# PROGNOSTICATION OF EEG SIGNAL USING WAVELETS

*Project report submitted in fulfillment of the requirements for the degree of*

**BACHELOR OF TECHNOLOGY**

**IN**

**ELECTRONICS AND COMMUNICATION ENGINEERING**

By

**AESHNA CHAWLA (131037)**

**IRESH RASTOGI (131040)**

**ANTRIKSH OJHA (131100)**

UNDER THE GUIDANCE OF

**Dr. MEENAKSHI SOOD**

JAYPEE UNIVERSITY OF INFORMATION TECHNOLOGY, WAKNAGHAT

May, 2017

# TABLE OF CONTENTS

## JAYPEE UNIVERSITY OF INFORMATIO TECHNOLOGY

(Established by H.P. State Legislative vide Act No. 14 of 2002)

P.O. Waknaghat, Teh. Kandaghat, Distt. Solan - 173234 (H.P.) INDIA

Website: www.juit.ac.in

Phone No. (91) 01792-257999

Fax: +91-01792-245362

# CERTIFICATE

This is to certify that the work reported in the B.tech project report entitled **“Prognostication Of EEG Signal Using Wavelets”** which is being submitted by **Aeshna Chawla, Iresh Rastogi, Antriksh Ojha** in fulfillment for the award of Bachelor of Technology in Electronics and Communication Engineering by the Jaypee University of Information Technology, is the record of candidate’s own work carried out by him/her under my supervision. This work is original and has not been submitted partially or fully anywhere else for any other degree or diploma.

----------------------------

**Dr. Meenakshi Sood**

Assistant Professor (Senior Grade)

Department of Electronics & Communication Engineering

Jaypee University of Information Technology, Waknaghat,

# ACKNOWLEDGEMENT

We have done hard work in this project. In any case, it would not have been possible without the kind support and help of numerous people and associations. We would like to broaden our appreciation towards every one of them. First and foremost, we would like to thank our project guide, **Dr. Meenakshi Sood**, for her guidance. We would like to extend our gratitude towards **Dr. Sunil Vidhya Bhooshan**, HOD, Electronics and communication department for allowing us to work on this project. Besides, we would like to thank the authority of Jaypee University of Information Technology for providing us with a good environment and facilities to complete this project.

# LIST OF FIGURES

# ABSTRACT

A comprehensive quantitative analysis of electroencephalogram signals is carried out. Due to the non-stationary nature of EEG signals the visual investigation of EEG information is restrictively tedious and wasteful, regardless of the possibility that the master clinician reads the data ten times quicker than the recording speed. The visual assessment needs quantitative investigation which can reveal concealed characters of the data. Wavelet provide a solution and provides functions for synthesizing and analyzing signals, pictures as well as information that show general conduct punctuated with sudden changes. Properties from the accessible database are separated and investigation of signal with various wavelets is prepared to identify and foresee the kind of disorders. This article proposes a method for reliable detection of different types of disorders by using different wavelets as haar wavelet, Shannon wavelet etc to the database signals and on the basis of which we are able to prognosticate. Further the type of disorder is predicted using Artificial Neural Network classifiers.

# CHAPTER 1

# INTRODUCTION

## 1.1 Electroencephalograph (EEG)

The brain normally produces little electrical signals which basically originate from the nerves and cerebrum cells which send messages to each other. Thus these types of electrical signals are identified and recorded by the EEG machine. The test of EEG is more or less an effortless test and a safe one. The machine records signals that are originating from the cerebrum which means that it does not put any kind of external power into the body or mind of an individual .It is a valuable test in diagnosing conditions, such as that of, epilepsy[1].

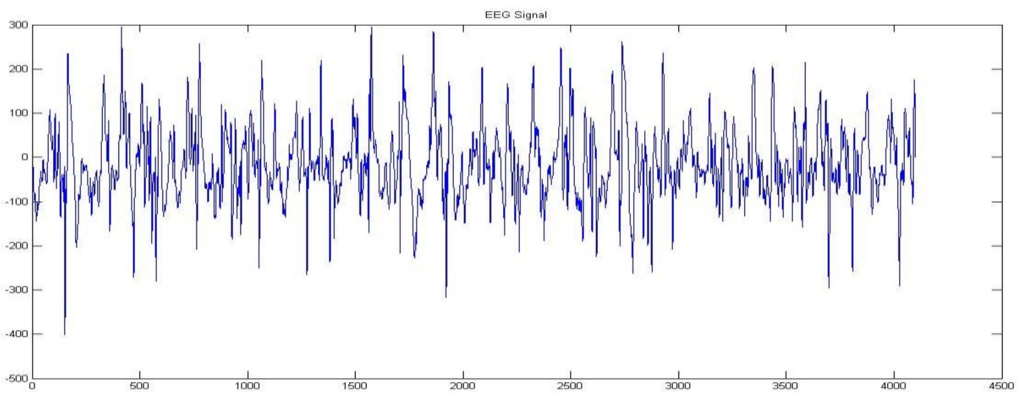



**Figure 1.1:** An Electroencephalograph (EEG) Signal

## 1.2 Brainwaves

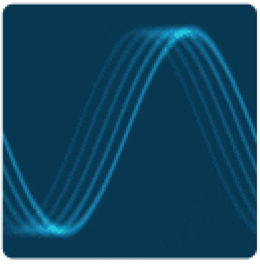
At the foundation of every one of the thoughts, feelings and practices is the contact between the brain and neurons. When an ample amount of neurons communicate with each other due to electrical pulses that are synchronized brainwaves are formed.

The brainwaves are identified utilizing sensors that are put on the scalp. They all have specific range of bandwidths so as to portray their respective functions (beneath), however they are considered to be the best as a it has a constant range of awareness, that is from moderate, loud and functional - to quick, complex and delicate. It is a suitable correlation to consider brainwaves as melodic notes; the low recurrence effect resembles a profoundly entering drum beat, whereas the other higher recurrence brainwaves are more likely to be similar to an unobtrusive pitched flute. The higher and lower frequencies interface and get connected to each other through music (harmonics) which are similar to a symphony. Our brainwaves keep on changing according to what we're feeling and doing. At a particular point when brainwaves that are slower are overwhelming one can feel totally drained, moderate, or lethargic [2]. The portrayals that take after are widely depictions - by and by things are significantly more difficult and brainwaves thus reflect diverse angles when happening in various parts in the mind. The brainwave speed is measured in Hertz (cycles every second) and are separated into groups portraying fair, direct, and rapid influence (waves).

## Infra-Low (<0.5 Hz)

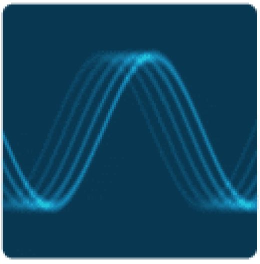
The Infra Low (brainwaves otherwise called Slow Cortical Potentials), are supposed to be the fundamental cortical rhythms that bring about one’s higher brain capacities. Their moderate nature makes them hard to distinguish and precisely analyze, therefore few of the reviews have been finished. They seem to play a noteworthy part in cerebrum timing and system work.

## Delta Waves (.5 to 3 Hz)



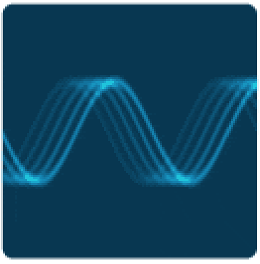
The delta brainwaves are fair, the ones that are loud (low recurrence and profoundly entering are similar to a drum beat). Such type of wave is formed in most profound meditation and dreamless rest. Mending and recovery are invigorated in this state, and that is the reason profound remedial rest is so fundamental to the procedure for recovering.

## Theta Waves (3 To 8 Hz)



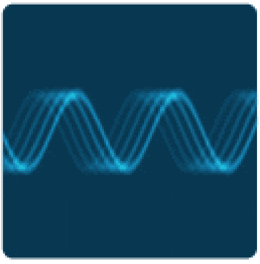
The theta brainwaves take consistently in rest however at the same time are established in significant thought. In theta, the senses are basically focused on signs that are starting from inside and get pulled once again from the external world. It is that kind of dusk state which we simply encounter quickly as we buoy off to rest or wake. In theta one is in clear fantasy; instinct and data that is past ordinary consciousness of a person. Such place is a part where we hold our 'stuff', feelings of dread, upset history, and all the bad dreams.

## Alpha Waves (8 To 12 Hz)



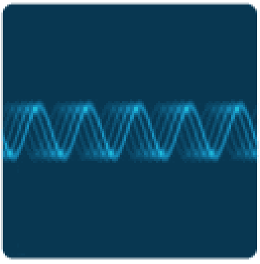
The alpha brainwaves are major thoughts are streaming, and in some considerate states. Alpha is 'the energy of now', that is being here, in the present state. It is kind of resting state for the mind. These waves help many parameters such as mental coordination, readiness, serenity, mind/body combination as well as learning.

## Beta Waves (12 To 38 Hz)



The beta brainwaves generally rule our ordinary waking condition of consciousness when consideration is coordinated towards the outside world and cognitive tasks. It is a "quick" activity, introduced at the time when a person is ready, alert, occupied with serious thoughts, judgment, and engaged with mental movement which is centered.

## Gamma waves (38 To 42 Hz)



The gamma brainwaves are the quickest of all brain waves (high recurrence, similar to that of a woodwind), and identify with side by side processing of data from various areas in the brain. It passes data quickly; the mind must be peaceful to get to it as it is the most unobtrusive of the brainwave frequencies. Gamma was rejected as 'extra cerebrum commotion' until the scientists found that it was exceedingly dynamic when in conditions of all inclusive love, selflessness, and the 'higher ideals'. Gamma is additionally over the recurrence of neuronal firing, so how it is created remains a secret. It is theorized that Gamma rhythms tweak observation and awareness, and that a more prominent nearness of Gamma identifies with extended awareness and profound development [3].

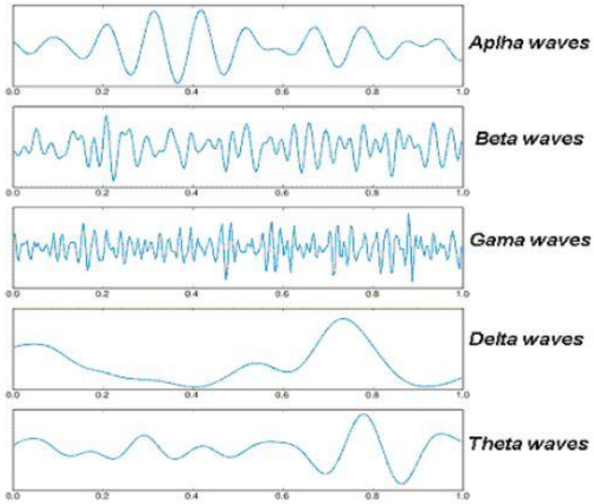



**Figure 1.2:** Various classification of brainwaves from alpha to theta waves

## 1.3 Acquisition of signals

As the machine recognizes and amplifies the electrical signals it records them on to a PC or paper. The test takes around 20-30 minutes of time. The electrodes are removed test is finished. For the span of the test one might be told to be seated in a seat or stretch out on a lounge chair. At a particular point of time one is made to blink a lot many times, or to inhale profoundly. These can at times trigger examples of electrical action in the brain which are related with specific sorts of epilepsy [4].

### A normal ('negative') result

This depicts a distinctive pattern of electrical action going on within the brain. Generally most people who do not suffer from epilepsy, and many people suffering from epilepsy, have a result that is absolutely normal. This is because when the test is done an electroencephalograph (EEG) only shows the electrical activity within the brain. One has an abnormal result only when a person is having a seizure. For the rest of the time, the resultant pattern comes out to be normal.

### An abnormal ('positive') result

This shows irregular examples of electrical movement. A few people with specific sorts of epilepsy have unusual examples constantly, not exactly when they have seizures.

(Despite the fact that, amid a seizure the activity is significantly stranger). For instance, kids with normal 'absent seizures' frequently have a trademark EEG design which affirms this kind of epilepsy. In any case, few individuals who never have seizures and who don't have epilepsy have some unusual examples of electrical action in the brain. In this way, on the off chance that you have side effects which are thought to be seizures, an unusual EEG implies that the conclusion is probably going to be epilepsy. In any case, an ordinary outcome does not preclude epilepsy, and an unusual outcome does not really imply that you have epilepsy.

## The 10-20 system

When a person goes through an EEG test, the number of electrodes utilized is (usually 25-30). There are particular positions in which the electrodes are placed on an individual's head, such that these electrodes pick up signals from various parts of the brain. When a professional or specialist checks the results of the EEG, they can provide the information as to what cerebrum action is going on, and that too in which part of the brain is it taking place.

The standard according to which the electrodes are placed on the head for testing is called the 10-20 system. Each electrode is placed either 10 or 20 for every percent of the total separation between the points that are made by measuring the individual's head and then denoting the position with the help of a delicate pencil. Each electrode is demarcated with a number [5] that is all the odd numbers are on the left half of the head, and the even numbers on the right half. Similarly the electrodes have a letter, depending upon the zone of mind where it is recording from: F for frontal lobe, T for temporal lobe, P for parietal and O for occipital lobes. And for the ones situated in the midline of the head are utilized by the letter Z.

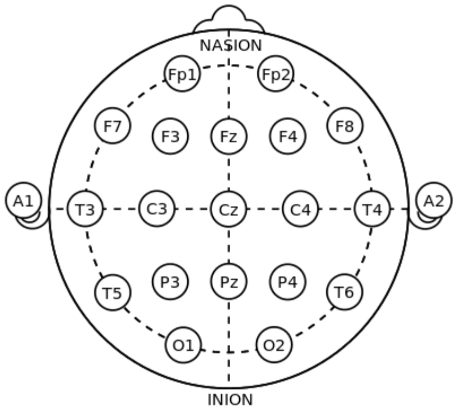



**Figure 1.3:** Electrode placement by 10-20 system

All the electrical movements are taking into account by the EEG amid the test. A lot many factors correspond to the movement of the brain: if the individual is up awake or is present in various phases of rest, what kind of action are they performing, and in which state are their eyes present i.e. either open or shut.

## 1.4 Epilepsy

Epilepsy is a chronic issue, the sign of which is repetitive, seizures that are unprovoked. Many individuals with epilepsy have more than one sort of seizure and may have different symptoms of neurological issues also [6]. Some of the time EEG testing, clinical history, family history and viewpoint are comparative among a gathering of individuals with epilepsy. In these circumstances, their condition can be characterized as a particular epilepsy disorder.

The human mind is the wellspring of human epilepsy. In spite of the fact that the manifestations of a seizure may influence any part of the body, the electrical occasions that deliver the symptoms happen in the brain. The area of that occasion, how it spreads and the amount of the cerebrum is influenced, and to what extent it keeps going all have significant impacts [7]. These elements decide the character of a seizure and its effect on the person. Basically, anything the brain can do, it can do as a seizure. Having seizures and epilepsy can influence one's security, connections, work, driving thus a great deal more. Open recognition and treatment of individuals with epilepsy are regularly more serious issues than real seizures.

## Causes of epilepsy

Distinctive epilepsies are because of a wide range of fundamental causes. The causes can be perplexing, and once in a while difficult to recognize. A person may begin having seizures since they have at least one of the accompanying.

• A hereditary propensity, go down from one or both parents (acquired).

• A hereditary propensity that is not acquired, but rather is another adjustment in the individual's genes.

• A basic (usually called 'symptomatic') change in the mind, for example, the cerebrum not growing fairly, or harm brought on by cerebrum damage, diseases like meningitis, a stroke or a tumor. Scanning of the brain, for example, Magnetic Resonance Imaging (MRI) may demonstrate this.

• Structural changes because of hereditary conditions, for example, tuberous sclerosis, or neurofibromatosis, which can bring about developments influencing the brain.

A few specialists now trust that the possibility of developing epilepsy is presumably constantly hereditary to some degree, in that any individual who begins having seizures has dependably had some level of hereditary probability to do as such. This level can run from high to low and anyplace in the middle of [8]. Regardless of the possibility that seizures begin after a mind damage or other auxiliary change, this might be because of both the basic change and the individual's hereditary propensity to seizures, consolidated. All this sounds correct if it is considered that many people might suffer from a similar brain injury, yet not every one of them create epilepsy a while later.

## 1.5 Data collection

Data collection is the first major step to start the analysis of the EEG signal. So, the benchmark database was used provided by the University of Bonn. Data consists of three types of EEG signals –that are of (i) Inter ictal patients represented by **F**, (ii) Normal represented by **Z** and (iii) Epileptic patients represented by **S**.

## 1.6 Role of EEG in epilepsy syndrome

Electroencephalography (EEG) is a fundamental part in the assessment of epilepsy. The EEG gives imperative data about foundation EEG and epileptiform releases and is required for the conclusion of particular electro-clinical disorders. Such a determination conveys imperative prognostic data, guides choice of antiepileptic medicine, and proposes when to stop the medication. Neurologic examination and imaging in the fundamental idiopathic, mostly hereditary, epilepsies are typically normal [9].

### EEG background frequencies and epileptiform discharges

Taking after a seizure (i.e., amid the postictal period) the EEG foundation might be moderate. However, the inter-ictal foundation EEG frequencies that are slower than typical for age mostly recommend symptomatic epilepsy (i.e., epilepsy optional to cerebrum affront). Typical foundation proposes essential epilepsy (i.e., idiopathic or conceivably hereditary epilepsy). Accordingly, EEG foundation offers critical prognostic and grouping data. Epileptiform releases help clinicians to isolate generalized from local (i.e., halfway or partial) seizures.

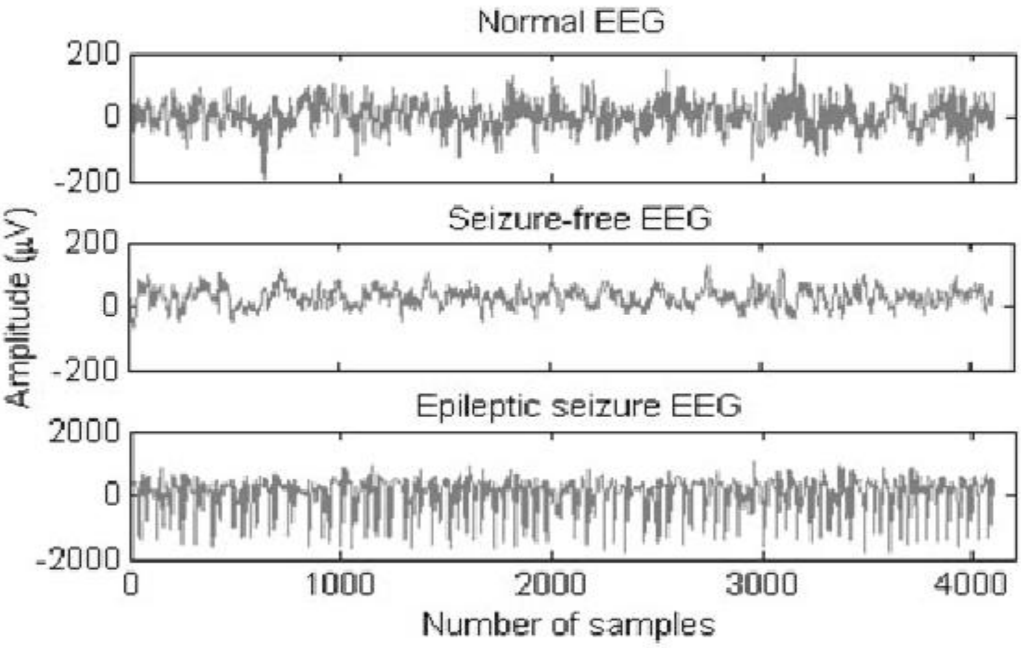



**Figure 1.4:** Seizure and epileptic seizure EEG signals

# CHAPTER 2

# OBJECTIVES

## 2.1 Related Work

EEG has always been a difficult field to work on, and certain advancements have been made in the extraction and prognostication of the signal. Some of the advancements are listed below that helped in extraction and analysis off the attributes of the signal.

Amid over 100 years of history of EEG, it has experienced huge advancement. The presence of electrical streams in the brain was found in the year 1875 by an English doctor basically a physician named Richard Caton. In the year 1924, Hans Berger, who was a German neurologist, to increase the electrical action of the brain that is measured on the human scalp utilized his common radio hardware to do so. He also declared that without opening the skull the frail electric currents that are produced in the mind can be recorded, and can be delineated graphically on a paper strip. The saw that the action changed according to the cerebrum( brain ), for example, in rest, state of anesthesia, when sufficient oxygen is not present and in certain kind of neural sicknesses i.e. in epilepsy. Berger established many uses in terms of EEG as advancement which are thus used in present time. Similarly he described the word electroencephalogram as the first to depict mind electric potentials in people. He gave an appropriate approach as he said that the cerebrum action changes in a reliable as well as a recognizable way the general status of the subject changes [10]. After some time in the year 1934 Matthews and Adrian came up with the publication of a paper confirming the idea of "human brain waves" and recognized "alpha rhythm" that is the usual oscillations were around 10 to 12 Hz [11].

## 2.2 Motivation

Presently, doctors as well as patients confront big issues related to medical testing as in accuracy issues and time delay issues which creates a lot of problems in further processing of the treatment. The testing is Now if we follow the objective of our project the above issues can be resolved in the following ways.

- Will be more effective due to increased accuracy.
- Less confusion and immediate results.
- Saves time of patients as well as doctors.
- Based on results further procedures can take place at a much faster pace.
- Cost effective as results will be concluded in a single accurate test.

## 2.3 Objectives

The objectives of the project that will improvise the testing method of EEG are:

- To analyze the EEG signal using Wavelets and to find out the optimum number of features to characterize the EEG signals.
- To detect and classify the EEG signals pertaining to epilepsy. To categorize the EEG signals and normalize the attributes using Neural Network Classifiers.

# CHAPTER 3

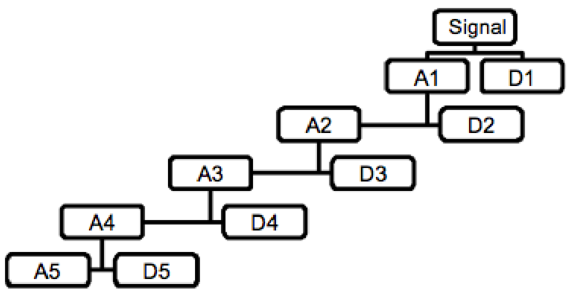
# PROPOSED METHODOLOGY

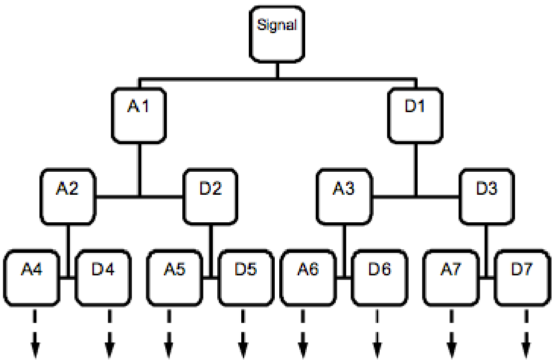
## 3.1 Diagnostic System and Design

A set of the source EEG signals is taken from the database selected. Inspection for signal distortions among basic evaluation of the EEG traces is called artefacts. In comparison to signal sequences not going through by any large contamination typically it is a sequence with higher amplitude. So artefacts and excessive noise will be eliminated from the signal. After the detachment of noise and artefacts, the signal would be categorized into following mentioned the frequencies:

δ (0.5-3 Hz) ϴ (3-8 Hz) α (8-12 Hz) β (12-38 Hz)γ (38-42 Hz)

For the final processing of the signal wavelet transform would be used. Once the wavelet theorem is applied, the attributes useful for the prediction of the seizure are selected. The principle point of information standardization is to enhance the levels of signals of intrigue, while lessening or dismissing undesirable signals in the recordings that are set apart by artifacts and noise. Finally, the attributes of all the signals are used for training the classifier and then classifying the signals for epilepsy using neural network.



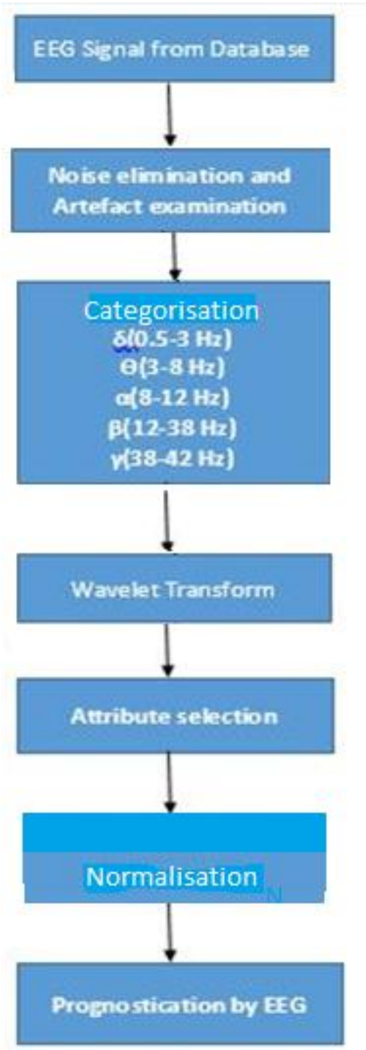



**Figure 3.1:** Flow chart of proposed methodology

## 3.2 Attributes

- **Mean**

A set of value corresponding to the center is known as mean. For every sub-band signal the mean is calculated.

$$m = \frac{x_1 + x_2 + x_3 + \ldots + x_n}{n}$$

- **Standard Deviation**

A simple measure corresponding to the variability of a data set is known as standard deviation. It is the root-mean-square deviation of its values from the mean.

$$\sigma = \sqrt{\frac{\sum (x - \mu)^2}{N}}$$

- **Skewness**

In a set of statistical data asymmetry from the normal distribution is basically skewness as data becomes more symmetrical as its value approaches zero [12].

$$Skewness = \frac{1}{n}\sum_{i=1}^{n}(\frac{x_i - \bar{x}}{SD(x)})^3$$

- **Kurtosis**

The peak of a real valued random variable or to be more precise degree of "peakedness" is Kurtosis. It is a statistical measure describing the distribution of observed data around the mean.

$$\text{Kurt} = \frac{n \sum_{i=1}^{n} (X_i - \bar{X})^4}{\left(\sum_{i=1}^{n} (X_i - \bar{X})^2\right)^2}$$

- **Energy**

  The signal energy content of a disease EEG signal is more as compared to normal EEG signal.

$$\boldsymbol{Energy} = \dot{\boldsymbol{\Sigma}}|\boldsymbol{x_j}|^{\mathbf{2}}$$

- **Entropy**

  When non-epileptic it is statistically null and for a sharp signal as the spike has a sensible deviation from zero. There are two types of entropy namely-
  Shanon Entropy- It is used in order to analyze patients with frontal lobe epilepsy by analyzing long term EEG signals.
  Spectral Entropy- Measures the contribution that is in proportion of each spectral component to the total spectral distribution.

$$Entropy = \mu \div \sigma$$

## 3.3 Matlab Toolbox

MATLAB (Matrix lab) is basically a multi-worldview numerical processing condition. It is an exclusive programming language which is created by Math Works. This MATLAB Toolbox allows many operations that can be performed like network controls, the basic plotting of functions and information, execution of all the calculations, making of UIs, and also the interfacing with programs which are written in languages that are altogether different, including Java C, C#, C++, Python and Fortran.

As MATLAB is usually expected to work for processing numerical values, a flexible toolbox utilizes the MuPAD which is the symbolic engine that provides access to various computing abilities. Simulink, which is an extra part, includes graphical multi-area recreation and a plan which is a model based for al the dynamic as well as frameworks that are implanted. Wavelet Toolbox™ gives capacities and applications for synthesizing and analyzing signals, pictures, and information that show general conduct punctuated with unexpected changes. The tool compartment incorporates calculations for continuous wavelet transform (CWT), wavelet coherence and scalogram. It likewise gives calculations and representations to discrete wavelet investigation, also including decimated, non-decimated, double tree, and wavelet packet transforms. Moreover, you can amplify the toolbox calculations with custom wavelets [13]. The tool stash allows one to analyze how the recurrence substance of signals changes after some time and uncovers time-fluctuating patterns most common in different signals. You can perform multiresolution examination to concentrate fine-scale or vast scale highlights, distinguish discontinuities, and identify change focuses or occasions that are not unmistakable in the crude information. You can likewise utilize Wavelet Toolbox to proficiently pack information while keeping up perceptual quality and to denoise signals and pictures while holding highlights that are frequently smoothed out by different methods.

# CHAPTER 4

# WAVELET TRANSFORM

A wavelet is a numerical capacity valuable in digital signal processing and picture compressing. The utilization of wavelets for these designs is a current advancement, in spite of the fact that the hypothesis is not new. It forms a kind of a wave which has a pattern of starting from zero, rising to a level, and then decreasing back to the original level that is zero. It can be compared to a “brief oscillation” very similar to that recorded by a heart screen or a seismograph. By and large, wavelets are purposely made or created in order to process signals. Wavelets can be joined by a strategy called convolution which utilizes a "switch, move, multiply and integrate" operation with bits of a signal that is known to concentrate data from a signal that is totally obscure.

Wavelets have an interesting property of recovering feeble signals from noise. This has helped a lot in medical applications like handling of magnetic-resonance and X-ray pictures. Such pictures can be "tidied up" without obscuring or jumbling the points of interest.

## 4.1 Wavelet Transform

The wavelet transform has a totally unique merit function more or less like the Fourier transform (or substantially more to the windowed Fourier transform). Now the basic contrast between the two is that in Fourier change deteriorates the signal into sines and cosines, i.e. Fourier space has functions restricted in it whereas wavelet change utilizes both the functions that are confined in the genuine (real) as well as Fourier space. Usually, the transformed wavelet can be communicated with the following condition:

$$F(a,b) = \int_{-\infty}^{\infty} f(x)\, \psi^*_{(a,b)}(x)\, \mathrm{d}x$$

In which the symbol * is the mind boggling or complex conjugate image and the factor or function ψ is some kind of a capacity that is present. Such a capacity can be used without any discretion such that it abides by certain given set of rules.

As it can be seen that a wavelet transform in actual is a vast arrangement of various transforms put altogether basically dependent upon all the merit work involved during or for its calculation. Similarly, there a lot many ways to sort or distinguish between different sorts of wavelet transform. Here only division is indicated based on wavelet orthogonality i.e. orthogonal wavelets for discrete wavelet change improvement and non-orthogonal wavelets for continuous wavelet transform advancement. These two changes have the accompanying properties:

1. In a discrete wavelet transform reverts back the information vector that is of an indistinguishable length which is similar to the info. Generally, all the info in such a vector revolves around zero value. So, this way it is broken down into same or lower number of the wavelet coefficient range which is almost similar to the quantity of flag information focuses. As we get no repetitive data here therefore such kind of a wavelet range is useful for signal preparing as well as compression.
2. The continuous wavelet transform on the other side returns back a cluster (an array) which is almost one measurement bigger than the provided information. A picture of the time and frequency domain is required for 1 dimensional. We can always see different signal frequencies when the signal is running and compare different signal spectra with its range. Here huge amount of repetition has taken place because non-orthogonal arrangement has been used and thus the information is highly correlated. Therefore this sees the outcomes in a much better way as compared to the other.

The major thought in a wavelet transform is that it should bring out the changes in the time expansion only whereas there should be no change seen in the shape. Such changes in time are required to relate to the frequency analysis. Now, based on the instability rule of handling the signal, As the required determination in time is more or much higher, lesser should be the determination for frequency.

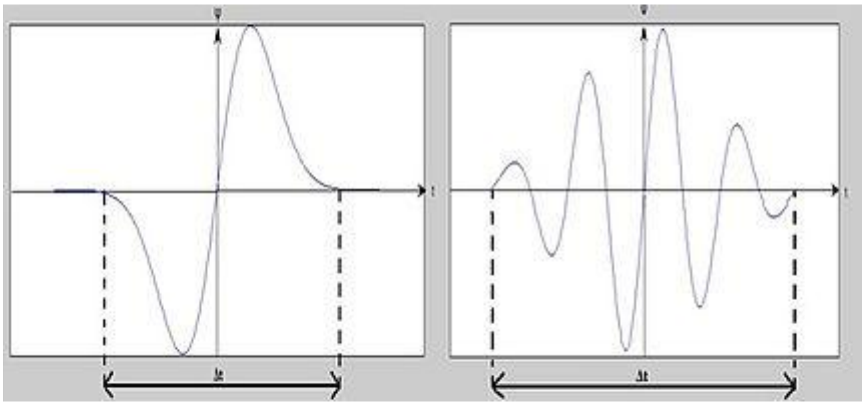


**Figure 4.1:** Wavelets for two different timing windows

At the point when Δt is extensive,

1. Bad time determination

2. Good recurrence determination

3. Low frequency, extensive scaling variable

At the point when Δt is small

1. Good time determination

2. Bad recurrence determination

3. High frequency, little scaling element

Additionally, the function Ψ (basis) can be viewed as a drive reaction or the impulse response of a framework with which the function x (t) has been sifted. The changed signal gives data about the time and the recurrence [14]. In this way, wavelet-change contains data like the short-time-Fourier-transformation, however with extra exceptional properties of the wavelets, which appear at the determination in time at higher examination frequencies of the basis function. The distinction in time determination at climbing frequencies for the Fourier change and the wavelet change is demonstrated as follows.

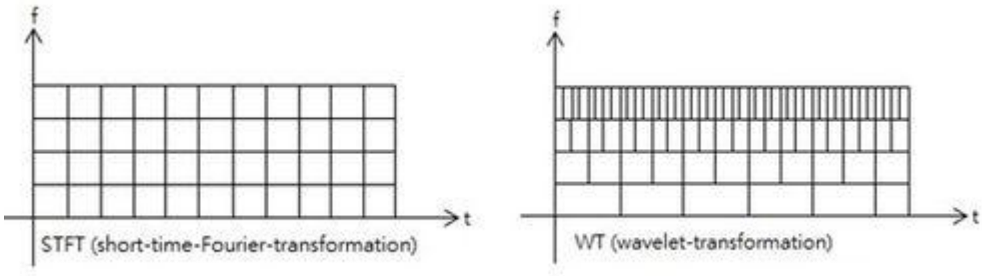



**Figure 4.2:** STFT and Wavelets packet division for signal frequencies

This demonstrates wavelet change is great in time determination of high frequencies, while for gradually fluctuating functions, the frequency determination is momentous.

## 4.2 Classification of Wavelets

### 4.2.1 Continuous wavelet transforms

In a continuous wavelet transforms, the signal which has a limited validity a given flag of limited vitality is expected to have a constant family of bands of frequency (or comparative subspaces of the Lp work space L2(R)).Such that, the signal will be represented on each frequency band of the form [f, 2f] for all positive frequencies f > 0. So, the first original signal can be remade by a reasonable combination over all the subsequent recurrence segments or components.

The recurrence groups or subspaces (sub-bands) are scaled adaptations of a subspace at scale 1. Such a subspace is mostly created by the movements or shifts of one producing function $\psi$ in L2(R), the mother wavelet. For the case of the scale one frequency band [1, 2] such a function is:

$$\psi(t) = 2\ \mathrm{sinc}(2t) - \mathrm{sinc}(t) = \frac{\sin(2\pi t) - \sin(\pi t)}{\pi t}$$

with the (standardized) sinc function.

The distinctive sorts of Continuous Real Valued Wavelet are:

- **Hermitian hat wavelet**

Another wavelet that is the Hermitian hat wavelet is a much complex wavelet as well as low-wavering. The parts in this wavelet that are real and nonexistent are characterized to be the second and first derivatives of a Gaussian:

$$\Psi(t) = \frac{2}{\sqrt{5}}\pi^{-\frac{1}{4}}(1 - t^2 + it)e^{-\frac{1}{2}t^2}.$$

The Fourier transform of such a wavelet is given by:

$$\hat{\Psi}(\omega) = \frac{2}{\sqrt{5}}\pi^{-\frac{1}{4}}\omega(1 + \omega)e^{-\frac{1}{2}\omega^2}.$$

The Hermitian hat wavelet thus satisfies the criterion of tolerability. The prefactor of resolution of the CWT is given by:

$$C_\Psi = \frac{16}{5}\sqrt{\pi}.$$

This wavelet was planned by Szu in 1997 for the numerical estimation of capacity derivatives within the sight of noise. The strategy used to separate these derivative values exploiting just the phase of the wavelet and, thus, the relative weights of the imaginary and real parts are immaterial.

- **Meyer wavelet**

The Meyer wavelet proposed by Yves Meyer is an orthogonal wavelet. It is vastly differentiable with unending backing and characterized in frequency area regarding function as:

$$\Psi(\omega) := \begin{cases} \frac{1}{\sqrt{2\pi}} \sin\left(\frac{\pi}{2}\nu\left(\frac{3|\omega|}{2\pi} - 1\right)\right) e^{j\omega/2} & \text{if } 2\pi/3 < |\omega| < 4\pi/3, \\ \frac{1}{\sqrt{2\pi}} \cos\left(\frac{\pi}{2}\nu\left(\frac{3|\omega|}{4\pi} - 1\right)\right) e^{j\omega/2} & \text{if } 4\pi/3 < |\omega| < 8\pi/3, \\ 0 & \text{otherwise,} \end{cases}$$

where:

$$\nu(x) := \begin{cases} 0 & \text{if } x < 0, \\ x & \text{if } 0 < x < 1, \\ 1 & \text{if } x > 1. \end{cases}$$

There are a wide range of routes for characterizing this auxiliary work, which yields variations of the Meyer wavelet. For example, another standard usage adopts

$$\nu(x) := \begin{cases} x^4(35 - 84x + 70x^2 - 20x^3) & \text{if } 0 < x < 1, \\ 0 & \text{otherwise.} \end{cases}$$

### 4.2.2 Discrete wavelet transforms

It is computationally difficult to investigate a signal utilizing all wavelet coefficients, so one may think about whether it is adequate to pick a discrete subset of the upper half plane to have the capacity to remake a signal from the comparing wavelet coefficients. One such framework is the relative system for some real parameters a > 1, b > 0. The relating discrete subset of the half plane comprises of the considerable number of points (am, namb) with m, n in **Z**. The resultant child wavelets are presently given as

$$\psi_{m,n}(t) = a^{-m/2}\psi(a^{-m}t - nb).$$

For the reconstruction of any signal *x* of finite energy a sufficient condition is given by the formula

$$x(t) = \sum_{m\in\mathbb{Z}} \sum_{n\in\mathbb{Z}} \langle x,\, \psi_{m,n}\rangle \cdot \psi_{m,n}(t)$$

Such that the functions form an orthonormal basis of $L^2$(**R**).

The types of Discrete wavelets are:

- **Haar Wavelet**

  The Haar wavelet according to science is a grouping of the rescaled capacities that is "square-shaped" which altogether forms a premise or a wavelet family. Wavelet investigation is somewhat like a Fourier examination in which it allows a function over a period to depict an orthonormal family. As the Haar wavelet is perceived to be the first wavelet that was known thus is broadly utilized to be an instructing case.

  When comes to the history of Haar wavelet, the haar arrangement was proposed in the year 1909 by a person named Alfred Haar. Haar utilized these capacities to give a case for the space of square-integrable capacities based on an orthonormal framework on the unit interval of [0, 1]. Till much later the investigation of wavelets as well as the expression of wavelet did not come into the picture. As an Haar wavelet is an exceptional instance of the Daubechies wavelet, thus it is otherwise called as Db1.

  The Haar wavelet is additionally the least complex possible wavelet. The specialized hindrance of the Haar wavelet is that it is not persistent, and in this way not differentiable. This property can, nonetheless, be favorable position for the examination of signs with sudden moves, for example, checking of hardware failure in machines

  The mother wavelet (of this Haar wavelet) capacity can be portrayed as under:

$$\psi(t) = \begin{cases} 1 & 0 \leq t < \frac{1}{2}, \\ -1 & \frac{1}{2} \leq t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

  And its scaling function is given as under:

$$\phi(t) = \begin{cases} 1 & 0 \leq t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

- **Coiflet Wavelet**

Coiflets are discrete wavelets outlined by Ingrid Daubechies, on the demand of Ronald Coifman, to have scaling capacities with moments that were vanishing. The wavelet is closely symmetric, their wavelet capacities have N/3 vanishing moments and scaling capacities (N/3)- 1, and has been utilized as a part of numerous applications utilizing Calderón-Zygmund Operators. Coiflet wavelet can be interpreted by:

$$B_k = (-1)^k C_{N-1-k}$$

where k is the coefficient index, B is a wavelet coefficient and C a scaling function coefficient. N is the wavelet index.

**Coiflet Coefficients**

Both the scaling capacity (low-pass channel) and the wavelet function (High-Pass Filter) must be standardized by a component 1/sqrt(2). The following are the coefficients for the scaling capacities for C6-30. The wavelet coefficients are inferred by turning around the request of the scaling capacity coefficients and afterward reversing the indication of every second one.

- **Daubechies wavelets**

The Daubechies wavelets, given by Ingrid Daubechies, are basically a group of orthogonal wavelets which have maximal number of vanishing moments and thus characterize a discrete wavelet transform. In such a wavelet class, there comes a scaling function (called the father wavelet) which further creates a multiresolution investigation which is orthogonal in nature [15].

If a signal f has an even number N of values, each value am of a1 = (a1,..., aN/2) is equal to a scalar product:

$$am = f \cdot V^1m$$

of ‘f’ with a 1-level scaling signal $V^1m$. Likewise, each value dm of d1 = (d1,..., dN/2) is equal to a scalar product:

$$dm = f \cdot W^1m$$

of ‘f’ with a 1-level wavelet $W^1$ m.

- **Legendre wavelets**

  In useful examination, wavelets compactly supported got from Legendre polynomials are named Legendre wavelets or spherical harmonic wavelets. Legendre capacities have boundless applications in which spherical coordinate framework is proper. Likewise with numerous wavelets there is no decent explanation for portraying these consonant spherical wavelets. The low-pass channel related to Legendre multiresolution analysis is a finite impulse response (FIR) filter.

  Wavelets related to FIR channels are normally favored in many applications. An additional engaging element is that the Legendre channels are linear phase FIR (i.e. multiresolution investigation related with linear phase filters). These wavelets have been executed in MATLAB (wavelet toolbox). In spite of the fact that being minimalistically upheld wavelet, are not orthogonal (but rather for N = 1).

## 4.3 Application of Wavelet

Wavelets have been utilized to compress pictures to a more noteworthy extent than is mostly possible with different techniques. Sometimes, a wavelet-compacted picture can be as little as around 25 percent the measure of a comparative quality picture utilizing the more recognizable JPEG technique. Along these lines, for instance, a photo that requires 200 KB and pauses for a moment to download in JPEG configuration may require just 50 KB and take 15 seconds to download in wavelet-compacted design.

Wavelet pressure works by examining a picture and changing over it into an arrangement of scientific expressions that can then be decoded by the receiver. A wavelet-packed picture record is regularly given a name suffix of "WIF." Either your program must support these documents or it will require a module program to peruse the documents. Wavelet compression is not yet generally utilized on the Web. The most well-known compacted picture positions remain the Graphics Interchange Format (GIF), utilized principally for drawings, and JPEG, utilized predominantly for photos.

As a numerical instrument, wavelets can be utilized to concentrate data from a wide range of sorts of information, including – however not constrained to – audio signals and pictures. Sets of wavelets are mostly expected to break down information completely [16]. An arrangement of "corresponding" wavelets will decay information without holes or cover so that the deterioration procedure is numerically reversible. In this manner, sets of correlative wavelets are valuable in wavelet based compression/decompression calculations where it is alluring to recoup the first data with negligible loss.

# CHAPTER 5

# NEURAL NETWORK

It is a model that prepares data in the same way as that in biological nervous systems, such as, the brain, which handles data. This network is made up of a highly interconnected network of processing components namely neurons in order to take special care of certain issues. As individuals learn by giving examples similarly this network learns when it is taught with the help of an example. Such type of networks is designed for classification as well as design acknowledgement and that through a learning process. Learning involves adjustments to the synaptic connections that are made and that exist between neurons. All the gained data is then stored in the inter neuron association strengths (weights). Amid the learning procedure the weights are changed with a specific end goal to demonstrate the specific learning assignment accurately. It can be visualized as a network of "neurons" organized in layers in Figure 5.1 where 'a' represents attributes, 'w' represents weights, 'x' and 'y' are inputs and output respectively.

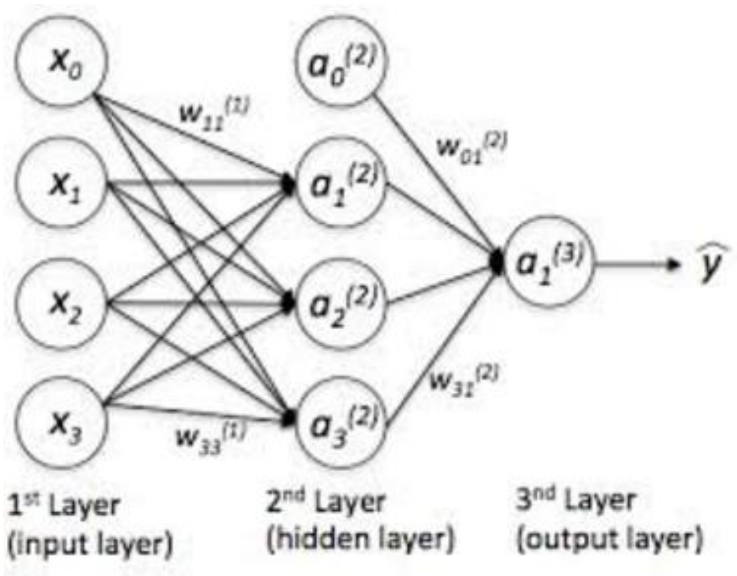



**Figure 5.1:** Neural Network

Neural networks, with their wonderful capacity to get significance from complex or loose information, can be utilized to concentrate designs and recognize patterns that are too complex to ever be seen by either people or other PC methods. Neural systems are made out of basic elements working in parallel. Generally neural networks are balanced, or trained, so that a specific input prompts a particular target yield. Similar situation is given as under in Figure 5.2

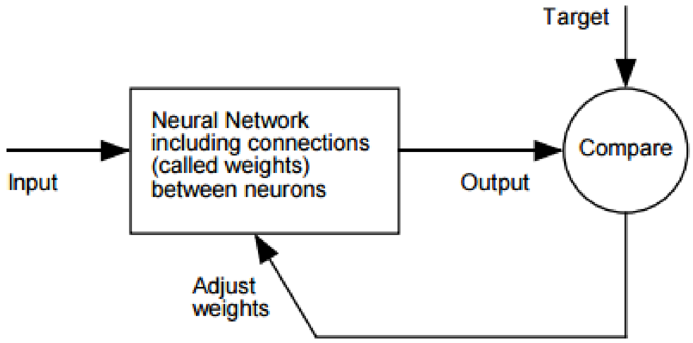



**Figure 5.2:** Block diagram of neural network

Neural systems have been prepared to perform complex capacities in different fields of use including design acknowledgment, distinguishing proof, grouping, speech, vision and control frameworks. Today neural systems can be prepared to take care of issues that are troublesome for conventional PCs or people. The field of neural systems has a background marked by approximately five decades however has discovered strong application just in the previous fifteen years, and the field is as yet growing quickly.

An Artificial Neuron Structure compared to a human neural network is given as under (Figure 5.3 and Figure 5.4), showing as to how an artificial network operates similar to that like a human brain [17].

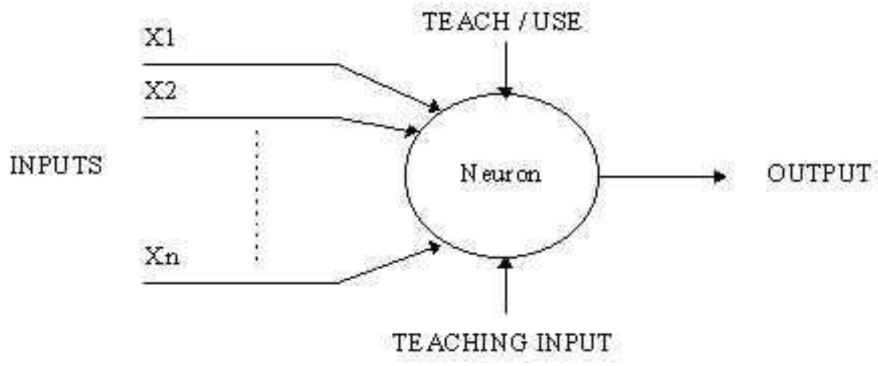



**Figure 5.3:** Artificial Neuron Structure

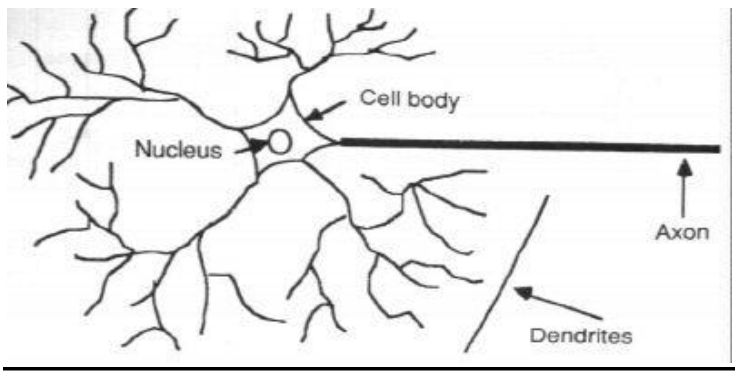



**Figure 5.4:** Human Neuron Structure

## 6.1 Learning Rules

It is basically a strategy that is utilized for changing the elements that are responsible for the outputs in a system that is the weights and the biases which is often referred to as a training algorithm. The learning rule is connected to prepare the system to perform some specific work. These rules are dropped down into two categories: Supervised Learning, and Unsupervised Learning [18].

***Supervised learning***, here the learning procedure is designed in a way that a proper system (the training set) is made so that any contribution made to the input gives a corresponding output or target. The outputs that are formed should be compared with the objectives as the system contains information sources connected to it. Thus the elements that determine the output that is the weights and the biases should be changed with the help of the learning rule so as to draw the system nearer to the desired output or objective. Also the rule of perceptron learning falls in the same class of supervised learning.

***Unsupervised learning***, in response to the sources, elements such as, biases and weights are altered. In such type of calculations there involves grouping operations. Thus classifying the information designs into classes that are only limited in number. In applications such as vector quantization this is quite valuable.

There are two ways in which a neural network operates:

1. Free Forward Neural Network
2. Feedback Neural Network

1. **Free Forward Neural Network,** In this (Figure 5.5) as the name suggests the information flow is in one direction only that is unidirectional [19]. This is like sending a piece of information from one unit to the other unit from which no information is returned. As it is there are no feedback loops present the network moves only in the forward direction. Such type are utilized in categorization of the pattern which has fixed amount of inputs as well as outputs.

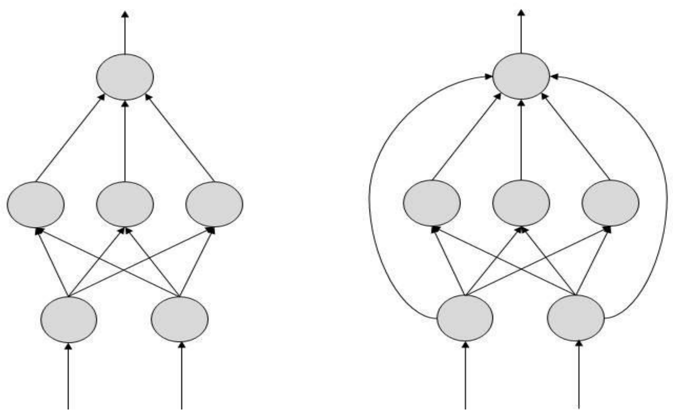


**Figure 5.5:** Free forward neural network

2. **Feedback Neural Network,** In this (Figure 5.6) as the name suggests the information flow is taking place in two directions. Here in this type of a network feedback loops are also allowed which are basically used in content addressable memories.

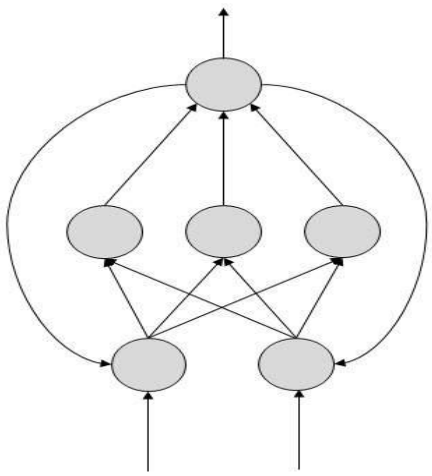
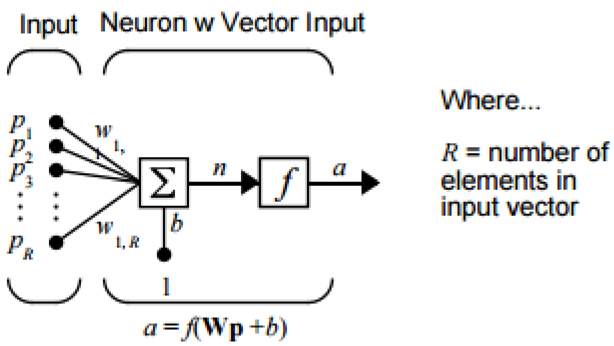


**Figure 5.6:** Feedback neural network

## 6.2 Operation behind Neural Networks:

A neuron with a single R-element input vector is depicted below. Here the individual element inputs $p_1, p_2, \dots p_R$ are multiplied by weights $w_{1,1}, w_{1,2}, \dots w_{1,R}$ and the values that are weighted are fed to the summing point. Their sum is simply Wp, the dot product of the (single row) matrix W and the vector p [20].



The neuron has a bias b, which is summed with the weighted inputs to form the net input n. This sum, n, is the argument of the transfer function f.

$$n = w_{1,1}p_1 + w_{1,2}p_2 + \ldots + w_{1,R}p_R + b$$

Now, according to the desired output the weights are adjusted and the whole function is then performed in MATLAB TOOLBOX.

# CHAPTER 6

# RESULT

In the experiments, the MATLAB Wavelet Toolbox was used to classify the wave into sub-waves delta, theta, alpha, beta and gamma. The data used in the experiments is labeled as inter-ictal (F), healthy (Z), and seizure(S). The inter-ictal data set has the same size as the healthy one.
Firstly, the attributes are calculated trough four different wavelets- haar, symlets, coiflets, and daubechies.

In this work we have used different wavelets – Haar Wavelet, Symlet Wavelet, Coiflet Wavelet and Daubechies Wavelets to divide a single EEG signal into 5 different signals – delta, theta, alpha, beta, and gamma in frequency domain.

**Here Following Variables are used:**

'F' - stands for Inter-ictal patient
'S' - stands for Seizure patient
'Z' - stands for Healthy patient

Figure 6.5, 6.6, 6.7 shows the results of a single patient (from each state i.e. healthy, inter-ictal and Ictal) of EEG using Symlet wavelet. Figure 6.6 shows the categorization of EEG signal of an ictal patient. In this the delta signal has high number of peaks which shows high order of randomness and instability of mind. The beta and gamma signals have very high frequency and rise and drops in the signal values.
Similarly, Figure 6.5 shows the categorization of EEG signal of a healthy patient. In this the delta signal has least number of peaks which shows low order of randomness and stability of mind. The beta and gamma signals have very high frequency and less rise and drop in the signal values.

Figure 6.7 shows the categorization of EEG signal of an inter-ictal patient. In this the delta signal has high number of peaks with respect to the healthy patient but low number of peaks with respect to ictal state patient which shows moderate order of randomness and less stability of mind. The beta and gamma signals have very high frequency and less rise and drop in the signal values compared to the ictal patient

Figure 6.8, 6.9, 6.10, 6.11 shows the graphs of the extracted features in comparison with all three states of mind (i.e. ictal, inter-ictal and healthy).

Hence we can observe that:

- Skewness and Kurtosis value is greatest in Inter-Ictal patient and least in Seizure patient.
- Energy value is greatest in Seizure patient and least in healthy individual.
- Entropy is positive in Seizure patient and negative in Healthy individual.

## 6.1 EEG signal outputs

- **USING HAAR WAVELET**

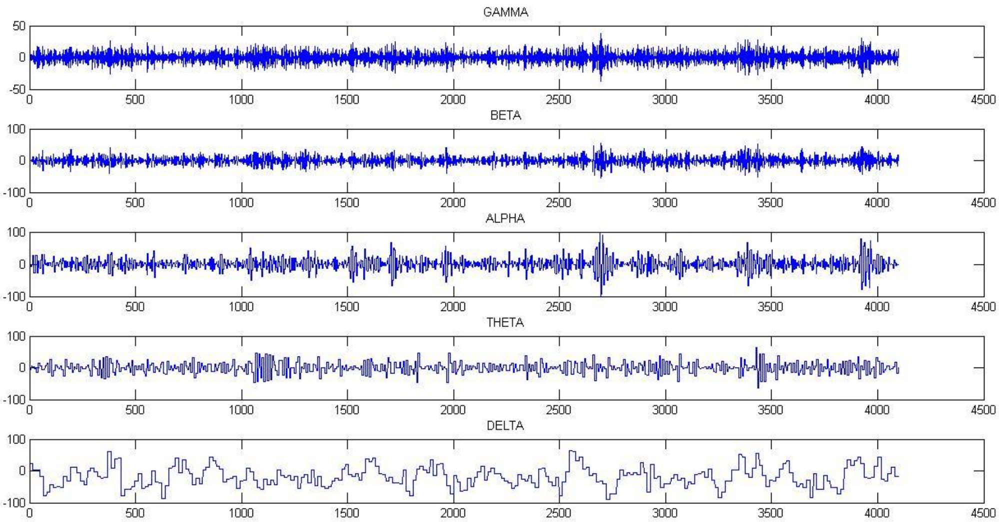
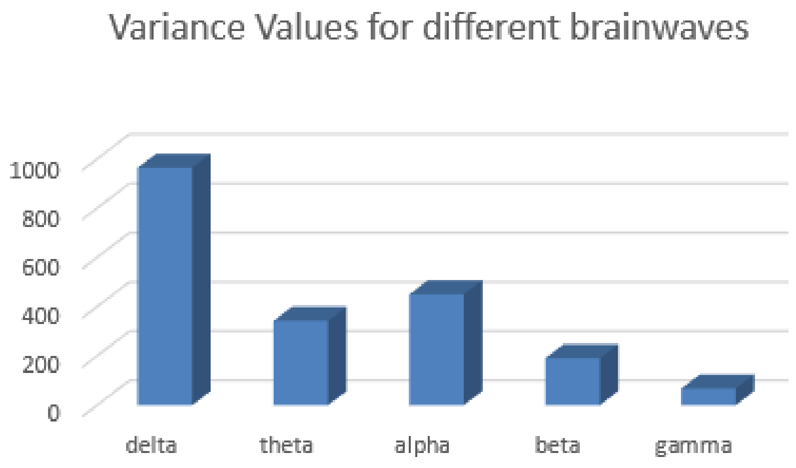
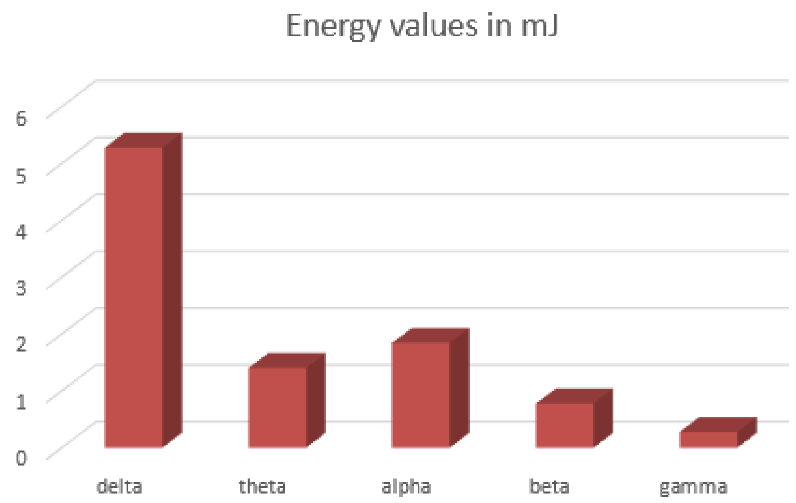



**Figure 6.1:** Waveform depicting result after using haar wavelet


Variance Values for different brainwaves
1000
800
600
400
200
0
delta
theta
alpha
beta
gamma


Energy values in mJ
6
5
4
3
2
1
0
delta
theta
alpha
beta
gamma

- **USING SYMLET WAVELET**

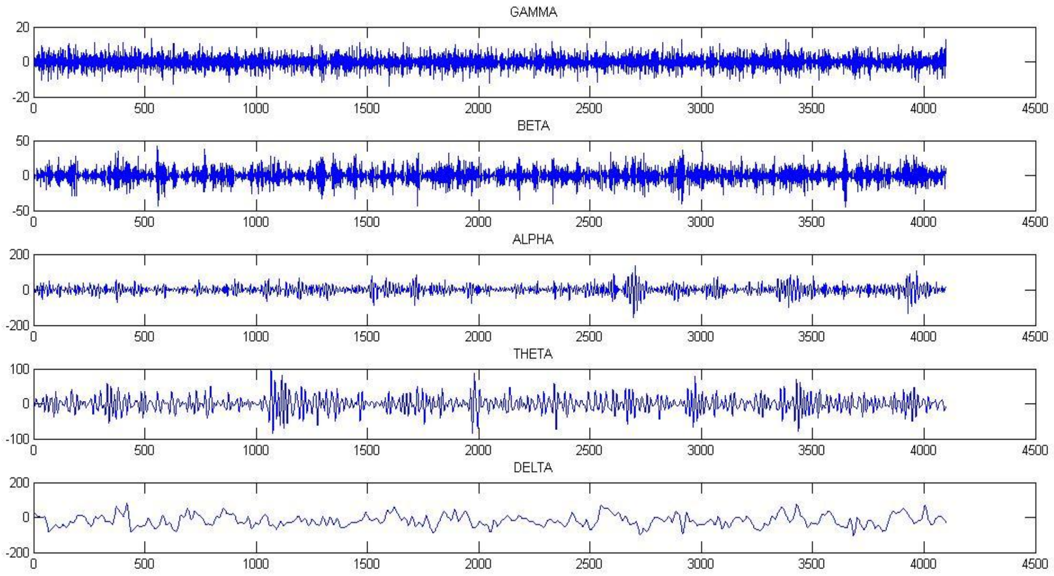
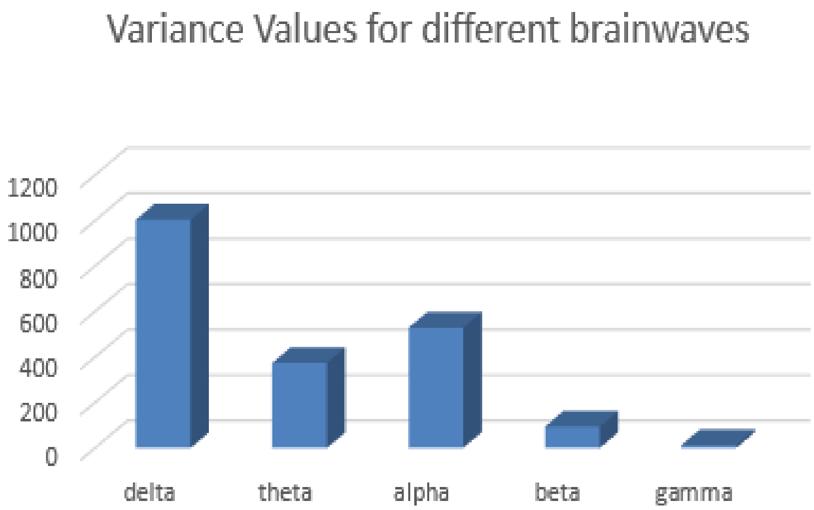
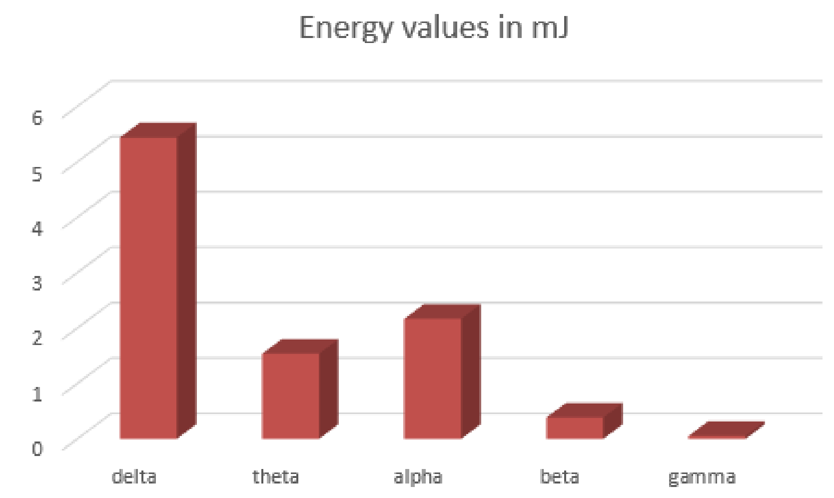



**Figure 6.2:** Waveform depicting result after using Symlet wavelet






- **USING DAUBECHIES WAVELET**

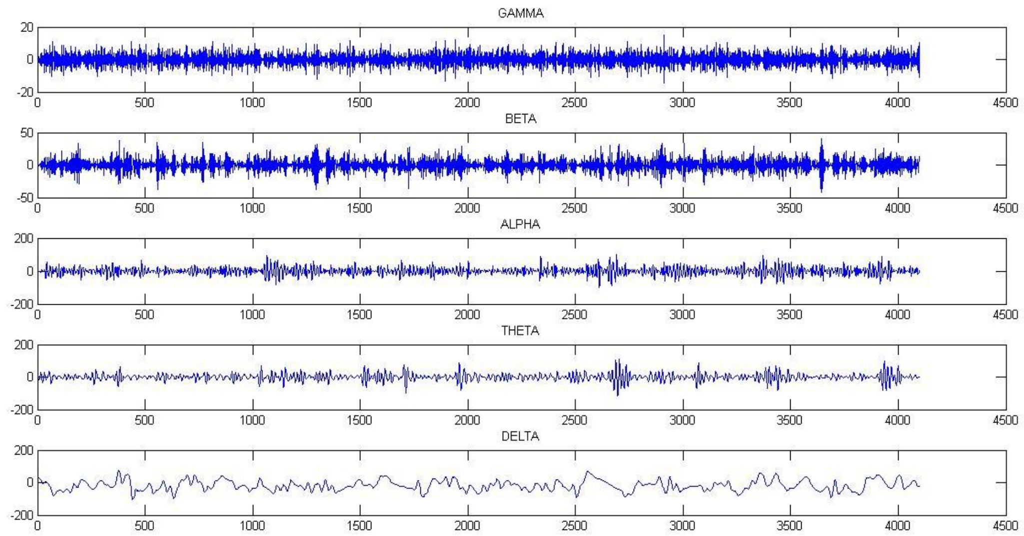
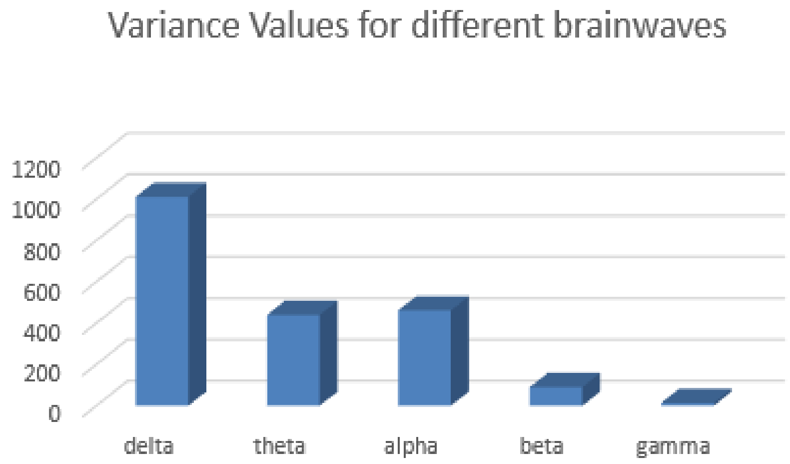
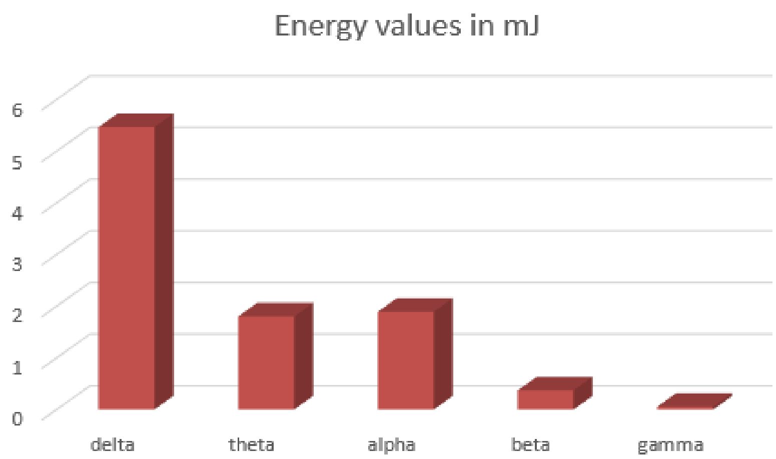



**Figure 6.3:** Waveform depicting result after using Daubechies wavelet


Variance Values for different brainwaves
1200
1000
800
600
400
200
0
delta
theta
alpha
beta
gamma


Energy values in mJ
6
5
4
3
2
1
0
delta
theta
alpha
beta
gamma

- **USING COIFLET WAVELET**

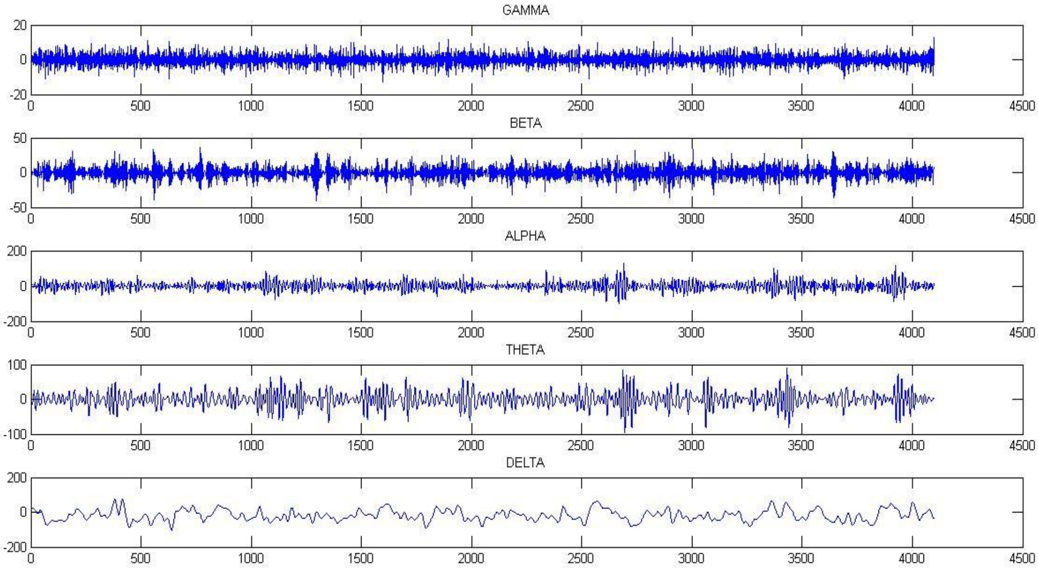
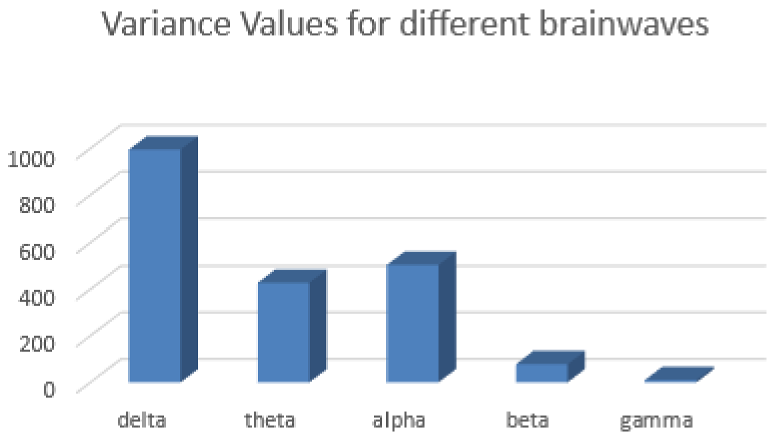
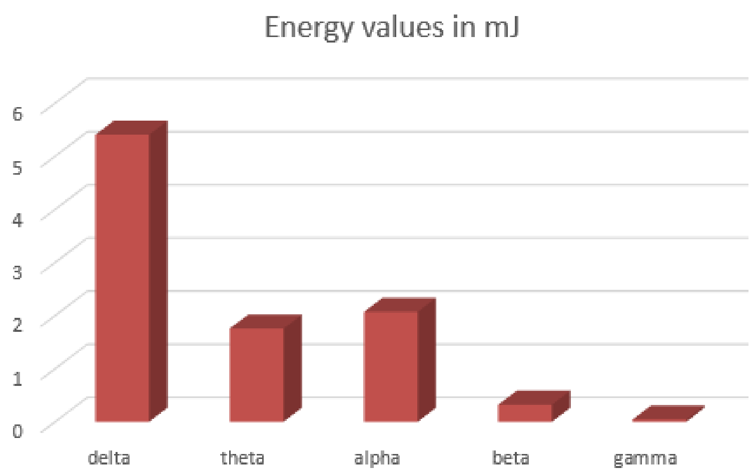



**Figure 6.4:** Waveform depicting result after using Coiflet wavelet






**COMPARISION BETWEEN INTER-ICTAL, SEIZURE AND HEALTHY PATIENT**

- **FOR A HEALTHY PERSON**

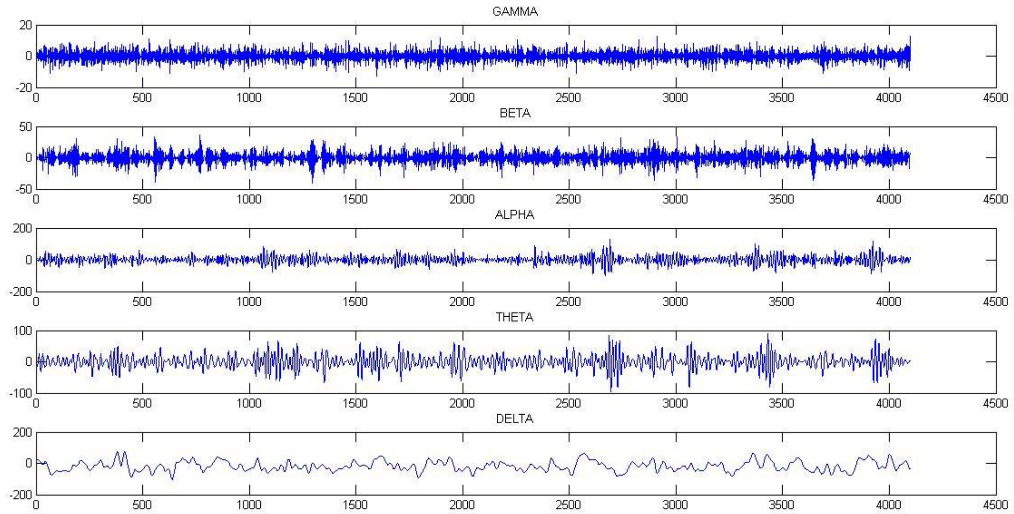



**Figure 6.5:** Waveform depicting result of a Healthy person

- **FOR AN INTER-ICTAL PATIENT**

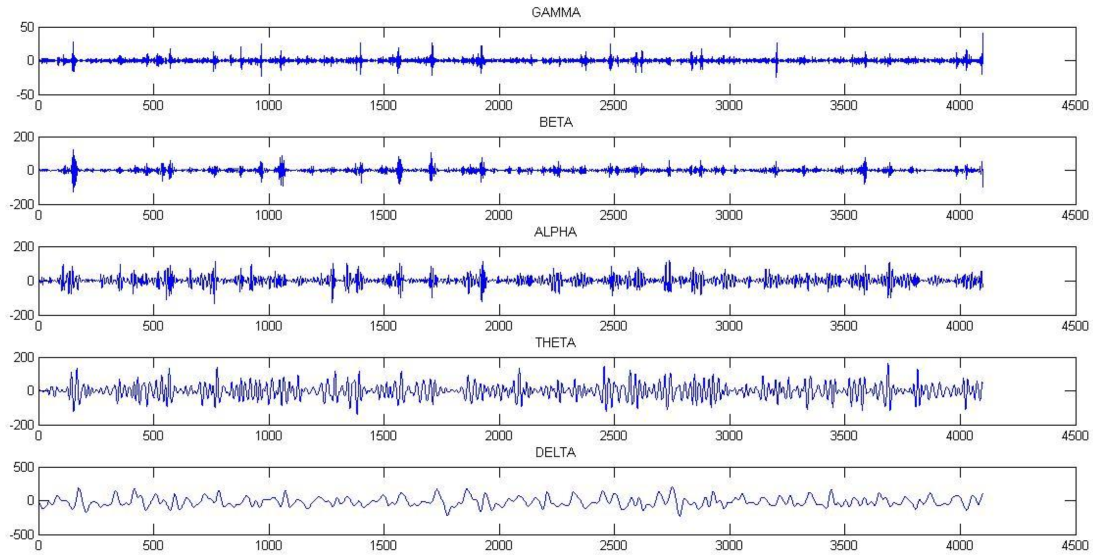



**Figure 6.6:** Waveform depicting result of an
Inter-Ictal person

- **FOR A SEIZURE PATIENT**

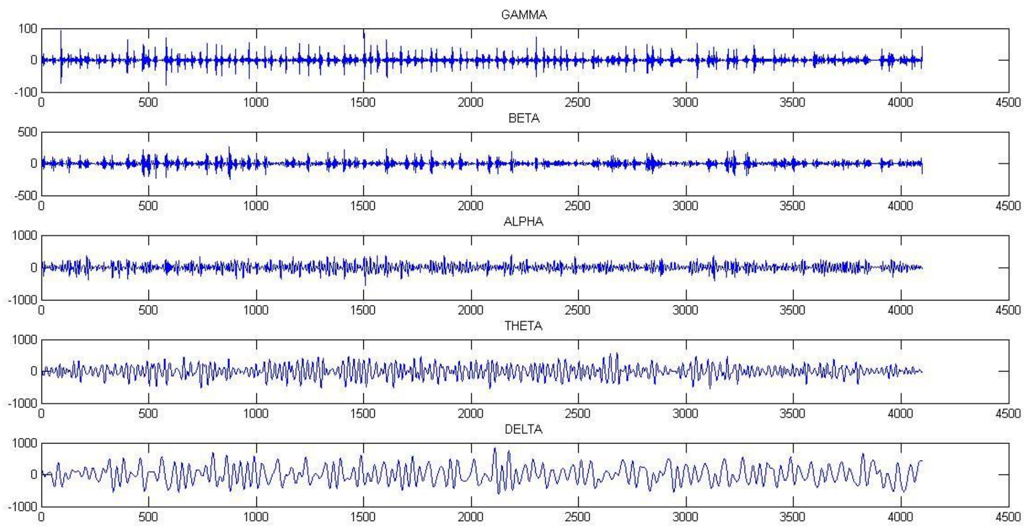



**Figure 6.7:** Waveform depicting result of a
Seizure patient

## 5.2 ATTRIBUTES

As per the attributes selected the following features are measured for a healthy, inter-ictal and an ictal person.

- **SKEWNESS**

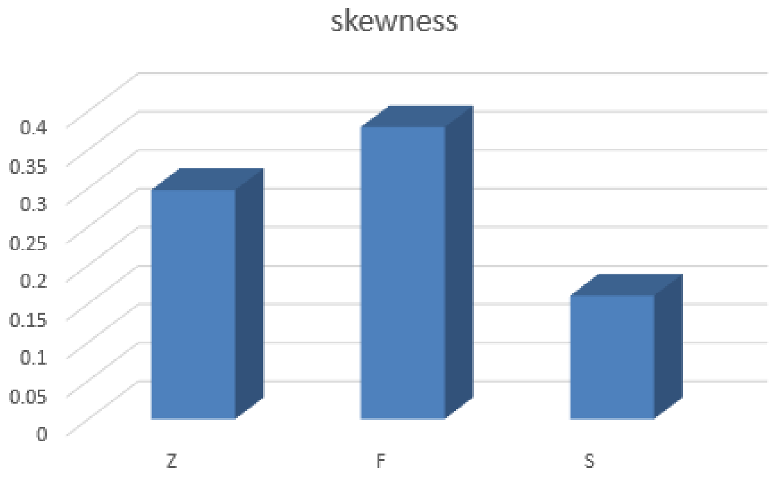



**Figure 6.8:** Skewness

- **KURTOSIS**

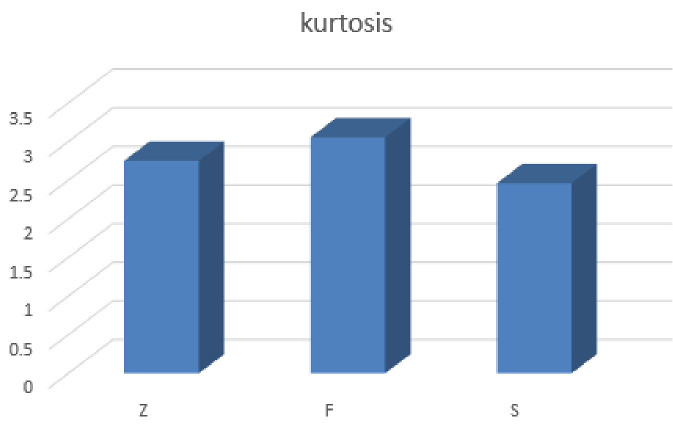



**Figure 6.9:** Kurtosis

- **ENERGY (SCALED TO- X $10^6$ )**

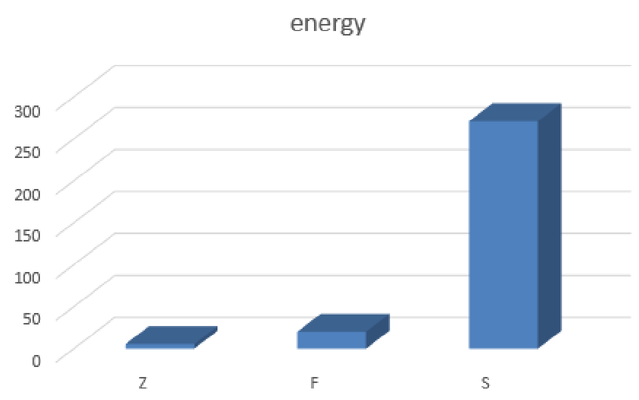



**Figure 6.10:** Energy

- **ENTROPY**

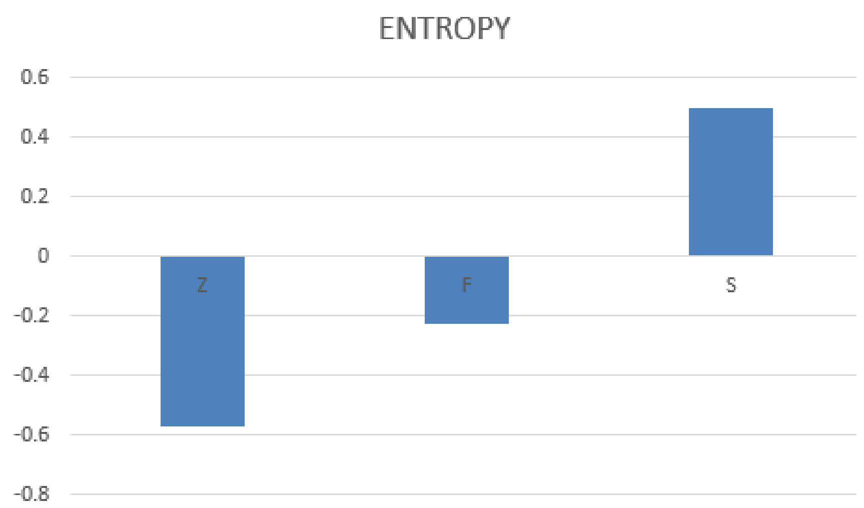



**Figure 6.11:** Entropy

## 6.3 NEURAL NETWORK RESULTS

The attributes (here Entropy) were used to establish the hidden layers of the neural network. Around 50 seizure and 50 healthy patient's attributes such as entropy was taken and transformed as the input for the neural network model after normalizing. The appropriate output and target was put to the neural network model. There were around 30 of each seizure and healthy patient's EEG signals used for training the neural network. Then there were around 10 of each seizure and healthy patient's EEG signals used for validation of the neural network. At last there were around 10 of each seizure and healthy patient's EEG signals used for testing the neural network.

Figure 6.12 shows the Confusion matrix for Training, validation, testing and all of the cases together. This shows that there was 71.2% of correct evaluation for the training samples, 80% correct evaluation for validation samples, 76% of correct evaluation of the test samples and 72.6% of correct evaluation for all the three cases considered together. Therefore, high efficiency can be deduced from this result. Figure 6.13 shows the validation performance of the neural network model. The best validation performance is 0.16932 at epoch 24, which is quite high. The lesser the validation mean squared error, the better is the neural network learning. The figure 6.14 shows the histogram of errors occurred during training, validation and testing time. The results show that there was very less error occurred during the operating time of neural network. The figure 6.15 shows the status of ROC at the end of the final execution of the network. The graph is around the straight line in all of the cases: Training, validation, testing and all taken together.

Hence, it was observed that the neural network for prognostication of EEG signals used so as to differentiate between the seizure and healthy patients was effectively tested and appropriate results were recorded.

## Entropy

- ## Confusion Matrix

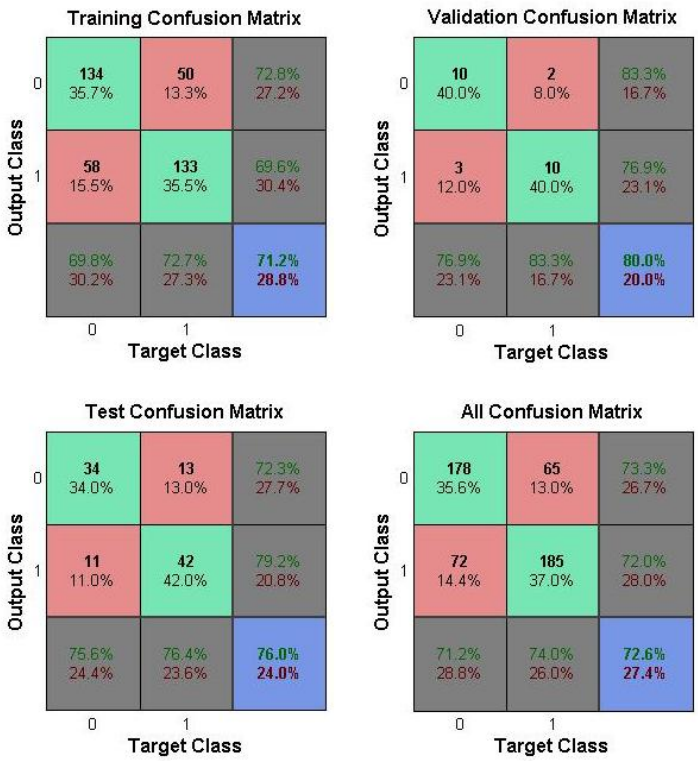



**Figure 6.12**: Training, validation, test and all Confusion matrix

- ## Validation Performance

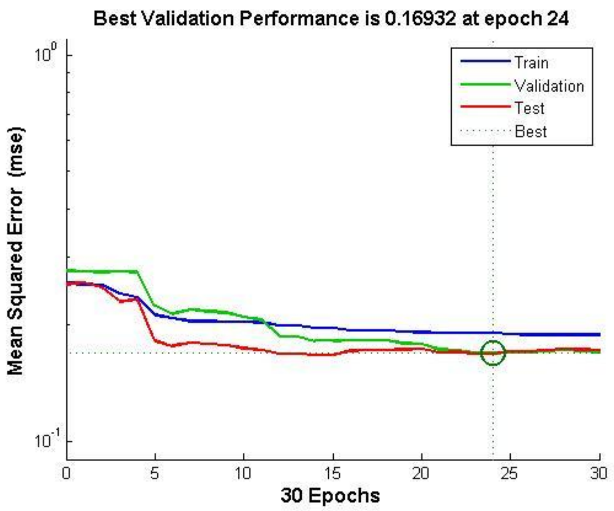



**Figure 6.13:** Best validation performance graph

- **Error Histogram:**

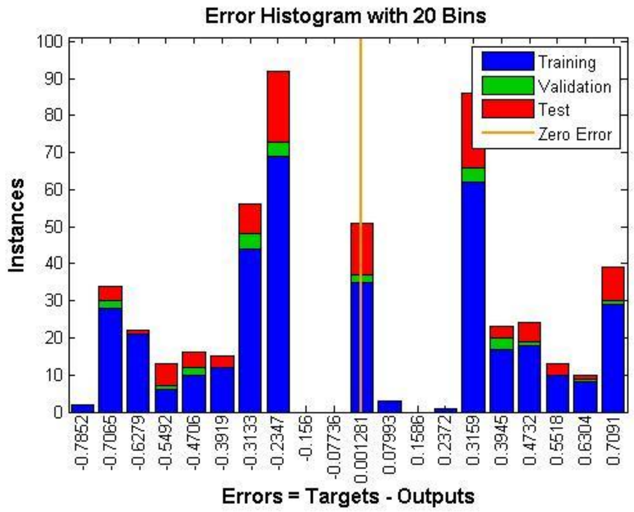



**Figure 6.14:** Error Histogram graph

- **ROC:**

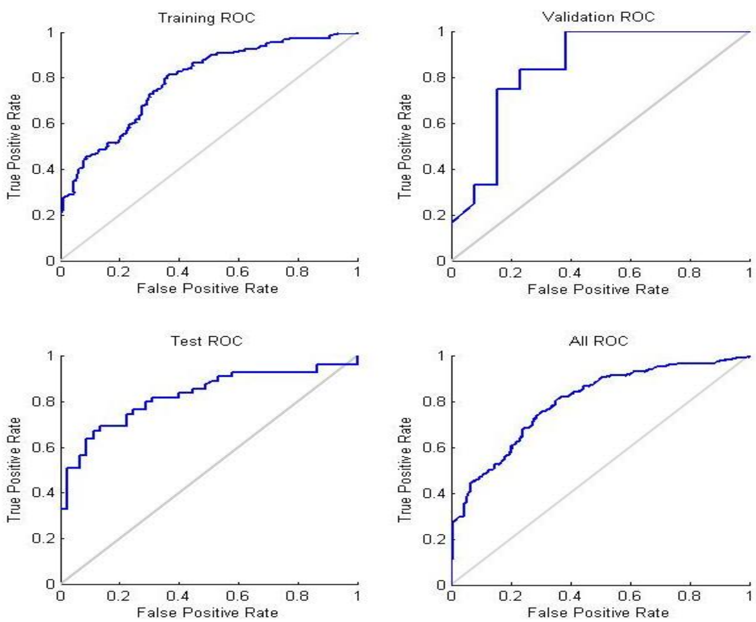



**Figure 6.15:** Training, validation, test and all ROC

# CONCLUSION

Electroencephalography belongs to the tools of electro biological imaging which are widely used in medical as well as for research purposes. As discussed earlier during neural excitations EEG measures changes in electric potentials which are caused due to number of electric dipoles. Thus this work results in design of a system for prognosis of epileptic seizure with less computational complexity as well as higher accuracy. We conclude from the demonstrated results that the proposed technique can be used for epileptic seizure detection efficiently. We can observe that: Skewness and Kurtosis value is greatest in Inter-Ictal patient and least in a Seizure patient. Energy value is greatest in Seizure patient and least in healthy individual. Entropy is positive in Seizure patient and negative in Healthy individual**.** Further various classifiers, here neural networks, give satisfactory results of classification of these signals using various attributes calculated from the wavelet coefficients.

# REFERENCES

[1] Meenakshi Sood, Sunil Vidya Bhooshan (2016.). A Novel Module Based Approach for Classifying Epileptic Seizures using EEG Signals. Proceedings of the International Conference on Industrial Informatics and Computer Systems, CIICS 2016 [American University of Sharjah, Sharjah, March 13-15, 2016], pp.1-5.

[2] Meenakshi Sood, Sunil Vidya Bhooshan (2015). Modular based dynamic analysis of EEG signals using non-linear feature. Proceedings of the International Conference on Parallel and Distributed Computing [Solan, India : 11-13 December 2014], pp.186-190.

[3] Guerrero-Mosquera, "Stochastic relevance analysis of epileptic EEG signals for channel selection and classification", Conference proceedings:. Annual International Conference of the IEEE Engineering in Medicine and Biology Society. Conference07/2013, pp.2104-2107, 2013.

[4] Meenakshi Sood, Sunil Vidya Bhooshan (2014). Automatic Processing of EEG signals for Seizure Detection using Soft Computing Techniques. Proceedings of the International Conference on Recent Advances and Innovations in Engineering, IEEE [Jaipur, India : 09-11 May, 2014].

[5] J.Gotman, “Automatic recognition of epileptic seizures in the EEG”, ElectroenClin Neuro., vol.54, pp.530–540, 1982.

[6] NabeelAhammad, T Fathima and Paul Joseph, "Detection of Epileptic Seizure Event and Onset Using EEG", BioMed Research International Volume vol.2014, Article ID 450573. 2014.

[7] J.C. Rajapakse, A. Cichocki and V.D. Sanchez, “Independent component analysis and beyond in brain imaging: EEG, MEG, fMRI, and PET”, In Proc. of IEEE Conf. on Neural Information Processing, vol.1, pp. 404-412, 2002

[8] H. Jokeit and M. Schacher, “Neuropsychological aspects of type of epilepsy and etiological factors in adults”, Epilepsy& Behavior, vol.5, pp.14–20, 2004.

[9] E. Hoffmann, “Brain Training against Stress: Theory, Methods and Results from an Outcome Study”, version 4.2., 2005.

[10] A.T Tzallas, M.G. Tsipouras and D.I. Fotiadis, "Automatic seizure detection based on time-frequency analysis and artificial neural networks", ComputIntellNeurosci. vol.7 (3): pp.1-13, 2007.

[11] Andrzejak, K. Lehnertz, F. Mormann, C.Rieke, P. David, and C. Elger, “Indications of nonlinear deterministic and finite dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state”, Phys. Rev. E., vol.4 (6), 2001

[12] V. Srinivasan, C. Eswaran, N. Sriraam, "Artificial neural network based epileptic detection using time-domain and frequency-domain features", J. Med. Syst, vol.29(6), pp.647–660. 2005.

[13] Meenakshi Sood, Sunil Vidya Bhooshan (2015). Hierarchical Computer Aided Diagnostic System for Seizure Classification. Proceedings of the Computing for Sustainable Global Development [2nd: New Delhi, India : 11-13 March 2015], pp.6.315-6.320.

[14] H. Ocak , "Automatic detection of epileptic seizures in EEG using discrete wavelet transform and approximate entropy", Exp. Syst. Appl., vol.36(2), pp.2027–2036, 2009.

[15] S. F. Liang, H.C Wang, W.L.Chang, “Combination of EEG Complexity and Spectral Analysis for Epilepsy Diagnosis and Seizure Detection", EURASIP Journal on Advances in Signal Processing, pp.853434, 2010.

[16] H. Adeli, Z Zhou N, Dadmehr, "Analysis of EEG records in an epileptic patient using wavelet transform", J.Neurosci. Meth. vol.123 (1), pp.69–87, 2003.

[17] A. Subasi, "Application of adaptive neuro-fuzzy inference system for epileptic seizure detection using wavelet feature extraction", Computers in Biology and Medicine, vol.37 (2), pp.227-244. 2007.

[18] V. Bajaj and R.B. Pachori, "Classification of Seizure and Non-seizure EEG signals using empirical mode decomposition", IEEE T INF TECHNOL B. vol.16 (6), pp.1135-1142, 2012.

[19] Teplan, “Fundamentals of EEG Measurement,” Measurement Science Review, vol.2, pp.1-11, 2002.

[20] J. D. Bronzino. 1995. Principles of Electroencephalography. In: J.D. Bronzino ed. The Biomedical Engeneering Handbook, pp. 201-212, CRC Press, Florida.

# PUBLICATION

Proceedings of the 11thINDIACom; INDIACom-2017
4rd 2016 International Conference on "Computing for Sustainable Global Development", 1st– 3rd March, 2017
BharatiVidyapeeth's Institute of Computer Applications and Management (BVICAM), New Delhi (INDIA)

# PROGNOSTICATION OF EPILEPSY BY EEG SIGNALS USING WAVELETS

**Antriksh Ojha[1], Iresh Rastogi[1], Aeshna Chawla[1], Meenakshi Sood[2]**
1 Student, Jaypee Univ. of Information Technology, Solan, Himachal Pradesh, India
2 Faculty, Jaypee Univ. of Information Technology, Solan, Himachal Pradesh, India

anterikshojha.sanjai@gmail.com, ireshrastogi@rediffmail.com, aesha51294@gmail.com, meenakshi.sood@juit.ac.in

***Abstract* - In this paper, a comprehensive quantitative analysis of electroencephalogram signals is carried out. As nature of EEG signals is non-stationary, the visual inspection of EEG data is time-consuming and inefficient. The visual inspection lacks quantitative analysis which can uncover hidden characters of the data. Wavelet provide a solution and provides functions for analyzing and synthesizing signals, images, and data that exhibit regular behavior punctuated with abrupt changes. Attributes from the available database are extracted and analysis of signal with different wavelets is processed to detect and predict the type of disorders. This article proposes a method for reliable detection of epilepsy by using different wavelets as Haar wavelet, Coiflet wavelet, DB and symlet to the database signals and on the basis of which we are able to prognosticate. Db wavelet provides the optimum results and best serves our objective.**

***Keywords*** – Electroencephalogram (EEG); Prognostication; Wavelet transform; Attributes; Skew; Kurtosis.

## I. INTRODUCTION

Electroencephalogram (EEG) is an unique and a valuable measure that provides information about the electrical activity of human brain. These signals play an important role for examining and diagnosing of neurological disorders, as epilepsy, Alzheimer, sleep problems and so on [1]. The primeval methods of analyzing EEG signals are based on the linear mathematics, though linearity is not appropriate for investigation of chaotic and complex seizures. In real time devices such as central nervous system, social behavior, chemical reaction, which are complicated and extremely input-sensitive behavior that cannot be analyzed linearly.

As EEG is a non-linear and a non-stationary signal; it is better to use frequency – time domain methods as discrete wavelet transform analysis to display different behavior of the EEG. These signals can be easily described in the time and frequency domain and have excellent time resolution and can be acquired non- invasively, which makes this technique more frequently used [2]. In the early days of digital processing, the most commonly used transform for signal representation was Fourier transform. However, bio-signals, characterized by a non-stationary time behavior would not produce the finest result if processed with Fourier transform. In this work, wavelet theorem has been used for analysis, diagnosis and processing of bio-signals for extracting features, firmness and de-noising purposes. Numerous wavelet families exist for signal characterization and selection of suitable wavelet is an open research issue[3]. A range of techniques for signal processing have already been proposed for characterization of non-stationary and non-linear signals like EEG [4]. Because of their very complex nature, there seems a necessity to investigate their joint time-frequency localization for more discriminatory features. A number of transformation methods such as Wavelet Packet transform (WPT), Wigner Valley (WV) decomposition, Wavelet Transform (WT), etc, are available for the representation of a signal in time-frequency domain [5].

The techniques used for the detection of seizures are be divided into domain based five groups: time-frequency domain, time domain, frequency domain, soft computing domain and nonlinear based methods [7]. In this paper time-frequency domain techniques are used to analyze the signals using wavelet transform. This paper reviews epilepsy detection by the techniques used for EEG signal processing, from analysis of EEG data acquisition leading to classification methods of EEG signal. The technique employed in this paper involves- finding out the optimal wavelet to analyze the EEG signals. Further, Signals are statistically analyzed by calculating first, second and higher order statistical parameters. Section II presents the materials & methods employed for this research work. Section III gives the details of the proposed methodology adopted in this paper. Results are shown in section IV and the final conclusions are drawn.

## II. MATERIALS AND METHODS

### 2. 1 *Acquisition of Signals*

Encephalographic signals are acquired by a particular system using recording device comprising electrodes, amplifiers with filters, A/D converter. A standard International system is adopted for acquisition known as 10-20 electrode placement system for the designations of electrodes and physical placement on the scalp. The head is divided into small distances proportional to the prominent skull landmarks to give proper coverage of all regions of the brain [6]. Electrode positioning are named as : F (frontal), C (central), T (temporal), P (posterior), and O (occipital) as shown in figure 1.

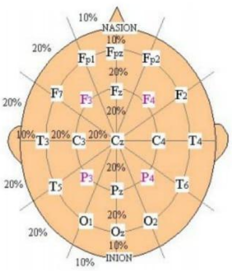



Fig1. Labelled 10-20 system of electrode placement

Each scalp electrode is positioned near certain brain centres, and each electrode position represents a lobe and number identifies hemisphere location. ‘C’ means central, ‘F’ means frontal, ‘P’ means parietal and T’ means temporal lobe of brain. The signal acquired by the electrodes from the head surface is in microvolt range which is amplified by the amplifiers to bring them in Volts range that can be further digitized accurately. Thus the computer aided system can be to store and display obtained data and can be further processed.

### *2.2 Database Selection*

The EEG database used in this study was provided by the University of Bonn [8]. This gathering contains EEG data coming from three different events, to be exact, healthy subjects, seizure-free intervals that is the inter-ictal states and during a seizure, that is ictal states. The perfect database constitutes three classes such as S, Z and F, each having 100 single channel EEG signals. The various human activities used for measuring the brain activity were Eye open (Z), Eye close (O), during ictal state (F), Seizure (S).

### *2.3 Attributes*

In this work, statistical parameters such as energy, standard deviation and entropy [9] were calculated for the different categories of signals at each decomposition level. The various attributes used are Energy, Standard Deviation, Mean, Kurtosis, Skewness SNR and Entropy. The attributes of all the signals are calculated and tabulated to be used for classification.

## III. METHODOLOGY ADOPTED

While recording EEG signal it gets contaminated by noise known as Artifacts which are caused by various factors, like EOG (electro-oculogram), EMG (electromyogram) and line interference. To extract the accurate information from EEG signal, it must be noise free and without any Artifacts[11]. After preprocessing of the signals, wavelets are used which divide data into various sub-components of frequency, and then each sub-component is analyzed with a particular resolution.

### *3.1 Wavelet transforms*

EEG being a non –linear, non-stationary signal, using wavelet transform for the signal analysis is preferred over other transforms. Wavelet transformation is divided broadly into two major categories: Discrete wavelet transform and Continuous wavelet transform. The Continuous wavelet transform similar to the Fourier transform and is normally used for feature detection and analyzing signals, whereas the latter is mostly used for compression and reconstruction of data. The frequency bands or sub-bands(subspaces) are scaled versions of a subspace[10]. This cause shifts in one of the generating function ψ in L2(R) i.e. the mother wavelet generates this subspace in all situations The frequency band [1/a, 2/a] of scale a is generated by the functions basically called child wavelets.

$$\psi_{a,b}(t)=\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)$$

where ***a*** is the positive defining of the scale and *b* defining the shift is any real number. The pair (*a*, *b*) defines a point in the right half-plane $\mathbf{R}_{+} \times \mathbf{R}$.

$$x_a(t)=\int_R WT_\psi\{x\}(a,b)\cdot\psi_{a,b}(t)\,db$$

The coefficients are given as*:*

$$WT_\psi\{x\}(a,b)=\langle x,\psi_{a,b}\rangle=\int_R x(t)\,\psi_{a,b}(t)\,dt$$

By using all wavelets coefficients, it is not possible to analyse computationally, thus a discrete subset is sufficiently picked to reconstruct a signal of the upper half-plane from the corresponding wavelet coefficients, thus resulting in use of discrete wavelet transform[14]. Therefore, the child wavelets are**:**

$$\psi_{m,n}(t) = a^{-m/2}\psi\left(a^{-m}t - nb\right)$$

For finite energy a sufficient condition for the reconstruction of any signal *x* is given as :

$$x(t) = \sum_{m\in Z}\sum_{n\in Z}\langle x, \psi_{m,n}\rangle \cdot \psi_{m,n}(t)$$

where,

$$\{\psi_{m,n} : m,n \in Z\}$$

Some of the wavelets used in this research work are briefed in the following section :

**Haar wavelet** – Haar wavelet is a sequence of functions that form a wavelet family of rescaled "square-shaped" thus considered to be the simplest wavelet among all.

The mother wavelet function $\psi(t)$ for haar wavelet is :

$$\psi(t) = \begin{cases} 1\,0 \le t < 1/2 \\ -1\,\frac{1}{2} \le t < 1 \\ 0\ otherwise \end{cases}$$

The scaling function is :

$$\phi(t) = \begin{cases} 1\,0 \le t < 1 \\ 0\ otherwise \end{cases}$$

**Daubechies wavelet-** This wavelet, is a family of orthogonal wavelets which defines a discrete wavelet transform and is classified by a maximum no. of disappearing moments[13]. So if there are even number N of values for a signal f, then each value am of a1 = ($a_1$,..., $a_{N/2}$) is equal to a scalar product:

$$a_m = f \cdot V^1_m$$

of f with a 1-level scaling signal $V^1$m. Similarly, each of the value $d_m$ of d1 = ($d_1$,..., $d_{N/2}$) is equal to a scalar product:

$$d_m = f \cdot W^1_m$$

of f with a 1-level wavelet $W^1_m$.

**Coiflet Wavelet-** These are a type of discrete wavelets that contains some scaling functions with disappearing moments[12]. Hence the two functions - the wavelet & scaling function must be normalized by a factor 1/sqrt(2). Mathematically, Coiflet wavelet can be represented as:

$$B_k = (-1)^k C_{N-1-k}$$

here N - wavelet index, k - coefficient index , B – wavelet coefficient and C – coefficient of scaling function.

### *3.2 Design flow*

The signals are taken from the database available online. Inspection for signal distortions among basic evaluation of the EEG traces is called artefacts. In comparison to signal sequences not going through by any large contamination typically it is a sequence with higher amplitude. So artefacts and excessive noise will be eliminated from the signal. After the detachment of noise and artefacts, the signal would be categorized into following mentioned the frequencies: δ (0.5-3 Hz) ϴ(3-8 Hz) α(8-12 Hz) β(12-38 Hz) γ(38-42 Hz).

For the final processing of the signal, various wavelets transform are used. Once the signal is passed through the wavelets, the attributes used for the analysis of the EEG signals are selected.
For all the 300 signals of ictal, normal and inter-ictal, attributes from all the coefficients are calculated and normalized in the max-min range. The main aim of data normalization is to improve the levels of signals of interest, while attenuating or rejecting unwanted signals. Finally the attributes of all the signals are used for training the classifier and then classifying the signals for epilepsy using SVM classifier.

## IV. RESULTS AND DISCUSSION

The data taken from Bonn University comprises EEG signals for three types of patients – Ictal, Inter-ictal and healthy man, with each categories comprising of a dataset of 100 patients. In this work we have used different wavelets – Haar Wavelet, Symlet Wavelet, Coiflet Wavelet and Daubechies Wavelets to divide a single EEG signal into 5 different signals – delta, theta, alpha, beta, and gamma in frequency domain .
Figure 2 shows the Extracted features of Ictal and healthy patients respectively. These features are extracted using coiflet

wavelet. Features includes mean, standard deviation, variance, skewness, kurtosis, energy which is scaled to x$10^6$, power, maximum/minimum value, and entropy.

Figure 3 shows the results of a single patient (from each state i.e. Ictal, inter-ictal and healthy) of EEG using Symlet wavelet. Figure 3 (i) shows the categorization of EEG signal of an ictal patient. In this the delta signal has high number of peaks which shows high order of randomness and instability of mind. The beta and gamma signals have very high frequency and rise and drops in the signal values.

Similarly , Figure 3 (ii) shows the categorization of EEG signal of a healthy patient. In this the delta signal has least number of peaks which shows low order of randomness and stability of mind. The beta and gamma signals have very high frequency and less rise and drops in the signal values.

Figure 3 (iii) shows the categorization of EEG signal of an inter-ictal patient. In this the delta signal has high number of peaks with respect to the healthy patient but low number of peaks with respect to ictal state patient which shows moderate order of randomness and less stability of mind. The beta and gamma signals have very high frequency and less rise and drops in the signal values compared to the ictal patient

Figure 4 shows the graphs of the extracted features in comparison with all three states of mind (i.e. ictal, inter-ictal and healthy). The observations noted here are- Skewness and Kurtosis value is greatest in Inter-Ictal patient and least in Seizure patient. Energy value is greatest in Seizure patient and least in healthy individual. Entropy is positive in Seizure patient and negative in Healthy individual.

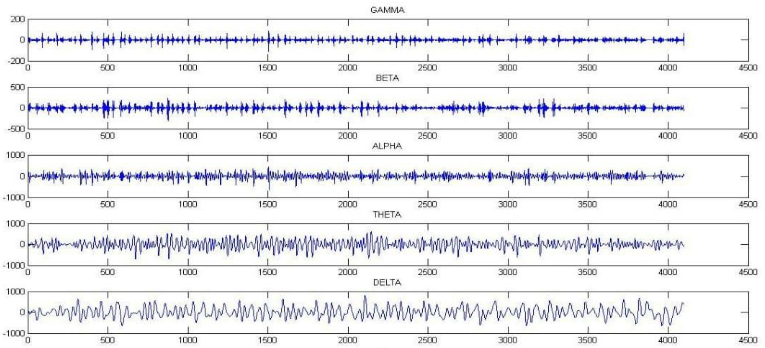
| | Ictal | | | | |
|---|---|---|---|---|---|
| **Parameters** | DELTA | THETA | ALPHA | BETA | GAMMA |
| | | | | | |
| Mean | 12.84092 | -0.02618 | 0.067574 | -0.01545 | 0.0035 |
| Standard Deviation | 256.8643 | 177.181 | 106.4368 | 41.23028 | 10.42 |
| Variance | 65979.29 | 31393.11 | 11328.79 | 1699.936 | 108.7 |
| Skewness | 0.160399 | -0.10393 | -0.07169 | 0.034158 | 0.3907 |
| Kurtosis | 2.46269 | 3.027537 | 3.81717 | 7.686291 | 14.190 |
| Energy (scaled to x10^6) | 270.9267 | 128.5862 | 46.40274 | 6.96294 | 0.4452 |
| Power | 66128.08 | 31385.45 | 11326.03 | 1699.522 | 108.68 |
| Max value | 839.297 | 572.8943 | 377.6055 | 254.2637 | 92.865 |
| Min value | -614.652 | -564.015 | -551.005 | -248.357 | -76.83 |
| Entropy | 0.049991 | -0.00015 | 0.000635 | -0.00037 | 0.0003 |

(a)

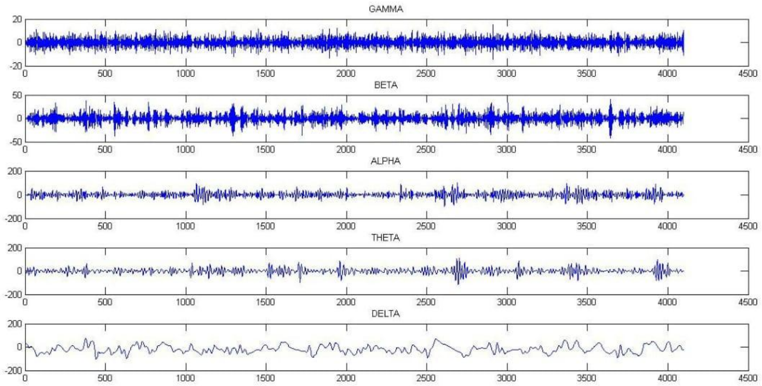
| | Healthy | | | | |
|---|---|---|---|---|---|
| **Parameters** | DELTA | THETA | ALPHA | BETA | GAMMA |
| | | | | | |
| Mean | -17.9943 | -0.00632 | 0.000507 | -0.0004 | 0.001287 |
| Standard Deviation | 31.5458 | 20.69438 | 22.47593 | 8.848159 | 3.207651 |
| Variance | 995.1376 | 428.2573 | 505.1676 | 78.28992 | 10.28902 |
| Skewness | 0.297508 | -0.04749 | 0.152259 | -0.04787 | 0.011297 |
| Kurtosis | 2.752754 | 4.473829 | 4.915403 | 3.804421 | 3.36615 |
| Energy (scaled to x10^6) | 5.402677 | 1.754142 | 2.069166 | 0.320676 | 0.042144 |
| Power | 1318.691 | 428.1528 | 505.0443 | 78.27081 | 10.28651 |
| Max value | 73.40109 | 89.37174 | 131.3493 | 36.44718 | 12.88376 |
| Min value | -102.51 | -95.0303 | -98.5605 | -40.3406 | -12.8102 |
| Entropy | -0.57042 | -0.00031 | 2.26E-05 | -4.5E-05 | 0.000401 |

(b)

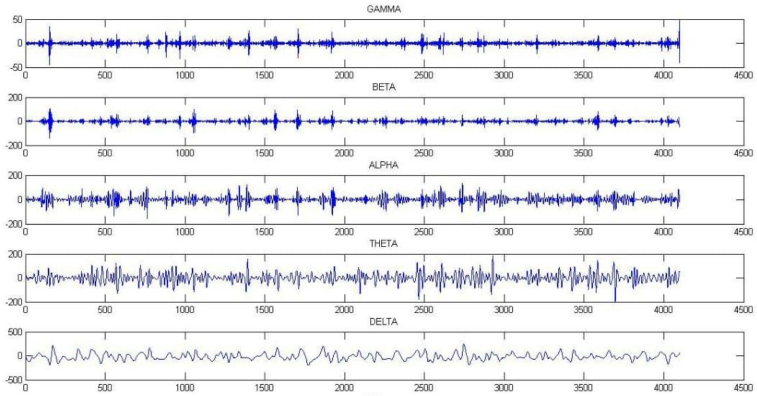
**Figure 2:** Extracted Features using coiflet wavelet for (a) ictal state patient and (b) healthy state patient.




(i)

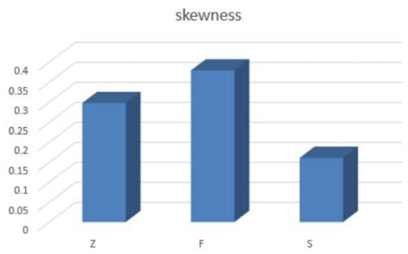



(ii)

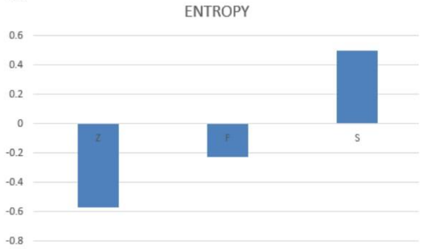



(iii)

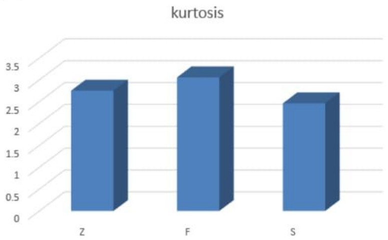
**Figure 3:** Extracted wavelet coefficients of (i) ictal state (ii) normal state and (iii) inter-ictal state



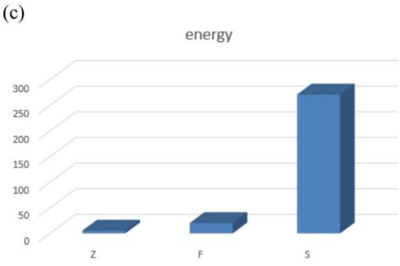

(a)




(b)




(c)




(d)

**Figure 4:** Extracted features of ictal state –S, normal state-Z and inter-ictal state-F. (a) Skewness, (b) Kurtosis, (c) Energy (scaled to $10^6$) and (d) Entropy.

## CONCLUSION

The work performed results in a designed system of prognostication of the epileptic seizure from EEG signals with high accuracy and less computational complexity. Hence we concluded from the results demonstrated, that this technique can be used for efficient and precise epileptic seizure detection. We can observe that: Skewness and Kurtosis value is greatest in Inter-Ictal patient and least in Seizure patient. Energy value is greatest in Seizure patient and least in healthy individual. Entropy is positive in Seizure patient and negative in Healthy individual. Further, various classifiers give satisfactory results of classification of these signals using various attributes calculated from the wavelet coefficients.

## REFRENCES

[1] J.Gotman, “Automatic recognition of epileptic seizures in the EEG”, *Electroen Clin Neuro.,* vol.54, pp.530–540, 1982.

[2] Meenakshi Sood, Sunil V. Bhooshan, “Parameter-Selective Based Cad System For Epileptic Seizure Classification” International Journal of Applied Engineering Research ISSN 0973-4562 Volume 10, Number 12 (2015) pp. 28751-28769.

[3] Nabeel Ahammad, T Fathima and Paul Joseph, "Detection of Epileptic Seizure Event and Onset Using EEG", BioMed *Research International* Volume vol.2014, Article ID 450573. 2014.

[4] J.C. Rajapakse, A. Cichocki and V.D. Sanchez, “Independent component analysis and beyond in brain imaging: EEG, MEG, fMRI, and PET”, In Proc. of IEEE Conf. on Neural Information Processing, vol.1, pp. 404-412, 2002

[5] H. Jokeit and M. Schacher, “Neuropsychological aspects of type of epilepsy and etiological factors in adults”, *Epilepsy & Behavior*, vol.5, pp.14–20, 2004.

[6] A.T Tzallas, M.G. Tsipouras and D.I. Fotiadis, "Automatic seizure detection based on time-frequency analysis and artificial neural networks", *Comput Intell Neurosci*. vol.7 (3): pp.1-13, 2007.

[7] E. Hoffmann, “Brain Training against Stress: Theory, Methods and Results from an Outcome Study”, version 4.2., 2005.

[8] Andrzejak, K. Lehnertz, F. Mormann, C.Rieke, P. David, and C. Elger, “Indications of nonlinear deterministic and finite dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state”, *Phys. Rev. E.,* vol.4 (6), 2001

[9] Liang, H.C Wang, W.L.Chang, “Combination of EEG Complexity and Spectral Analysis for Epilepsy Diagnosis and Seizure Detection", *EURASIP Journal on* Advances in Signal Processing, pp.853434, 2010.

[10] H. Adeli, Z Zhou N, Dadmehr, "Analysis of EEG records in an epileptic patient using wavelet transform", J. Neurosci. Meth. vol.123 (1), pp.69–87, 2003.

[11] Guerrero-Mosquera, "Stochastic relevance analysis of epileptic EEG signals for channel selection and classification", Conference proceedings:. Annual International Conference of the IEEE Engineering in Medicine and Biology Society. Conference07/2013, pp.2104-2107, 2013

[12] V. Bajaj and R.B. Pachori, "Classification of Seizure and Non-seizure EEG signals using empirical mode decomposition", *IEEE T INF TECHNOL B* . vol.16 (6), pp.1135-1142, 2012

[13] A. Subasi, "Application of adaptive neuro-fuzzy inference system for epileptic seizure detection using wavelet feature extraction", *Computers in Biology and Medicine,* vol.37 (2), pp.227-244. 2007.

[14] H. Ocak , "Automatic detection of epileptic seizures in EEG using discrete wavelet transform and approximate entropy", *Exp. Syst. Appl*., vol.36(2), pp.2027–2036, 2009