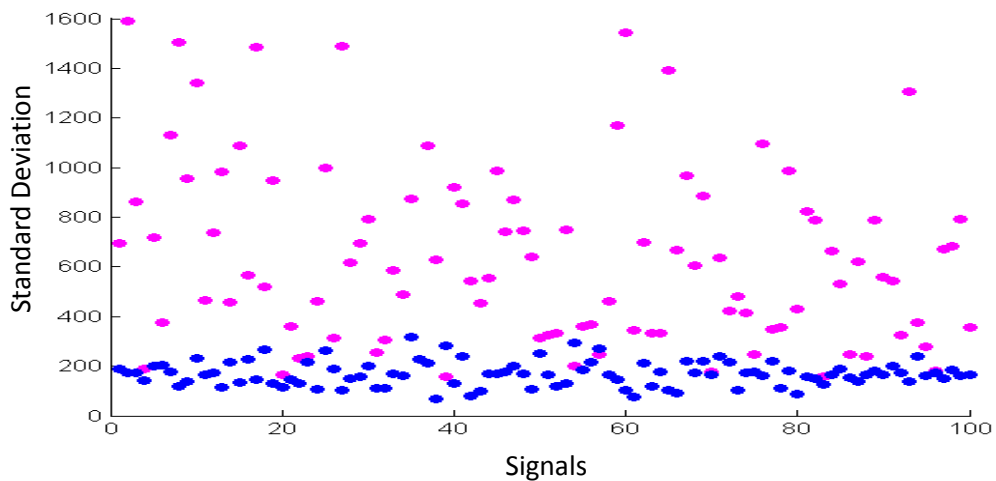


Figure 6.3: Scatter Plot for Standard Deviation

The magenta values represent the values for normal EEG and the blue ones represent those for Epileptic EEG.

The epileptic values has standard deviation values mainly concentrated near 200. Then, another selected feature L1 norm also distributes to largely varying values for normal and diseased signal. This can be seen in figure 6.4.

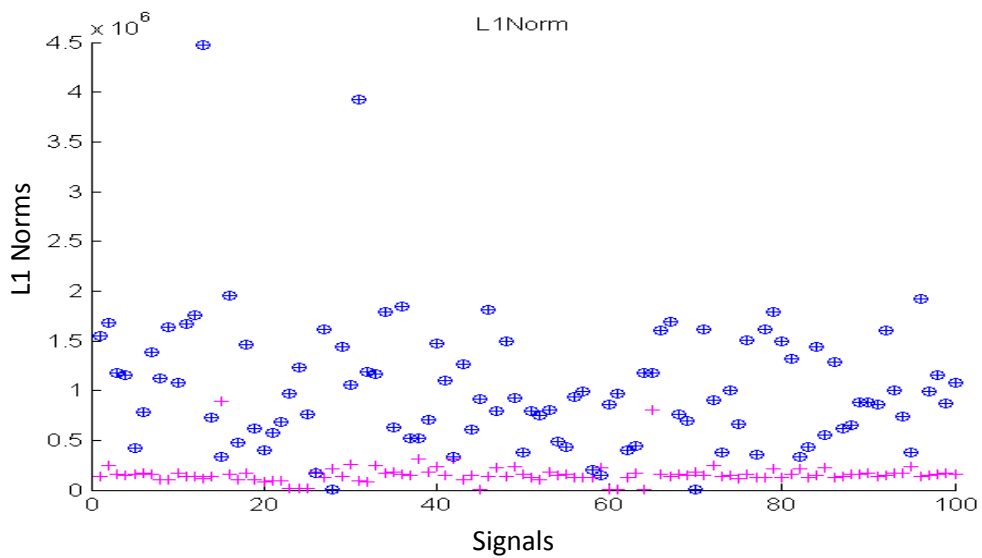


Figure 6.4: Scatter Plot for L1 norm

The above scatter plot gives the normalized values of two kinds of signals in time-frequency domain. This is better understood if we visualize it in graphical form as in figure 6.5.

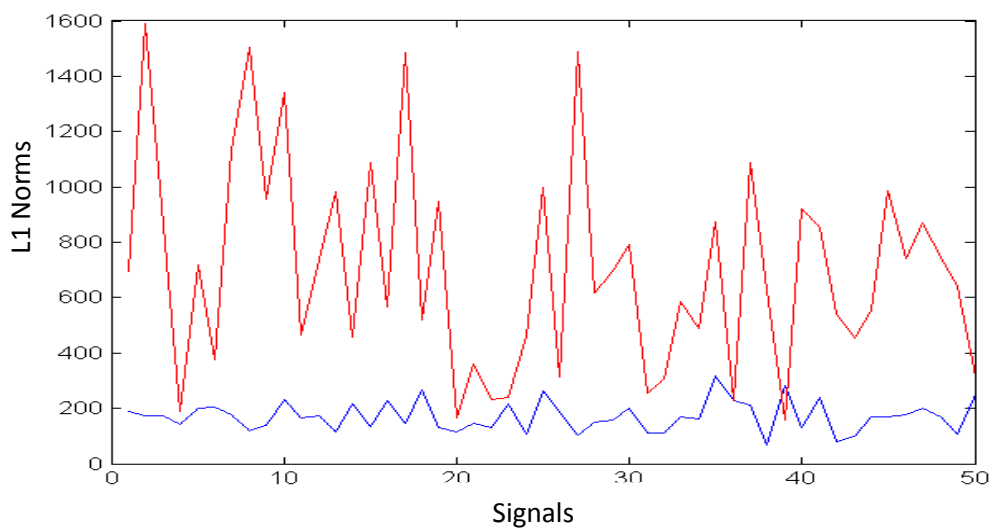


Figure 6.5: L1 norm Graphical

As is seen in the above figure the normalized values of the coefficients overlap in negligible values. However, it should be kept in mind that these represent the static significant values for the two kinds of signals.

Then for measuring the numerical randomness of the signal we perceive the statistical host of variability in terms of entropy, figure 6.6.

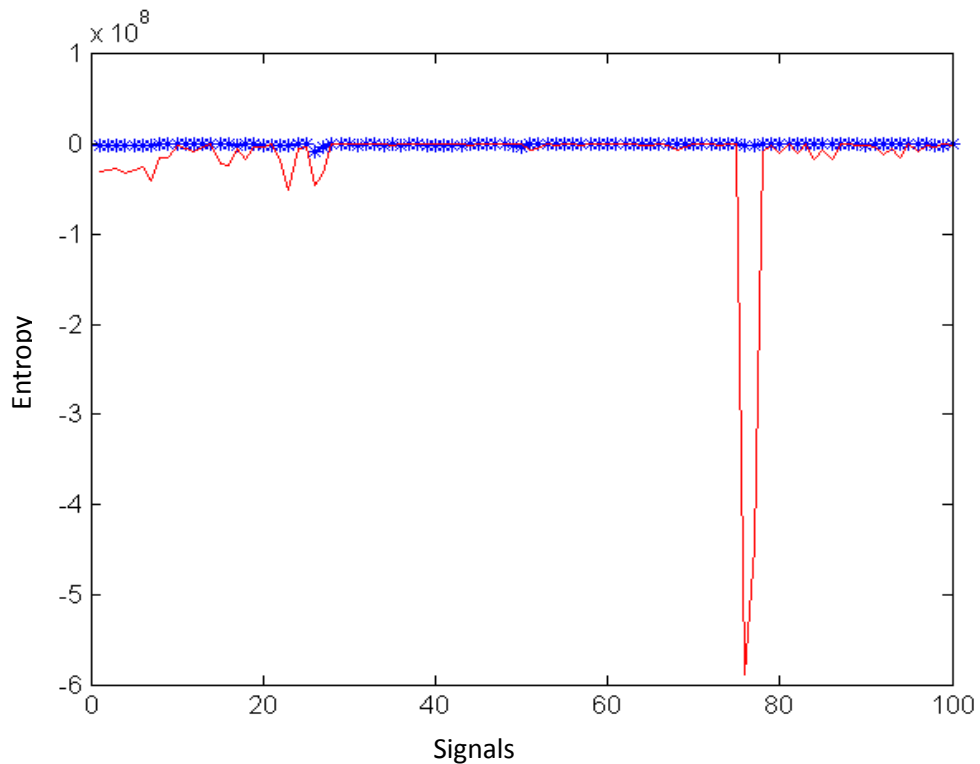


Figure 6.6: Entropy Values

Here, we see that for diseased signals the entropy values can find a sudden large variation for some signals (red line represents an epilepsy affected signal). Clinically, such signals are recorded when there is an extreme epileptic attack [37].

Then the values for maxima are calculated for two kinds of signals. The magenta colour represents a normal signal and the blue colour represents seizures in the signal. It is very clear from the figure that the diseased signals are having very high amplitudes. Also in some cases, the normal signals are having null values.

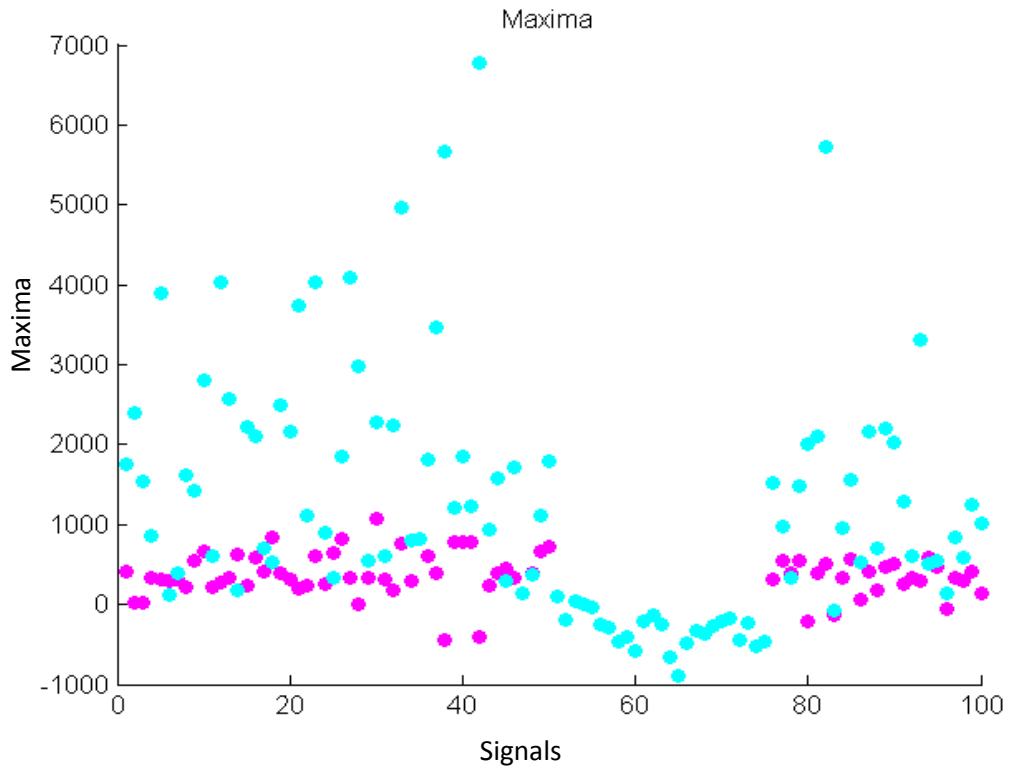


Figure 6.7: Maxima for sixth decomposition

Another useful feature to act as an input for the classifier considered was the third quantiles or tertiles of the wavelet transformed signal. The figure 6.8 shows plot of tertiles for two kinds of signals.

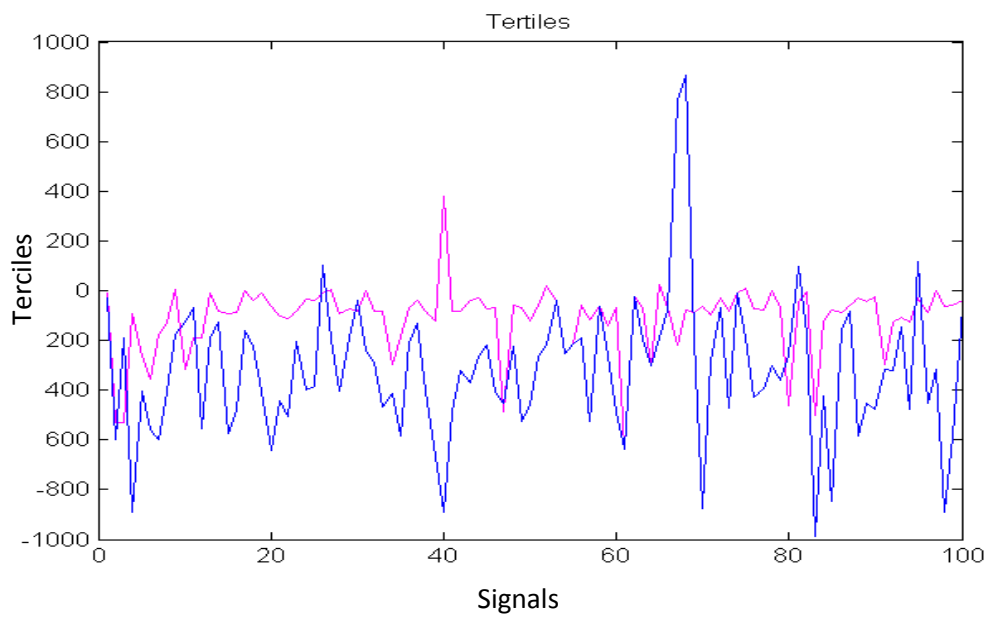


Figure 6.8: Third Quantiles for sixth decomposition level

The parameters calculated for two different Subjects having 90 sets each are given to linear state support vector machine as input. A total of 450 feature sets are generated for each subject making 900 input values for the network. The class and group values are defined according to the signal. The random arrangement of features is made to train the network.

The classified and training results for SVM classifier are shown using a scatter plot in the figure 6.9. It should be noted that an SVM classifier result can be plotted in 2-dimensional plot only, i.e only two features will represent the figure. The line represents the differentiating line between two features.

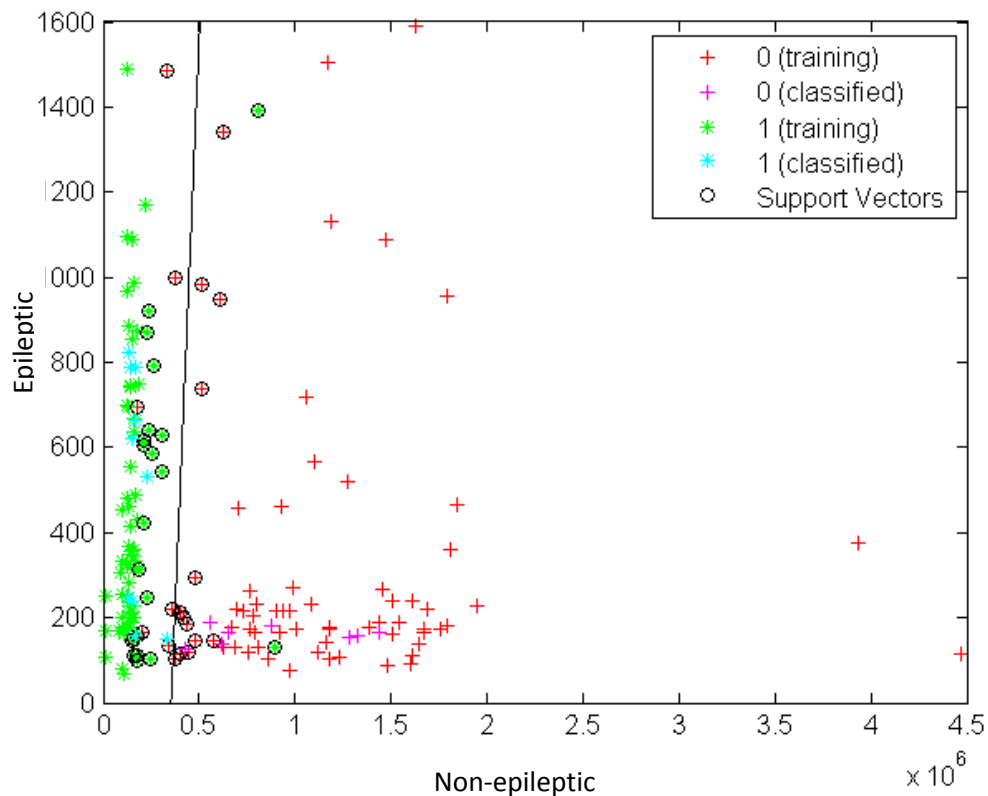


Figure 6.9: SVM Result

The system took bias value as 1.1544 and employed the linear kernel to perform the operation on 40 values of alpha (which was decided by the amount of test data used for training). Ten values of each diseased and non-diseased data were used for testing. Firstly, the test values were arranged in serial order, i.e., first 10 as diseased and next ten as non-diseased. And then they were randomly arranged. It was found

that the position of the values did not matter. The SVM was able to perform properly in both the cases. This method achieved the accuracy of 98.9%.

Same features were used for classifying the epileptic and non-epileptic signals using feed-forward multilayer neural network. The training values are defined according to the signal. The random arrangement of features is made to train the network.

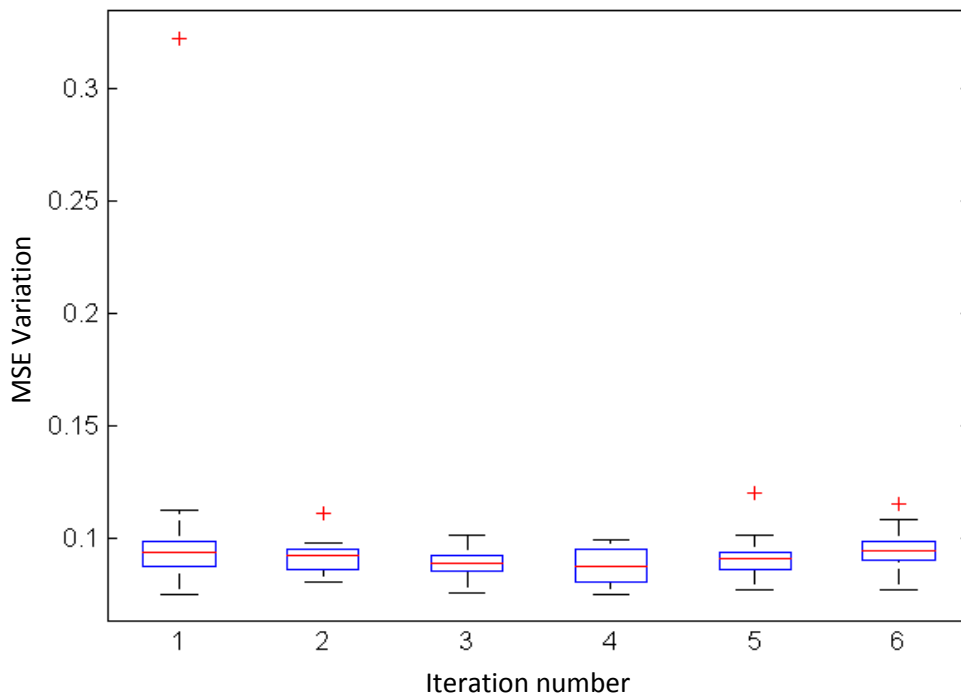


Figure 6.10: MSE Matrix (above); MSE Boxplot (below)

The simulation is performed for varying number of neurons from 1 to 21 in six iterations. This situation is shown with the help of boxplot shown in figure 6.9.

The MSE for different number of neurons is calculated and the number of neurons with best performance is applied for final classification.

On the basis of calculation of MSE, average MSE is calculated and the best result is by fourth value in MSE plot, as shown in figure 6.9. The number of neurons represented by fourth value is 13.

The performance validation chart (as shown in figure 6.10) represents good performance in the beginning. The accuracy is calculated for the proposed method and it came out to be 99.00% accurate.

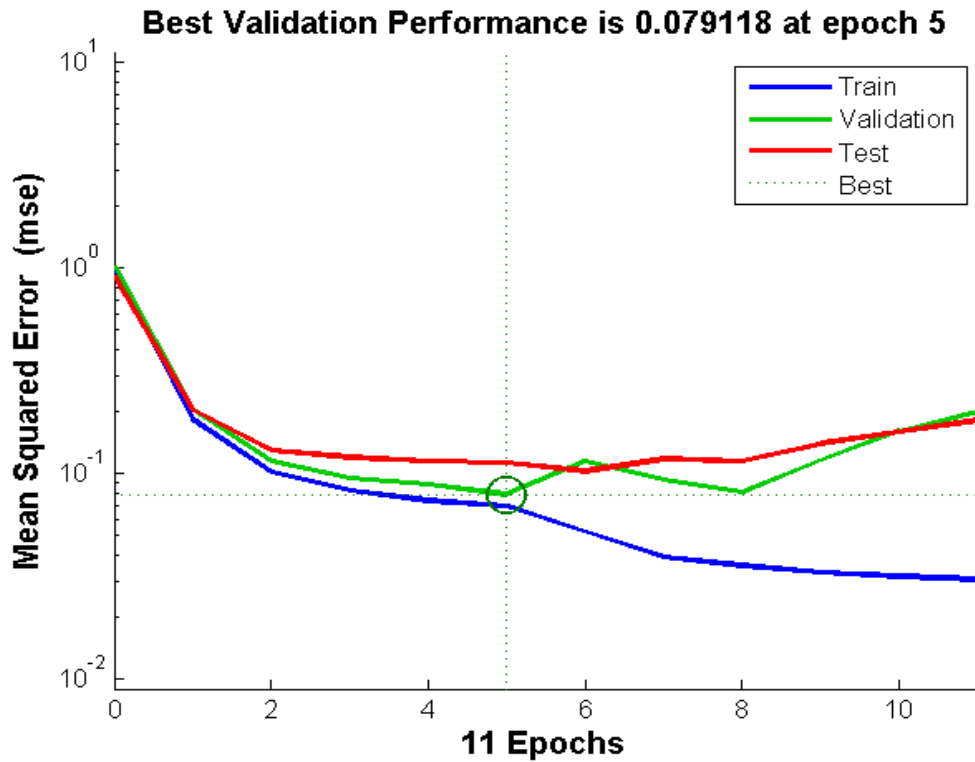


Figure 6.11: Performance of Neural Network

As compared to previous works, accuracy table is shown below. However, the method was explored further for a lesser number of feature sets, in order to compete with itself. The results are shown in the next couple of pages.

Table 6.1: Performance Accuracy

Work Year	Accuracy (%)
2012 [14]	80
2013 [10]	98.87
2014 [2]	84.2
2015(This Work)	99.00

The ANN and SVM performed quiet equally well for the five sets of features. When required to look for real-time occurring epileptic seizures, a robust and still accurate system needs to be designed. So, for such a system a reduced set of features is required without compromising the efficiency of the system. Further, the features were divided into sets of three features at a time i.e. a total of 270 feature sets are generated for each subject making 540 input values for the network. This reduces

the load on the system and execution time. The following table shows the efficiency of different parameters when applied on SVM.

Table 6.2: Efficiency using Different Feature Sets for SVM

Combination	Specificity (%)	Sensitivity (%)	Accuracy (%)
S-E-L	98.9	98.9	98.95
S-E-M	95.93	95.90	95.92
S-E-Q	90.98	90.00	90.94
S-L-M	90.87	90.98	90.93
S-L-Q	90.92	90.93	90.93
S-M-Q	84.89	85.00	84.95
E-L-M	89.98	91.20	90.59
E-L-Q	88.68	87.85	88.27
E-M-Q	84.56	85.78	85.17
L-M-Q	82.33	80.87	81.60

The training and test data sets were shuffled and tests were performed repeatedly in order to jot down the most appropriate results. An error percentage of $\pm 2\%$ was neglected. An overall efficiency of 89.83% was achieved using SVM.

Similarly the efficiency table was constructed for feed-forward ANN classifier. Same parameters in the same shuffled order were classified and tested.

From table 6.2 and table 6.3, it is inferred that that the combination of three features viz. standard deviation, entropy and L1norm provide best results when classified through neural networks. However, SVM also classifies with an accuracy of 98.95%.

Table 6.3: Efficiency using Different Feature Sets for ANN

Combination	Specificity (%)	Sensitivity (%)	Accuracy (%)
S-E-L	99.98	99.93	99.95
S-E-M	99.89	99.89	99.92
S-E-Q	97.96	97.96	97.96
S-L-M	96.45	96.86	96.66
S-L-Q	94.33	95.65	94.99
S-M-Q	90.01	90.57	90.30
E-L-M	96.78	95.87	96.33
E-L-Q	96.73	96.66	96.70
E-M-Q	94.70	94.78	94.74
L-M-Q	89.97	88.87	89.42

It has also been noticed that despite neglecting the quantile and maximal value from the features, the efficiency of both the classifiers is increased and input required is reduced.

Chapter 7

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Chapter 7 – Conclusion and Future Scope

7.1 Conclusion

Epilepsy is one of the major neurological disorders found commonly in people. According to a medical survey, more than 2% of the world's population is affected by some degree of epilepsy. In most of the mild cases, the disorder gets overlooked because of its congruence with many day-to-day problems. However, the disease needs to be correctly diagnosed in the early stages. EEG is a good technique to accurately detect the emergence of epileptic seizures. The sooner the disease is correctly diagnosed, the effective the treatment will be. The correct classification epileptic seizure requires watchful observation of the patient and the medical diagnosis through EEG.

In this study, it can be said that an expert automated model to detect epilepsy has been worked upon.

Firstly, the pre-processing of EEG signals through the discrete wavelet transform reduces large chunk of EEG data into smaller sets of coefficients. This smaller set of data is easier to handle and store.

Second, this study discussed two approaches for developing an algorithm to classify the signals. One approach is that of traditional SVM technology and the other approach follows the classification through the multi-layered artificial neural networks. The comparison of the two techniques was done on scalar basis. It was inferred that the overall performance of neural network was more than that of SVM classifier.

Third, the process of feature selection then provides a means of setting up some criteria that helps in distinguishing between an epilepsy affected signal and a normal EEG recording. The five sets of features were originally used as input to the classifiers and later, they were reduced to combinations of three feature sets as input to the classifiers. It has been observed that selection of features play an important role in the classification of signals. The combination of three features *viz.* standard deviation, entropy and l1 norm contributed to better results.

The good classification efficiency of the systems, it may be said that the use of Discrete Wavelet Transform and the selected feature sets make a good decision support for classifying the results using SVM and Neural Networks.

7.2 Future Scope

The present work distinguishes between the seizure activity and normal activity in the epileptogenic zone only i.e. only the localised seizures are detected. This work can be further extended to determine the generalised seizures. The feature used in this case may be replaced with some better features would encourage in setting up a better distinguishing criteria. A reduced feature set will add to reduction in cost and complexity of the system. Also, because this is an automated method for the detection of epilepsy, so software can be developed to interface this with a device such that real-time seizures can be detected.

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