كليـة الدراسات العليا

Sudan University of Science and Technology

College of Graduate Studies

EEG Signals Processing by Using Wavelet Technique and Artificial Neural Networks

معالجة اشارات تخطيط كهربية الدماغ باستخدام تقنية المويجات والشبكات العصبية الاصطناعية

A Thesis Submitted in Partial Fulfillment of the Requirements of The Degree awards of M.Sc in Biomedical Engineering

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DEDICATION

I would like to dedicate this work to …

My parent and families …

My friends …

All whom I love with respect …

ACKNOWLEDGMENT

Firstly I would like to thanks Allah for every thing

My deep thanks and respect to …

Dr. Eltahir Mohammed Hussein

My supervisor for his continuous guidance throughout the project

My thanks and respect to …

Biomedical Engineering Department especially Dr. Mohammed Yagoub

&

Deep thanks to all help and support during this project My family, My Friends especially Eng. Wahiba Hamdan

ABSTRACT

Two artificial neural network systems were designed by using wavelet based features for the classification of normal and abnormal EEG signals were decomposed to 4 levels using Daubechies wavelet of order 2.These EEG signals were decomposed to four statistical features: minimum, maximum, mean and standard deviation to depict their distribution. These features computed over the wavelet coefficients for each level, and used as input to the artificial neural network systems. After training and testing the systems results were obtained for classification of signals. The Two type of neural networks**(**Feed Forward Back propagation and Cascade Forward Back propagation) were tested for sensitivity, specificity and accuracy it was found that the Cascade Forward Back propagation (CFBP) give more accurate results with an accuracy of 96.67%.

المستخلص

تم تصميم نظامين من الشبكات العصبية الاصطناعية باستخدام تحليل المويجات (Wavelet) المبني علي المؤشرات لتصنيف بين الإشارات الطبيعية وغير الطبيعية لتخطيط كهربية الدماغ (EEG). تم تحليل الإشارات الطبيعية وغير الطبيعية لاربعة مستويات باستخدام طريقة تحليل المويجات (Daubechies) من الدرجة الثانية .هذه الإشارات حُللت الي أربعة مؤشرات احصائية : الحد الأدنى،الحد الأقصى،الوسط الحسابي والانحراف المعياري وذلك بغرض توزيعها .

هذه المؤشرات بعد حساب عوامل كل مستوي من التحليل الموجي استخدمت كمعطيات مدخله لنظامي الشبكات العصبية الاصطناعية. بعد تدريب واختبار النظامين تم الحصول على نتائج لوصف الإشارات الطبيعية وغير الطبيعية. تم اختبار النوعين من انواع الشبكات العصبية الاصطناعية

(Feed Forward Back propagation and Cascade Forward Back propagation)

لتحديد الحساسية والنوعية والدقة وقد اتضح ان (CFBP) تعطي نتائج افضلبدقة تساوي96.67٪.

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ABBREVIATIONS

EEG: Electroencephalography.

WT: Wavelet Transform.

DWT: Daubechies Wavelet.

ANN: Artificial Neural Network.

MCP: McCulloch and Pitts.

FFBP: Feed – Forward Back Propagation.

CFBP: Cascade Forward Back Propagation.

CHAPTER ONE

INTRODUCTION

1.1 General view

Many neurointensivists share the opinion that EEG can become an integral part of monitoring in the ICU. In this context, EEG recordings have been useful in the investigation of various disorders, sub-clinical seizures and coma. The technique is non-invasive, and advances in technology have made possible the collection, storage and analysis of continuously recorded EEG.

An EEG monitor should continuously record brain activity of patients in the ICU over several hours. In order to have a chance to detect cerebral dysfunction at a reversible stage, rapid interpretation of EEG is crucial [1].

The total of 60 patients have undergone EEG test recorded at the Sudan Heart Instituted were used as the training and testing data for the monitoring system. Among them, 50 were recorded in the intensive care unit after corrective cardiac surgery, and 10 were recorded at another monitoring unit for suspected seizures or for coma. All recordings that took place after our decision to start data collection were used (none were rejected for poor technical quality or any other reason). Thus, data selection was unbiased. The basic section of EEG used in this system lasted 6 h. Each one of the 60 EEG signals depending on the length of the recording. In all, sections were available from the 60 EEGs for training and testing. [1] The recordings were interpreted by electroencephalographers who acted and every six hour section was graded for each of the 4 features described below, and given an overall evaluation a of abnormality .

1.2 Problem statement

The usage of manual prediction cases is a difficult to get accurate classification of EEG signal. This problem increases the number of miss diagnose and classification of the signal**.** EEG signal consist of 5 sub band signals which can be traced and analyzed to detect many disease. However, the presence of an EEG throughout the entire period of recording is impractical and the complexity of EEG patterns discourages interpretation by a non-expert. In practice, there may be a considerable time lag between recording and interpretation, which may reduce significantly the effectiveness of EEG monitoring. Also, visual interpretation of long-term recordings is quite tedious and time consuming, and it is difficult to evaluate gradual changes and long-term trends.

1.3 Objectives

The objective of this research are to:

1- to design system for automated neurophysiological monitoring in the pediatric ICU.

2- be used as a bedside EEG warning device for pediatric patients who may suffer neurological dysfunction such as those subsequent to cardiac surgery, trauma or hemorrhage.

1.4 Hypothesis

Well trained artificial neural network based on EEG signal obtained from wavelet (WT) give reliable results. That can be used to diagnose the abnormality of EEG signal.

1.5 Methodology

The methodology of carrying out this research is:

Comprehensive literature reviews based on studying publish papers, books and expert opined. After that collected data from 60 patients in the intensive care unit after corrective cardiac surgery or coma (20 normal and 40 abnormal EEG signals) .then analysis for EEG signal detection by using wavelet based features. Normal and Abnormal EEG signals were decomposed at level 4 using Daubechies wavelet of order 2. After that four statistical features minimum, maximum, mean and standard deviation were computed over the wavelet coefficients for each level. These variables will be the input for an artificial neural network. A feed forward back propagation algorithm and Cascade forward back propagation model will construct to predict the output of artificial neural network.

1.6 Literature reviews

Many neurointensivists share the opinion that EEG can become an integral part of monitoring in the ICU (Emmerson and Chiappa, 1988; Jordan, 1993).

Background abnormalities are reported as the best prognostic indicator in longterm EEG monitoring (Lombroso, 1985; Watanabe et al.,1980).

An analysis of background and ictal abnormalities may give maximum prognostic information. Seizure detection methods have been described for adults and newborns (Gotman, 1990; Gotman et al., 1997).

In 2002, M. Teplan, presents an introduction into EEG measurement. Its purpose is to help with orientation in EEG field and with building basic knowledge for performing EEG recordings. The article is divided into two parts. In the first part, background of the subject, a brief historical overview, and some EEG related research areas are given. The second part explains EEG recording.

Electroencephalography belongs to electro biological imaging tools widely used in medical and research areas. EEG measures changes in electric potentials caused by a large number of electric dipoles formed during neural excitations. EEG signal consists of different brain waves reflecting brain electrical activity according to electrode placements and functioning in the adjacent brain regions.[7]

In 2005, Rakendu Rao and Reza Derakhshani are processed Multichannel recordings of EEG data during various mental tasks using two popular methods, independent component analysis (ICA) and matching pursuit (MP). The results are fed to a time delay neural network (TDNN) for classification of each mental task. Based on the results of the test sets, we analyzed the effectiveness of ICA and MP methods for use in EEG preprocessing and TDNN classification. It is shown that ICA is more effective than MP in lowering the neural network classification error, however this advantage is not significant.

In this study we used MP with only a 6-component output to have a better comparison with the 6-component output ICA. However, MP has the capability to decompose input signals into many more components. Increasing the number of MP output components may improve MP's lackluster performance. ICA too can be run in more than one way by using different settings.[13]

In 2007, AndrzejCichocki, propose a novel framework to reduce background electroencephalogram (EEG) artifacts from multitrial visual-evoked potentials (VEPs) signals for use in brain-computer interface (BCI) design. An algorithm based on cyclostationary (CS) analysis is introduced to locate the suitable frequency ranges that contain the stimulus-related VEP components. CS technique does not require VEP recordings to be phase locked and exploits the intertrial similarities of the VEP components in the frequency domain. The obtained cyclic frequency spectrum enables detection of VEP frequency band.

A new framework for enhanced visual-evoked potentials (VEPs) signal detection is presented. It was also observed that the frequency bands and mixing matrix do not change over trials for a given subject; hence the cyclostationary (CS) and genetic algorithm and independent component analysis methods need to be applied only to training data.[17].

In 2007, Dr. (Mrs.) R.Sukanesh, R. Harikumar Member, IAENG , compare the performance of a Genetic Algorithm (GA) and Multi- Layer Perceptron (MLP) neural network in the classification of epilepsy risk level from Electroencephalogram (EEG) signal parameters. The epilepsy risk level is classified based on the extracted parameters like energy, variance, peaks, sharp and spike waves, duration, events and covariance from the EEG of the patient.

This paper aims at classifying the epilepsy risk level of epileptic patients from EEG signals.The goal was to classify perfect risk levels with high rate of classification, a short delay from onset, and a low false alarm rate.[18]

In 2008, Aleˇ sProch´azka and Jarom´ırKukal, The paper is devoted to the use of discrete wavelet transform (DWT) both for signal preprocessing and signal segments feature extraction as an alternative to the commonly used discrete Fourier transform (DFT). Feature vectors belonging to separate signal segments are then classified by a competitive neural network as one of methods of cluster analysis and processing. The paper provides a comparison of classification results using different methods of feature extraction most appropriate for EEG signal components.

The paper presents results of a classification for signal segments detected by the Bayesian approach for a selected EEG channel. The following signal classification assumed the knowledge of the range of the number of classes to apply a self-creating classification method to find their optimal value and to exclude the possibility of dead neurons. Results of signal classification can be further improved by various methods but one the most important problems is in the right definition of signal segment features using both its frequency domain and time-domain properties and it seems that the DWT can be used in this area very efficiently.[14]

In 2011, H. Vélez-Pérez, R. Romo-Vázquez, R. Ranta, V. Louis-Dorr and L. Maillard, The global framework of this paper is the synchronization analysis in EEGrecordings. Two main objectives are pursued: the evaluation of the synchronizationestimation for lateralization purposes in epileptic EEGs and the evaluation ofthe effect of the preprocessing (artifact and noise cancelling by blind source separation,wavelet denoising and classification) on the synchronization analysis. Wepropose a new global synchronization index, based on the classical cross power spectrum, estimated for each cerebral hemisphere. After preprocessing, the proposed index is able to correctly lateralize the epileptic zone in over 90% of the cases.[21]

In 2012, Md Ashraf Jamal, this paper proposed committee neural network for classification of EEG signals. Committee neural network consists of different neural network that used multilayer perceptron back propagation algorithm. Redundant features and excessive hidden nodes of ANN increases modeling complexity without improving discrimination performance. Therefore optimum design of neural network which intern optimizes the committee neural network is required towards real time detection of EEG signals.

Used the signal processing tools to distinct EEG signal and provide the status of the individual. discrete wavelet transform (DWT) and Autoregressive (AR) method are used for the feature extraction. Performance of proposed mixture of features is compared to the DWT features and AR features using artificial neural network (ANN) classifier. Experiment result shows that the every optimized member network of CNN classify the EEG signal more accurately than the optimized network.[16]

In 2012, MasihTavassolia, Mohammad Mehdi Ebadzadeha, HamedMalek, analyzedheart rate variability signals and various features including time domain, frequency domain and nonlinear parameters are extracted. Moreover, additional nonlinear features are extracted from electrocardiogram (ECG) signals. These features are helpful in classifying cardiac arrhythmias. In this paper, genetic programming is applied to classify heart arrhythmias using both HRV and ECG features. Genetic programming selects effective features, and then finds the most suitable trees to distinguish between different types of arrhythmia. 12 features are extracted from heart rate variability signals and 3 nonlinear features are extracted from ECG signals. To classify cardiac arrhythmias, these features are used as terminal in genetic programming and the algorithm selects affective features to distinguish each arrhythmia from others. Due to short processing time and relatively high accuracy of the proposed method, it can be used as a real-time arrhythmia classification system.[19]

In 2012, Nandish.M, Stafford Michahial, Hemanth Kumar P, Faizan Ahmed, used two-features to improve the performance of EEG signals. Neural Network based techniques are applied to feature extraction of EEG signal. This paper discuss on extracting features based on Average method and Max & Min method of the data set. The Extracted Features are classified using Neural Network Temporal Pattern Recognition Technique.

The two methods are compared and performance is analyzed based on the results obtained from the Neural Network classifier.

Features were Extracted using Average method and Max_Min method. Two Features extraction methods are evaluated for their performance using Pattern Recognition tool box from the obtained results it has observed that the Max_Min feature extraction method gives better accuracy compared to the Average Feature Extraction Method and Accuracy of Max_Min method is 80%Accuracy of Average method is 41%.[20]

In 2013, DiptiUpadhyay ,EEG signals were used to extract the information and classify with different mental task. EEG data was collected from a source. This data contains recording of 5 subjects in different mental task conditions (Resting, math, letter composition, geometric figure rotation task). EEG Signals were pre-processed and filtered. EOG artifacts were removed by visual inspection. For classification of these mental tasks wavelet was used to extract the features. Second order Daubechies mother wavelet has been used to get the wavelet coefficients for the selected EEG epochs. Mean, maximum, minimum and standard deviations values of wavelet coefficients for the EEG epochs were selected as inputs for the training the network and to classify mental tasks. This architecture of ANN was also found effectively differentiating the EEG from different mental tasks conditions Resting (98%) multiplication (92%), Letter composition (92%) and rotation (96%).[11]

1.7 Thesis layout

This research is consists of six chapters: Chapter one is an introduction. Theoretical Background is found in Chapter two. Expert System and Neural Networks are presented in chapter three. The proposed system is presented in chapter Four. Chapter five describes the results and discussion. Finally chapter six is conclusion and recommendation.

CHAPTER TWO

THEORETICAL BACKGROUND

The human nervous system is consist of two main components: the central nervous system (CNS) and the peripheral nervous system (PNS). The CNS is composed of the brain, the cranial nerves, and the spinal cord. The PNS is made up of the nerves that exit from the spinal cord at various levels of the spinal column as well as their tributaries. The autonomic nervous system (divided into the sympathetic and parasympathetic nervous system) is also considered to be a part of the PNS and it controls the body's many vegetative (non-voluntary) functions[4][5].

2.1 Nervous system anatomy and physiology and EEG:

The neural activity of the human brain starts between the 17th and 23rd week of prenatal development. It is believed that from this early stage and throughout life electrical signals generated by the brain represent not only the brain function but also the status of the whole body. This assumption provides the motivation to apply advanced digital signal processing methods to the electroencephalogram (EEG) signals measured from the brain of a human Activity. Your brain is active all the time, and its cells communicate with each other via electrical signals. An electroencephalogram (also called an EEG) is a special test that records these electrical signals that occur within the brain. History of EEG measurements is first provided.

2.2 Electroencephalogram (EEG):

Electroencephalography (EEG) is the recording of electrical activity along the scalp. EEG measures voltage fluctuations resulting from ionic current flows within the neurons of the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time, usually 20–40 minutes, as recorded from multiple electrodes placed on the scalp. Diagnostic applications generally focus on the spectral content of EEG, that is, the type of neural oscillations that can be observed in EEG signals.[18]

Carlo Matteucci and Emil Du Bois-Reymond were the first people to register the electrical signals emitted from muscle nerves using a galvanometer and established the concept of neurophysiology [11]. Richard Caton, a scientist from Liverpool, England, used a galvanometer and placed two electrodes over the scalp of a human subject and thereby first recorded brain activity in the form of electrical signals in 1875[12].Since then, the concepts of electro-(referring to registration of brain electrical activities) encephalon- (referring to emitting the signals from the head), and gram (or graphy), which means drawing or writing, were combined so that the term EEG was henceforth used to denote electrical neural activity of the brain. [13]

2.2.1 Neural Activities

The CNS generally consists of nerve cells and glia cells, which are located between neurons. Each nerve cell consists of axons, dendrites, and cell bodies. Nerve cells respond to stimuli and transmit information over long distances. A nerve cell body has a single nucleus and contains most of the nerve cell metabolism especially that related to protein synthesis. The proteins created in the cell body are delivered to other parts of the nerve. An axon is a long cylinder, which transmits an electrical impulse and can be several meters long in vertebrates. In humans the length can be a percentage of a millimeter to more than a meter. An axonal transport system for delivering proteins to the ends of the cell exists and the transport system has ‘molecular motors’, which ride upon tubulin rails. Dendrites are connected to either the axons or dendrites of other cells and receive impulses from other nerves or relay the signals to other nerves. In the human brain each nerve is connected to approximately 10,000 other nerves, mostly through dendrite connections [17].

2.2.2 Action Potentials

The information transmitted by a nerve is called an action potential (AP). APs are caused by an exchange of ions across the neuron membrane and an AP is a temporary change in the membrane potential that is transmitted along the axon. It is usually initiated in the cell body and normally travels in one direction. The membrane potential depolarizes (becomes more positive), producing a spike. After the peak of the spike the membrane repolarizes (becomes more negative). The potential becomes more negative than the resting potential and then returns to normal. The action potentials of most nerves last between 5 and 10 milliseconds. Figure ((2.1) shows an example AP [11].

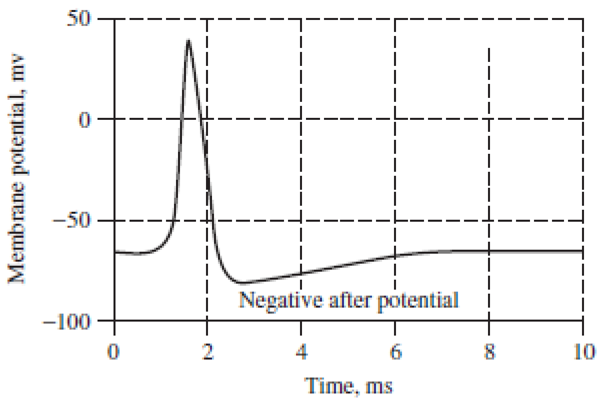


Figure (2.1) An example action potential

2.2.3 EEG Generation

An EEG signal is a measurement of currents that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex. When brain cells (neurons) are activated, the synaptic currents are produced within the dendrites. This current generates a magnetic field measurable by electromyogram (EMG) machines and a secondary electrical field over the scalp measurable by EEG systems.

Differences of electrical potentials are caused by summed postsynaptic graded potentials from pyramidal cells that create electrical dipoles between the soma (body of a neuron) and apical dendrites, which branch from neurons (Figure 2.2). The current in the brain is generated mostly by pumping the positive ions of sodium, Na+, potassium, K+, calcium, Ca++, and the negative ion of chlorine, Cl−, through the neuron membranes in the direction governed by the membrane potential [18].

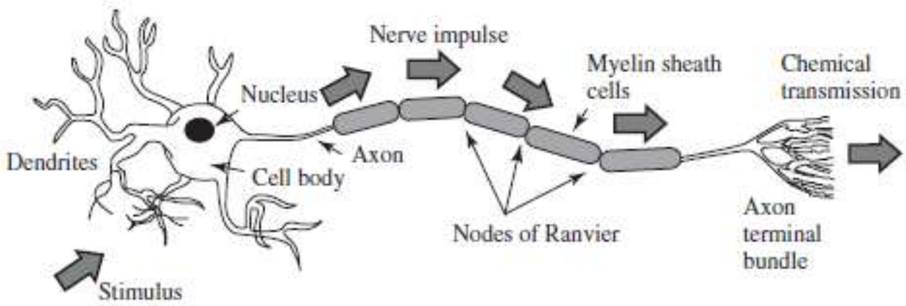
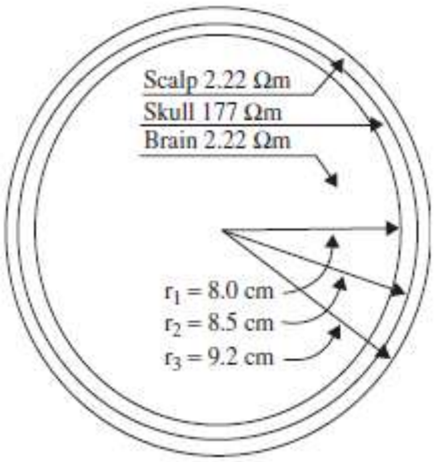


Figure (2.2) Structure of a neuron

The human head consists of different layers including the scalp, skull, brain (Figure 2.3), and many other thin layers in between. The skull attenuates the signals approximately one hundred times more than the soft tissue. On the other hand, most of the noise is generated either within the brain (internal noise) or over the scalp (system noise or external noise). Therefore, only large populations of active neurons can generate enough potential to be recordable using the scalp electrodes. These signals are later amplified greatly for display purposes. Approximately 10^{11} neurons are developed at birth when the central nervous system (CNS) becomes complete and functional [18]. Neurons are interconnected into neural nets through synapses. The number of synapses per neuron increases with age,



whereas the number of neurons decreases with age.

Figure (2.3) The three main layers of the brain including their approximate resistivity and thicknesses (_= ohm)

From an anatomical point of view the brain may be divided into three parts: the cerebrum, cerebellum, and brain stem (Figure 2.4). The cerebrum consists of both left and right lobes of the brain with highly convoluted surface layers called the cerebral cortex. The cerebrum includes the regions for movement initiation, conscious awareness of sensation, complex analysis, and expression of emotions and behavior. The cerebellum coordinates voluntary movements of muscles and maintains balance. The brain stem controls involuntary functions such as respiration, heart regulation, biorhythms, and neurohormone and hormone sections [15].

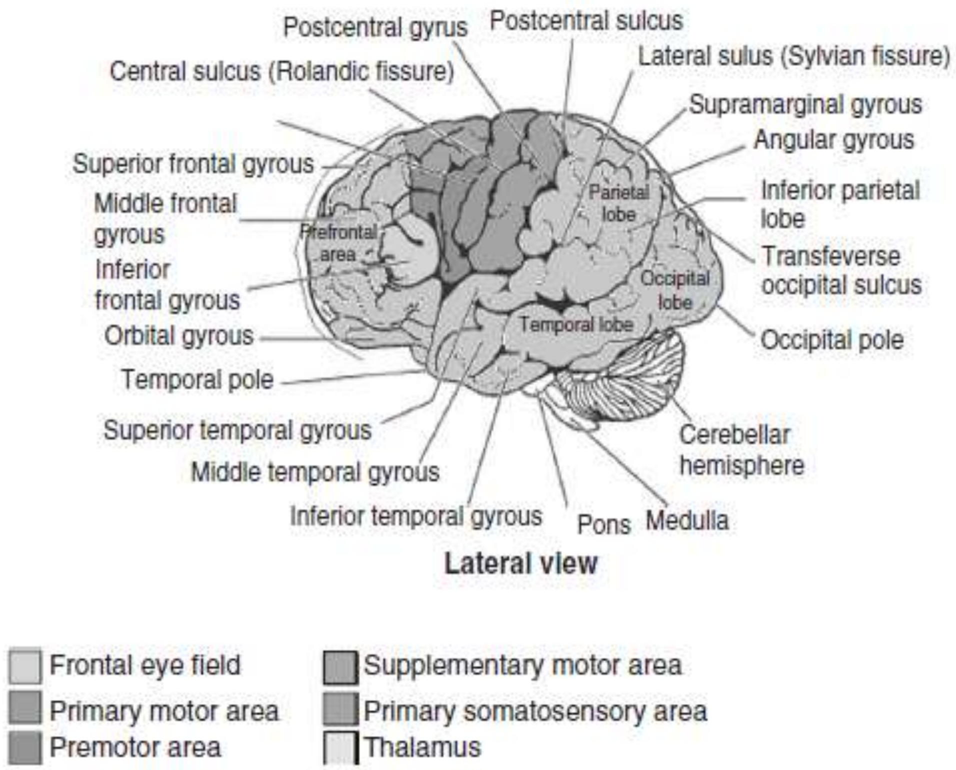


Figure (2.4) Diagrammatic representation of the major parts of the brain

2.2.4 Brain Rhythms

Many brain disorders are diagnosed by visual inspection of EEG signals. The clinical experts in the field are familiar with manifestation of brain rhythms in the EEG signals. In healthy adults, the amplitudes and frequencies of such signals change from one state of a human to another, such as wakefulness and sleep. The characteristics of the waves also change with age. There are five major brain waves distinguished by their different frequency ranges. These frequency bands from low to high frequencies respectively are called delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ).

Delta waves lie within the range of 0.5–4 Hz. These waves are primarily associated with deep sleep and may be present in the waking state. It is very easy to confuse artifact Signals caused by the large muscles of the neck and jaw with the genuine delta response.

This is because the muscles are near the surface of the skin and produce large signals, whereas the signal that is of interest originates from deep within the brain and is severely attenuated in passing through the skull.

Theta waves lie within the range of 4–7.5 Hz. **Theta** waves appear as consciousness slips towards Drowsiness. The theta wave plays an important role in infancy and childhood. Larger Contingents of theta wave activity in the waking adult are abnormal and are caused by various pathological problems. [20].

Alpha waves appear in the posterior half of the head and are usually found over the occipital region of the brain. They can be detected in all parts of posterior lobes of the brain. For alpha waves the frequency lies within the range of 8–13 Hz, and commonly appears as a round or sinusoidal shaped signal. Alpha waves have been thought to indicate both a relaxed awareness without any attention or concentration.

A beta wave is the electrical activity of the brain varying within the range of 14–26 Hz (though in some literature no upper bound is given). A beta wave is the usual waking rhythm of the brain associated with active thinking, active attention, focus on the outside world, or solving concrete problems, and is found in normal adults. A high-level beta wave may be acquired when a human is in a panic state. The amplitude of beta rhythm is normally under 30 μV. The frequencies above 30 Hz (mainly up to 45 Hz) correspond to the **gamma** range (sometimes called the fast beta wave). Although the amplitudes of these rhythms are very low and their occurrence is rare, detection of these rhythms can be used for confirmation of certain brain diseases [20].

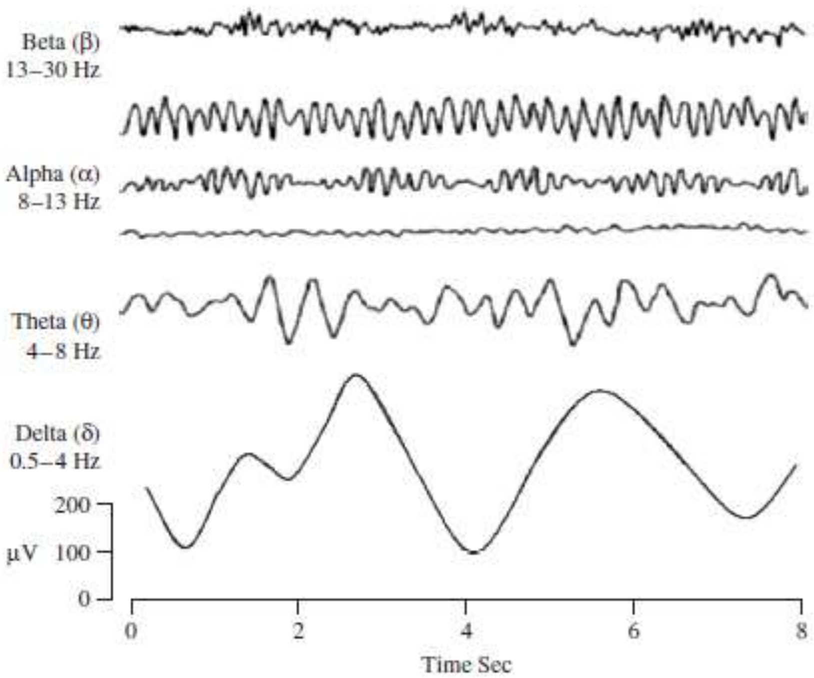


Figure (2.5) Shows the typical normal brain rhythms with their usual amplitude levels.

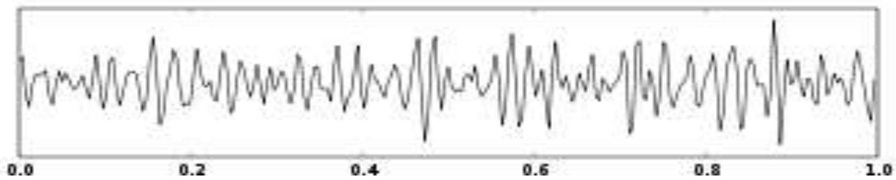


Figure (2.6) Gamma wave form

Automated EEG analysis:

EEG contains a vast amount of information, not all EEG components are useful. Very high frequency fluctuations can be attributed to electromagnetic interference. Artifacts in various frequency ranges may be generated due to electrical events such as muscle movements, eye binks, and heart beats, to name a few . These components of the EEG can be characterized as noise and need to be discarded. Signal analysis and processing techniques such as time-frequency analysis and wavelet transforms are used to extract relevant information.

Denoising the EEG using time – frequency analysis and wavelet analysis attempts to yield a clean signal which needs to be mathematically analyzed in order to obtain features or markers of abnormality that can distinguish between normal and abnormal states. Recent research has demonstrated that a spatiotemporal investigation of the underlying non-linear chaotic dynamics of EEGs can yield such marker. To discover the chaotic dynamics underlying the EEG, Studies have been performed, with some success, on EEGs obtained from both:

(a) Normal states of the brain such as sleep and meditation.

(b) Pathological states such as schizophrenia.

Although the wavelet transform can be used for denoising, in this book it also forms the basis for a novel integrated wavelet choose methodology. This methodology challenges the assumption the EEG represents the dynamics of the entire brain as a unified system and needs to be treated as a whole for investigation of the chaotic dynamic-chaos and wavelet analyses are adroitly integrated to identify features that best characterize the state of the brain.

2.3 Artifacts of EEG

Biological artifacts:

Electrical signals detected along the scalp by an EEG, but that originate from non-cerebral origin are called artifacts. EEG data is almost always contaminated by such artifacts. The amplitude of artifacts can be quite large relative to the size of amplitude of the cortical signals of interest. This is one of the reasons why it takes considerable experience to correctly interpret EEGs clinically. Some of the most common types of biological artifacts include:

- Eye-induced artifacts (includes eye blinks, eye movements and extra-ocular muscle activity (0.1-10Hz).

- ECG (cardiac) artifacts (110-60Hz).
- EMG (muscle activation)-induced artifacts (5-500Hz)[14].

2.2.7.2 Environmental artifacts

In addition to artifacts generated by the body, many artifacts originate from outside the body. Movement by the patient, or even just settling of the electrodes, may cause electrode pops, spikes originating from a momentary change in the impedance of a given electrode. Poor grounding of the EEG electrodes can cause significant 50 or 60 Hz artifact, depending on the local power system's frequency. A third source of possible interference can be the presence of an IV drip; such devices can cause rhythmic, fast, low-voltage bursts, which may be confused for spikes.[14]

Abnormal activity:

Abnormal activity can broadly be separated into Epileptiform and non-Epileptiform activity. It can also be separated into focal or diffuse.

Focal Epileptiform discharges represent fast, synchronous potentials in a large number of neurons in a somewhat discrete area of the brain.

Generalized Epileptiform discharges often have an anterior maximum, but these are seen synchronously throughout the entire brain. They are strongly suggestive of generalized epilepsy.

Focal non-Epileptiform abnormal activity may occur over areas of the brain where there is focal damage of the cortex or white matter. It often consists of an increase in slow frequency rhythms and/or a loss of normal higher frequency rhythms. It may also appear as focal or unilateral decrease in amplitude of the EEG signal.

Diffuse non-Epileptiform abnormal activity may manifest as diffuse abnormally slow rhythms or bilateral slowing of normal rhythms.[13]

Epilepsy:

Is a group of long-termneurological disorders characterized by epileptic seizures . These seizures are episodes that can vary from brief and nearly undetectable to long periods of vigorous shaking.

In most cases the cause is unknown, although some people develop epilepsy as the result of brain injury, stroke, brain cancer, and drug and alcohol misuse, among others. Epileptic seizures are the result of excessive and abnormal cortical nerve cell activity in the brain.

This list confirms the rich potential for EEG analysis and motivates the need for advanced signal processing techniques to aid the clinician in their interpretation. The brain rhythms will next be described, which are expected to be measured within EEG signals [12]

2.4 Electroencephalogram; Brain wave test:

Brain cells communicate with each other by producing tiny electrical signals, called impulses. An EEG measures this activity. The test is done by an EEG specialist in a doctor's office or at a hospital or laboratory. Patient’s asked to lie on back on a bed or in a reclining chair.

Flat metal disks called electrodes are placed all over scalp. The disks are held in place with a sticky paste. The electrodes are connected by wires to a speaker and recording machine.

The recording machine changes the electrical signals into patterns that can be seen on a computer. It looks like wavy lines.

Patients will need to lie still during the test with eyes closed because movement can change the results. But may be asked to do certain things during the test, such as breathe fast and deeply for several minutes or look at a bright flashing light.

2.5 Performed of EEG:

EEG is used to look at brain activity. It can help diagnose seizures. It may also be used to diagnose or monitor the following health conditions:

1. Abnormal changes in body chemistry that affects the brain.
2. Brain diseases such as Alzheimer's disease.
3. Confusion.
4. Head injuries.
5. Infections.
6. Tumors.

Doctors can also use an EEG to confirm brain death in someone who is in a coma.

EEG is also used to:

1. evaluate problems with sleep (sleep disorders).
2. investigate periods of unconsciousness.
3. monitor the brain during brain surgery.

An EEG may be done to show that the brain has no activity, in the case of someone who is in a deep coma. It can be helpful when trying to decide if someone is brain dead.

EEG cannot be used to measure intelligence. The test itself will take about 30-60 minutes. Placing the electrodes usually takes 20 minutes, but can take up to an hour, so the entire procedure may take about one to 2 hours. If you have an ambulatory EEG, brain activity is recorded for 24 hours or more.

Sometimes, it is necessary to have less sleep the night before the test, so that doctor can assess the effect of sleep deprivation on brain’s electrical activity. Some people may need to take a sedative to help them sleep during the test.[20]

2.5.1 Normal Results for EEG test:

Brain electrical activity has a certain number of waves per second (frequencies) that are normal for different levels of alertness. For example, brain waves are faster when was awake, and slower when was sleeping.

Results: The EEG will show patterns of brain waves that can help doctor determine whether there is a problem. A change in the normal pattern of brain waves may indicate epilepsy and can help determine the type of epilepsy. It is not necessary for a seizure to occur during the test for epilepsy to be diagnosed, because people with epilepsy often have small changes in brain wave patterns even when they are not having a seizure. However, it is also true that a normal EEG result does not always rule out epilepsy, because some people with seizure disorders have normal EEG readings between seizures.

The EEG results will need to be interpreted by a specialist before any formal diagnosis can be made. You should make a follow-up appointment with doctor to discuss your test results. There are also normal patterns to these waves.

2.5.2 Abnormal Results for EEG test mean:

Abnormal results on an EEG test may be due to:

1. Abnormal bleeding (hemorrhage)
2. An abnormal structure in the brain (such as a brain tumor)
3. Attention problems
4. Tissue death due to a blockage in blood flow (cerebral infarction)
5. Drug or alcohol abuse
6. Head injury
7. Migraines (in some cases)
8. Seizure disorder (such as epilepsy or convulsions)

9. Sleep disorder (such as narcolepsy)
10. Swelling of the brain (encephalitis)

Note: A normal EEG does not mean that a seizure did not occur.

The Risks of the test:

The procedure is very safe. The flashing lights or fast breathing (hyperventilation) required during the test may trigger seizures in those with seizure disorders. The health care provider performing the EEG is trained to take care of you if this happens.

In this project uses EEG monitoring in the pediatric intensive care unit.

Many types of childhood epilepsy have characteristic epileptic activity on the EEG that leads to a specific diagnosis and treatment. Focal abnormalities seen on an EEG occasionally warrant a child having a brain scan.

Minor irregularities of no significance are frequently seen in EEG recordings of normal children, especially infants and young children. Non-epileptic abnormalities and even epileptic activity may be recorded in children with neurological and behavioral problems (e.g. cerebral palsy, autism, speech delay).

Conversely, a normal EEG does not exclude epilepsy. Many types of epilepsy may be associated with a normal EEG between seizures. A normal EEG during a "seizure" usually excludes epilepsy as the cause. The interpretation of EEG findings in children can be difficult and it is recommended that EEGs in children are recorded and interpreted by clinicians experienced in paediatric EEG.[20]

The test usually takes an hour, but sometimes it takes longer, especially if a sleep recording is needed. In this project the test takes 6 hour. The result recorded and used as input to the neural networks.

CHAPTER THREE

ARTIFICIAL NEURAL NETWORKS TECHNIQUES

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurones) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurones. This is true of ANNs as well.

The first artificial neuron was produced in 1943 by the neurophysiologist Warren McCulloch and the logician Walter Pits. But the technology available at that time did not allow them to do too much.

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyses. This expert can then be used to provide projections given new situations of interest and answer "what if" questions[23].

Other advantages include:

1. Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience.

2. Self-Organization: An ANN can create its own organization or representation of the information it receives during learning time.
3. Real Time Operation: ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.
4. Fault Tolerance via Redundant Information Coding: Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

3.1.1 Neural networks versus conventional computers:

Neural networks take a different approach to problem solving than that of conventional computers. Conventional computers use an algorithmic approach i.e. the computer follows a set of instructions in order to solve a problem. Unless the specific steps that the computer needs to follow are known the computer cannot solve the problem. That restricts the problem solving capability of conventional computers to problems that we already understand and know how to solve. But computers would be so much more useful if they could do things that we don't exactly know how to do.

Neural networks process information in a similar way the human brain does. The network is composed of a large number of highly interconnected processing elements (neurones) working in parallel to solve a specific problem. Neural networks learn by example. They cannot be programmed to perform a specific task. The examples must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly. The disadvantage is that because the network finds out how to solve the problem by itself, its operation can be unpredictable.

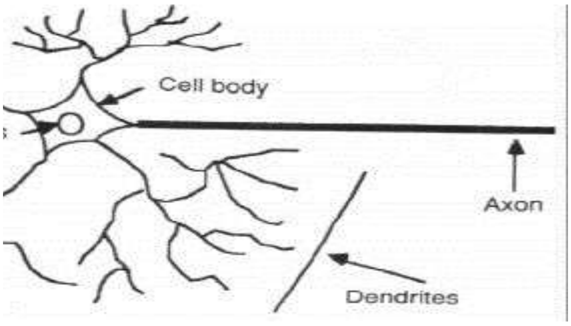
On the other hand, conventional computers use a cognitive approach to problem solving; the way the problem is to solved must be known and stated in small unambiguous instructions. These instructions are then converted to a high level language program and then into machine code that the computer can understand. These machines are totally predictable; if anything goes wrong is due to a software or hardware fault.

Neural networks and conventional algorithmic computers are not in competition but complement each other. There are tasks are more suited to an algorithmic approach like arithmetic operations and tasks that are more suited to neural networks.

3.1.2 Human and Artificial Neurones - investigating the similarities:

Much is still unknown about how the brain trains itself to process information, so theories abound. In the human brain, a typical neuron collects signals from others through a host of fine structures called dendrites. The neuron sends out spikes of electrical activity through a long, thin stand known as an axon, which splits into thousands of branches. At the end of each branch, a structure called a synapse converts the activity from the axon into electrical effects that inhibit or excite activity from the axon into electrical effects that inhibit or excite activity in the connected neurones. When a neuron receives excitatory input that is sufficiently large compared with its inhibitory input, it sends a spike of electrical activity down its axon. Learning occurs by changing the effectiveness of the synapses so that the influence of one neuron on another changes.

From Human Neurones to Artificial Neurones: We conduct these neural networks by first trying to deduce the essential features of neurones and their interconnections. We then typically program a computer to simulate these features. However because our knowledge of neurones is incomplete and our computing power is limited, our models are necessarily gross idealisations of real networks of neurones.



Figure(3.1) Components of a neuron

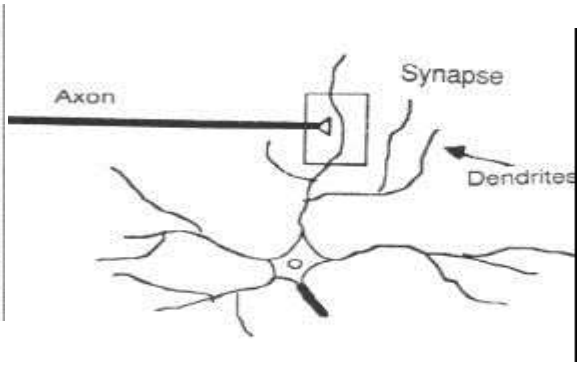


Figure (3.2) The synapse

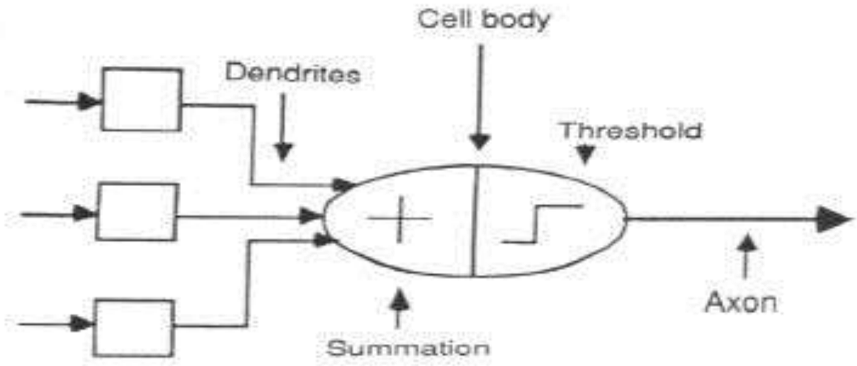


Figure (3.3) The neuron model

3.1.3 An engineering approach

A simple neuron: An artificial neuron is a device with many inputs and one output. The neuron has two modes of operation; the training mode and the using mode. In the training mode, the neuron can be trained to fire (or not), for particular input patterns. In the using mode, when a taught input pattern is detected at the input, its associated output becomes the current output. A more complicated neuron:The previous neuron doesn't do anything that conventional computers don't do already. A more sophisticated neuron (figure 3.5) is the McCulloch and Pitts model (MCP).

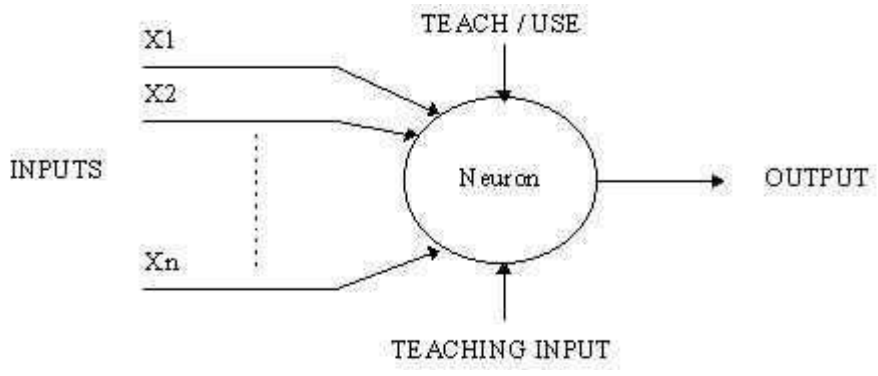


Figure (3.4) A simple neuron

The difference from the previous model is that the inputs are 'weighted', the effect that each input has at decision making is dependent on the weight of the particular input. The weight of an input is a number which when multiplied with the input gives the weighted input. These weighted inputs are then added together and if they exceed a pre-set threshold value, the neuron fires. In any other case the neuron does not fire.

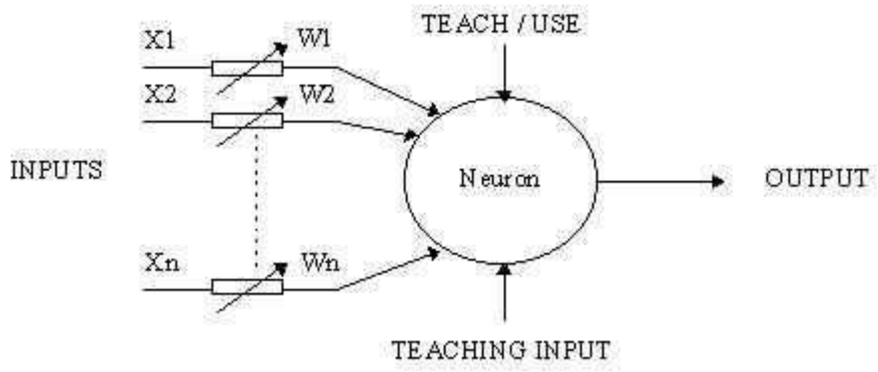


Figure (3.5) An MCP neuron

In mathematical terms, the neuron fires if and only if;

$$X1W1 + X2W2 + X3W3 + ... > T$$

The addition of input weights and of the threshold makes this neuron a very flexible and powerful one. The MCP neuron has the ability to adapt to a particular situation by changing its weights and/or threshold. Various algorithms exist that cause the neuron to 'adapt'; the most used ones are the Delta rule and the back error propagation. The former is used in feed-forward networks and the latter in feedback networks.

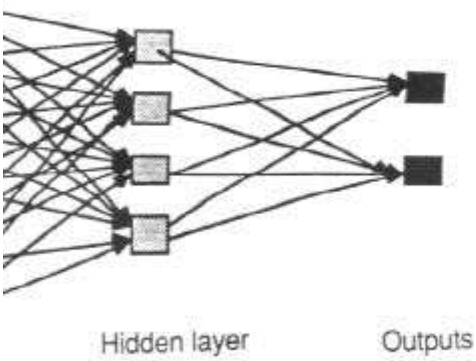
3.2 An Architecture of neural networks:

Feed-forward networks: Feed-forward ANNs (figure 3.6) allow signals to travel one way only; from input to output. There is no feedback (loops) i.e. the output of any layer does not affect that same layer. Feed-forward ANNs tend to be straight forward networks that associate inputs with outputs. They are extensively used in pattern recognition. This type of organization is also referred to as bottom-up or top-down.

Feedback networks: Feedback networks can have signals travelling in both directions by introducing loops in the network. Feedback networks are very powerful and can get extremely complicated. Feedback networks are dynamic; their 'state' is changing continuously until they reach an equilibrium point. They remain at the equilibrium point until the input changes and a new equilibrium needs to be found. Feedback architectures are also referred to as interactive or recurrent, although the latter term is often used to denote feedback connections in single-layer organizations.

Network layers:

The commonest type of artificial neural network consists of three groups, or layers, of units: a layer of **"input"** units is connected to a layer of **"hidden"** units, which is connected to a layer of **"output"** units. **Perceptrons**: The most influential work on neural nets in the 60's went under the heading of 'perceptrons' a term coined by Frank Rosenblatt. The perceptron (figure 3.8) turns out to be an MCP model (neuron with weighted inputs) with some additional, fixed, pre--processing. Units labelled A1, A2, Aj , Ap are called association units and their task is to extract specific, localised featured from the input images. Perceptrons mimic the basic idea behind the mammalian visual system. They were mainly used in pattern recognition even though their capabilities extended a lot more.



Figure(3.6) An example of a simple feed forward network

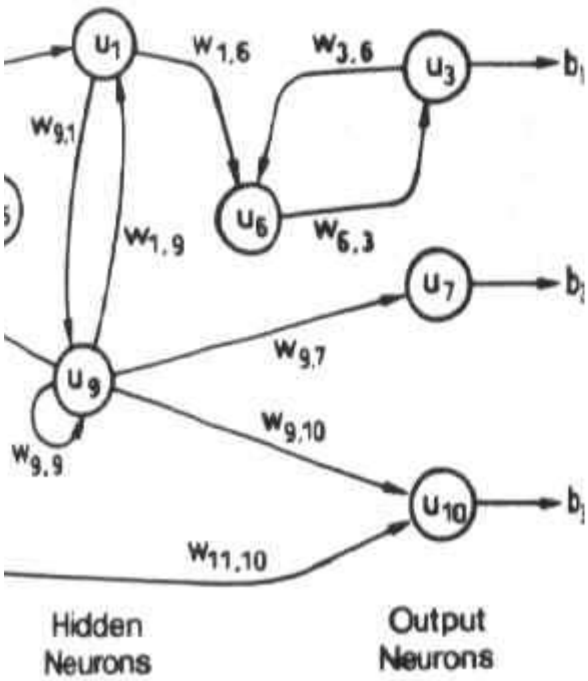


Figure (3.7) An example of a complicated network

3.1.4 The Learning Process: The memorisation of patterns and the subsequent response of the network can be categorised into two general paradigms:

- Associative mapping in which the network learns to produce a particular pattern on the set of input units whenever another particular pattern is applied on the set of input units.
- Regularity detection in which units learn to respond to particular properties of the input patterns. Whereas in associative mapping the network stores the relationships among patterns, in regularity detection the response of each unit has a particular 'meaning'.

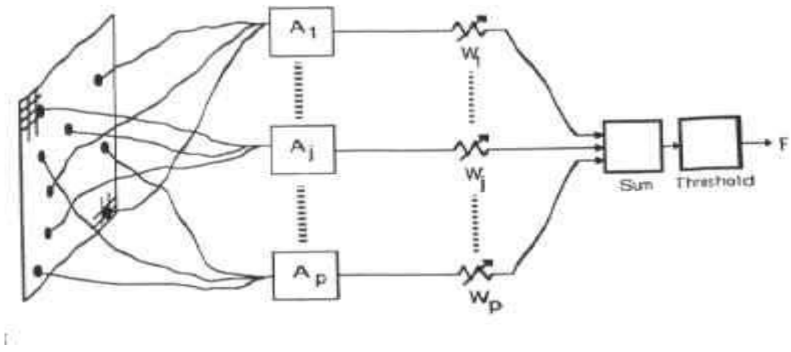


Figure (3.8) Show the Perceptron

3.1.6 Transfer Function:

The behavior of an ANN (Artificial Neural Network) depends on both the weights and the input-output function (transfer function) that is specified for the units. This function typically falls into one of three categories: linear (or ramp), Threshold and Sigmoid.

3.2.7The Back-Propagation Algorithm:

Units are connected to one another. Connections correspond to the edges of the underlying directed graph. There is a real number associated with each connection, which is called the weight of the connection. We denote by w_{ij} the weight of the connection from unit ui to unit uj. It is then convenient to represent the pattern of connectivity in the network by a weight matrix W whose elements are the weights w_{ij}. Two types of connection are usually distinguished: excitatory and inhibitory. A positive weight represents an excitatory connection whereas a negative weight represents an inhibitory connection. The pattern of connectivity characterizes the architecture of the network. A unit in the output layer determines its activity by following a two steps procedure.

First, it computes the total weighted input xj, using the formula:

$X_j = \sum_i y_i W_{ij}$ (1)

where yi is the activity level of the jth unit in the previous layer and Wij is the weight of the connection between the ith and the jth unit.

Next, the unit calculates the activity yj using some function of the total weighted input. Typically we use the sigmoid function:

$y_j = \frac{1}{1+ e^{-x_j}}$ (2)

Once the activities of all output units have been determined, the network computes the error , which is defined by the expression:

$E = \frac{1}{2} \sum_i (y_j - d_j)^2$ (3)

where yj is the activity level of the jth unit in the top layer and dj is the desired output of the jth unit.

The back-propagation algorithm consists of four steps:

1. Compute how fast the error changes as the activity of an output unit is changed. This error derivative (EA) is the difference between the actual and the desired activity.

$EA_j = \frac{\partial E}{\partial y_j} = y_j - d_j$ (1)

2. Compute how fast the error changes as the total input received by an output unit is changed. This quantity (EI) is the answer from step 1 multiplied by the rate at which the output of a unit changes as its total input is changed.

$EI_j = \frac{\partial E}{\partial x_j} = \frac{\partial E}{\partial y_j} \times \frac{\partial y_j}{\partial x_j} = EA_j y_j (1 - y_j)$ (2)

3. Compute how fast the error changes as a weight on the connection into an output unit is changed. This quantity (EW) is the answer from step 2 multiplied by the activity level of the unit from which the connection emanates.

$$EW_{ij} = \frac{\partial E}{\partial W_{ij}} = \frac{\partial E}{\partial x_j} \times \frac{\partial x_j}{\partial W_{ij}} = EI_j y_i \qquad (3)$$

4. Compute how fast the error changes as the activity of a unit in the previous layer is changed. This crucial step allows back propagation to be applied to multilayer networks. When the activity of a unit in the previous layer changes, it affects the activities of all the output units to which it is connected. So to compute the overall effect on the error, we add together all these separate effects on output units. But each effect is simple to calculate. It is the answer in step 2 multiplied by the weight on the connection to that output unit.

$$EA_i = \frac{\partial E}{\partial y_i} = \sum_i \frac{\partial E}{\partial x_j} \times \frac{\partial x_j}{\partial y_i} = \sum_i EI_j \, W_{ij} \qquad (4)$$

By using steps 2 and 4, can be convert the EAs of one layer of units into EAs for the previous layer. This procedure can be repeated to get the EAs for as many previous layers as desired. Once we know the EA of a unit, we can use steps 2 and 3 to compute the EWs on its incoming connections.

3.3 Basic Structure of artificial neural network:

1. Input layer:

The bottom layer is known as input neuron network in this case x1 to x5 are output neurons input layer neurons.

2. Hidden layer:

The in-between input and output layer the layers are known as hidden layers where the knowledge of past experience

3. Output Layer:

The top most layer which give the final output. In this case z1 and z2 are [9]

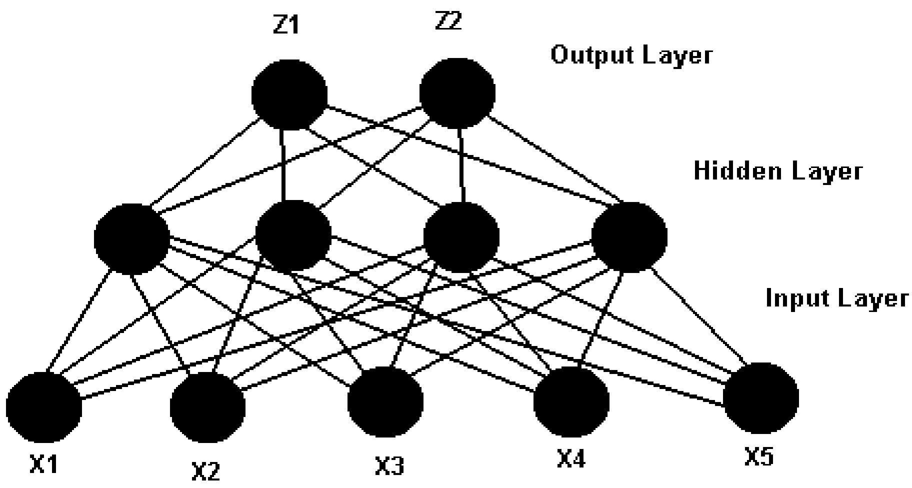


Figure (3.9) Basic structure of Artificial Neural Network [9]

3.3.1 Network architectures

1). Single layer feed forward networks:

In this layered neural network the neurons are organized in the form of layers.

In this simplest form of a layered network, we have an input layer of source nodes those projects on to an output layer of neurons, but not vise-versa. In other words, this network is strictly a feed forward or acyclic type [5]. It is as shown in figure:

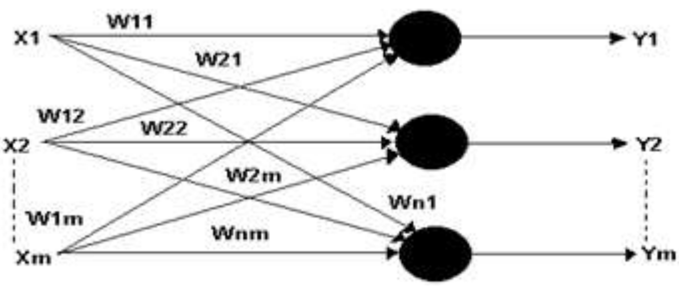


Figure (3.10) Single –layer feed forward Network

Such a network is called single layered network, with designation “single later” referring to the o/p layer of neurons.

2). Multilayer feed forward networks: The second class of the feed forward neural network distinguishes itself by one or more hidden layers, whose computation nodes are correspondingly called neurons or units. The function of hidden neurons is intervenue between the external i/p and the network o/p in some useful manner. The ability of hidden neurons is to extract higher order statistics is particularly valuable when the size of i/p layer is large.

The i /p vectors are feed forward to 1st hidden layer and this pass to 2nd hidden layer and so on until the last layer i.e. output layer, which give actual network response [5].

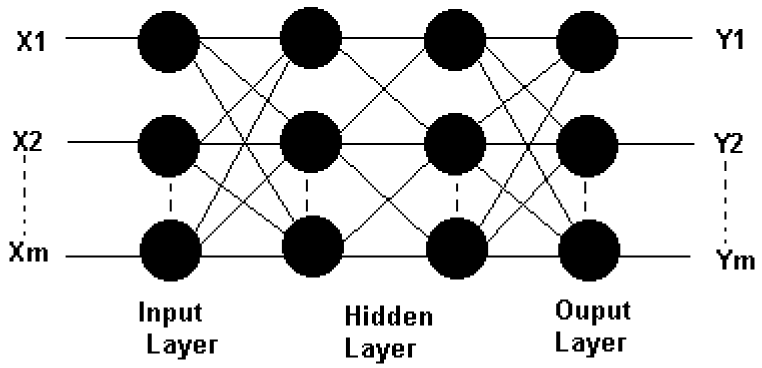


Figure (3.11) Multilayer feed forward network

3). Recurrent networks:

A recurrent network distinguishes itself from feed forward neural network, in that it has least one feed forward loop. As shown in figures output of the neurons is fed back into its own inputs is referred as self-feedback

A recurrent network may consist of a single layer of neurons with each neuron feeding its output signal back to the inputs of all the other neurons. Network may have hidden layers or not.

Figure (3.12) Single node with feedback to it self

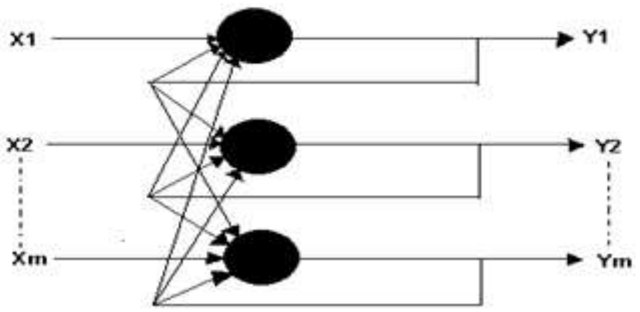


Figure (3.13) Multilayer recurrent network

3.3.2 Training of ANN

Supervised training:

- Supplies the neural network with the input and desired output.

- Response of the network is measured.

Unsupervised training:

- Only supplies input without desired output.

- The neural network adjusts its own weighs so that similar input causes similar output [7].

3.4 Advantages of Neural Networks

1) Networks start processing the data without any preconceived hypothesis. They start random with weight assignment to various input variables. Adjustments are made based on the difference between predicted and actual output. This allows for unbiased and batter understanding of data.

2) Neural networks can be retained using additional input variables and number of individuals. Once trained they can be called on to predict in a new patient.

3) There are several neural network models available to choose from in a particular problem.

4) Once trained, they are very fast.

5) Due to increased accuracy, results in cost saving.

6) Neural networks are able to represent any functions. Therefore they are called '**Universal Approximators**'.

7) Neural networks are able to learn representative examples by back propagating errors

3.5 Application of Artificial Neural Network

1. Classification

   Pattern recognition, feature extraction, image matching.

2. Noise reduction

   Recognize pattern in the input and produce noiseless outputs.

3. Prediction

   Extrapolation based on historical data. [10]

In this research used:

1 .Feed Forward Back propagation Network:

Feed forward back propagation artificial neural network model shown in figure (3.14) consists of input, hidden and output layers. Back propagation learning algorithm was used for learning these networks.

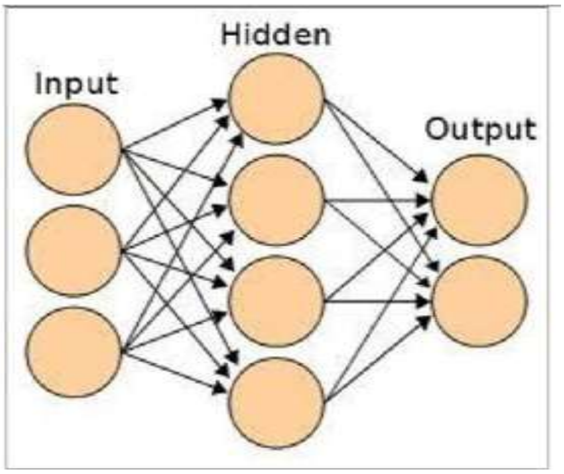


Figure (3.14) Feed Forward Back propagation Network

During training this network, calculations were carried out from input layer of network toward output layer, and error values were then propagated to prior layers. Feed forward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. The outputs of a network such as between 0 and 1 are produced, then the output layer should use a sigmoid transfer function (tansig**).**

2 .Cascade Forward Back propagation Network:

Cascade forward back propagation model shown in figure(3.14) is similar to feed-forward networks, but include a weight connection from the input to each layer and from each layer to the successive layers. While two-layer feed forward networks can potentially learn virtually any input output relationship, feed-forward networks with more layers might learn complex relationships more quickly.

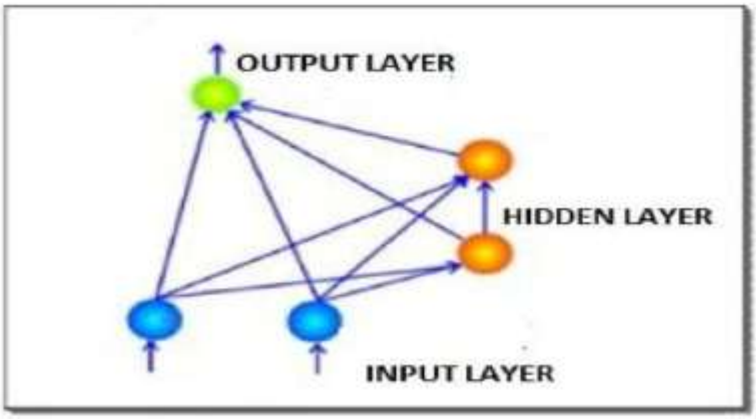


Figure (3.14) Cascade Forward Back propagation Network

Cascade forward back propagation ANN model is similar to feed forward back propagation neural network in using the back propagation algorithm for weights updating, but the main symptom of this network is that each layer of neurons related to all previous layer of neurons.

CHAPTER FOUR

THE PROPOSED SYSTEM

Introduction

The system includes three major steps:

1- Collect data from 60 patient have undergone EEG test for six hour.

2- Wavelet based features extraction (Statistics features).

3- Neural Network classification (combining the probabilities to obtain a final evaluation).

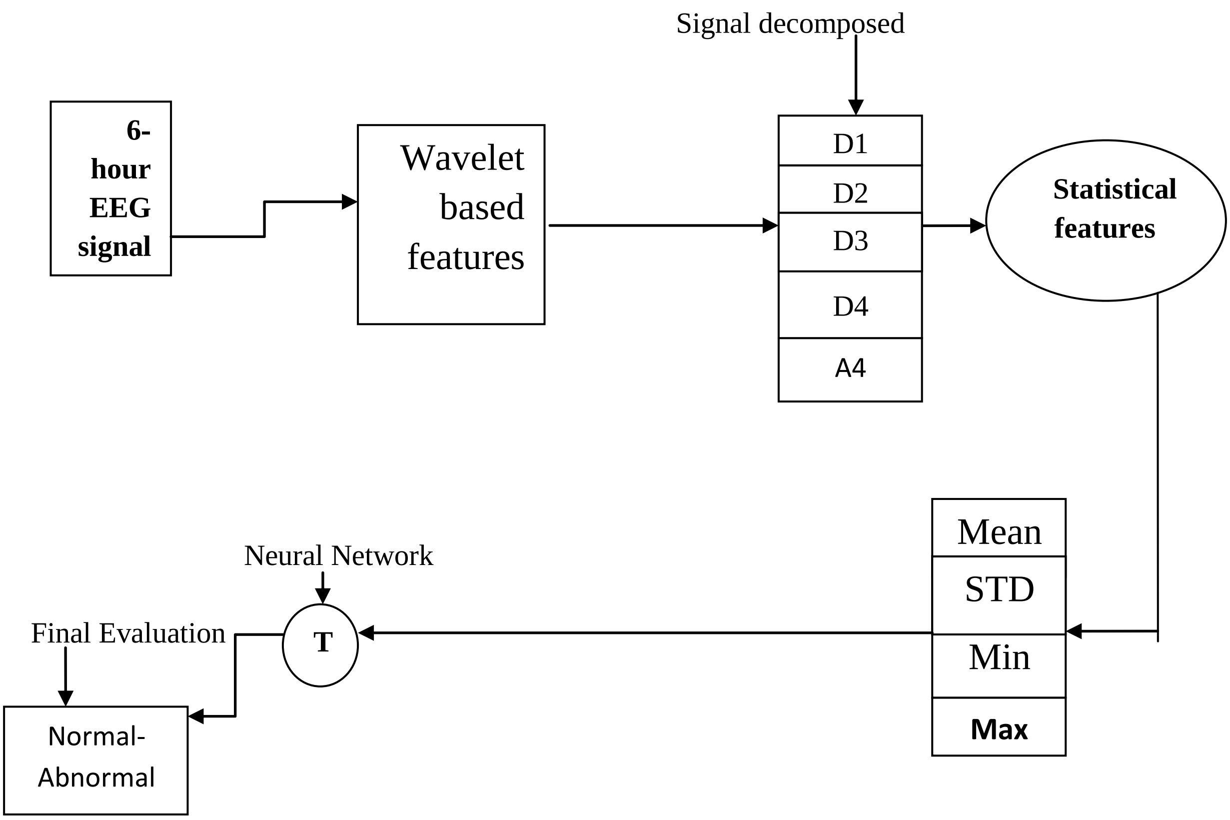


Figure (4.1) Show the proposed system

4.1 Data Acquisition:

The device used is EEG from SIMtechno ltd.co with specification below:

Sample-rate options: (sample rate is adjustable by user)	2048 Hz	4096 Hz	8192 Hz	16,384 Hz
Max. number of channels @ selected sample rate:	280	280	280	152
Bandwidth (-3dB):	DC - 400 Hz	DC - 800 Hz	DC - 1600 Hz	DC - 3200 Hz
Low-pass response	5^{th} order sinc digital filter			
High-pass response	fully DC coupled			
Digitalization:	24 bit, 4^{th} order Delta-Sigma modulator with 64x oversampling, one converter per channel			

To make a recording of 64 channels at 256 Hz sample rate:

- Select speed mode 4. The AD-box will sample 256 channels at 2 kHz.

- In Act View (at the right bar) select a decimation of 1/8. So the sample rate will be 2048/8 = 256 Hz.

- When saving in Act View, select to save only 'A1-B32 (64)' so Act View will save 64 channels.

4.2 Method approach:

The system based mainly on classification process which produce the final results, the classification step require multiple data processing before classification, these steps starts from the entering data into the system this data can be given in two formats vector data which require a processing before entering to preprocessing stage and the other type is Raw Data type which used in this case.

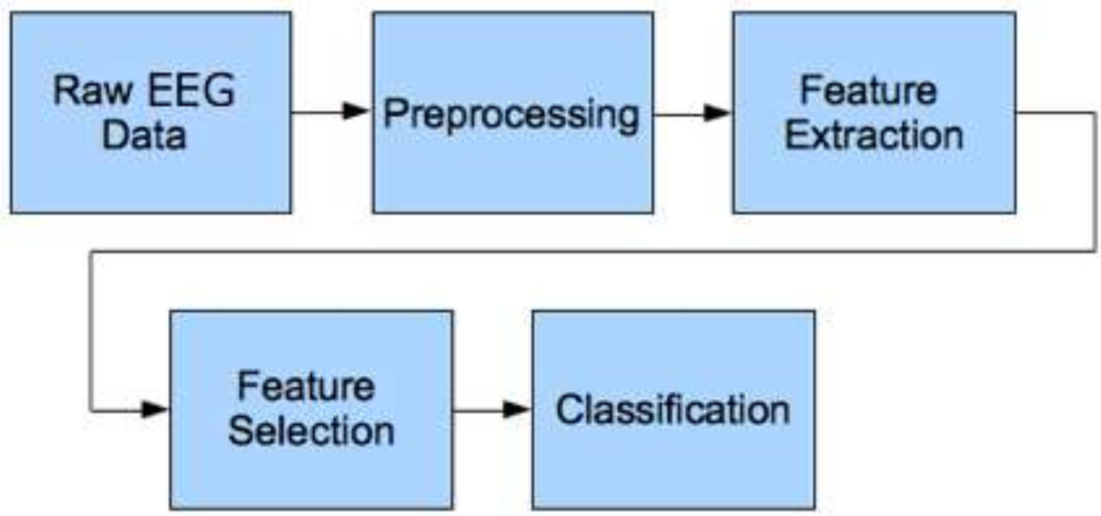


Figure (4.2) Basic steps applied in EEG data analysis

1. Raw EEG signal data:

The EEG signals are composed by records of 60 patients. The used signals present the following settings: referential montage with Pz as the reference electrode, 64 channels, 256 Hz of sample rate, band limited DC - 400 Hz.

2. Data processing:

Artifact rejection:

The EEG signal processing system can generally be subdivided to three functional modules: Preprocessing, feature extraction and classification. Normally the EEG data is corrupted by the artifacts which are electrical signals that are picked up by the scalp electrodes that do not originate from cortical neurons. One of the most common causes of artifacts is eye movement and blinking. Strong signals from A/C power supplies with 50Hz line frequency is another source of artifact. Signals originated due to muscle movements are another artifact. So the first step is to preprocess the data to remove these artifacts. The artifacts due to the patient movement usually appear as very high amplitude rapid transients, while the artifacts generated by poor electrode contact appear as sustained high amplitude activities.

The next step is to process the filtered signal and extract features that represent or describe the status and conditions of the system under study. Such features are expected to distinguish between normal and deviating cases. The last step is the classification and diagnostics. In this step, all the extracted features are submitted to a classifier that distinguishes among different classes of samples, for example, normal and abnormal.

4.3 WAVELET TRANSFORM:

The wavelet transform (WT) is designed to address the problem of non-stationary signals. It involves representing a time function in terms of simple, fixed building blocks, termed wavelets. These building blocks are actually a family of functions which are derived from a single generating function called the mother wavelet by translation and dilation operations. The main advantage of the WT is that it has a varying window size, being broad at low frequencies and narrow at high frequencies, thus leading to an optimal time–frequency resolution in all frequency ranges. The analysis in time-frequency domain by Wavelet Transform is performed by taking a Wavelet prototype function called Mother-Wavelet. This Mother-Wavelet suffers dilations and translations, forming the Daughter-Wavelets.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}.\psi(\frac{t-b}{a}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{(4.1)}$$

Where: $\psi(t)$ is the Mother-Wavelet , $\psi_{a,b}$ is the Daughter-Wavelet, $a^{-1/2}$ is the constant of energy normalization, b is the translation factor and a is the dilation factor

The Continuous Wavelet Transform uses continuous parameters of time and scales .Using discrete parameters to a and b ($a \geq 1$, $b \geq 1$) determines the Discrete Wavelet Transform.

$$\boldsymbol{DWT(a,b)} = \frac{1}{a_0^i}\int_{-\infty}^{\infty} x(t) \cdot \psi^*\left(\frac{t-kb_0\, a_0^i}{a_0^i}\right) dt \text{.............................. } \textbf{(4.2)}$$

Where: k and i are integers; b_0 and a_0 are the parameters of translation and dilation, respectively.

Therefore discrete wavelet transform (DWT) is often used. Advantage of wavelet transform used in: object detection, feature extraction, and time scale or space- scale analysis. WT adapts the window size according to the frequencies. At high frequencies short windows are used (fine resolution) and low frequencies, large windows are used (Coarse resolution) to encompass the frequency .The WT can be thought of as an extension of the classic Fourier transform, except that, instead of working on a single scale (time or frequency), it works on a multi scale basis. The procedure of multi resolution decomposition of a signal x[n] is schematically shown in Fig. (4.3)Each stage of this scheme consists of two digital filters and two down samplers by 2. The first filter is high-pass in nature and the second is its mirror version, low-pass in nature. The down sampled outputs of first high-pass and low-pass filters provide the detail D1 and the approximation A1 respectively.

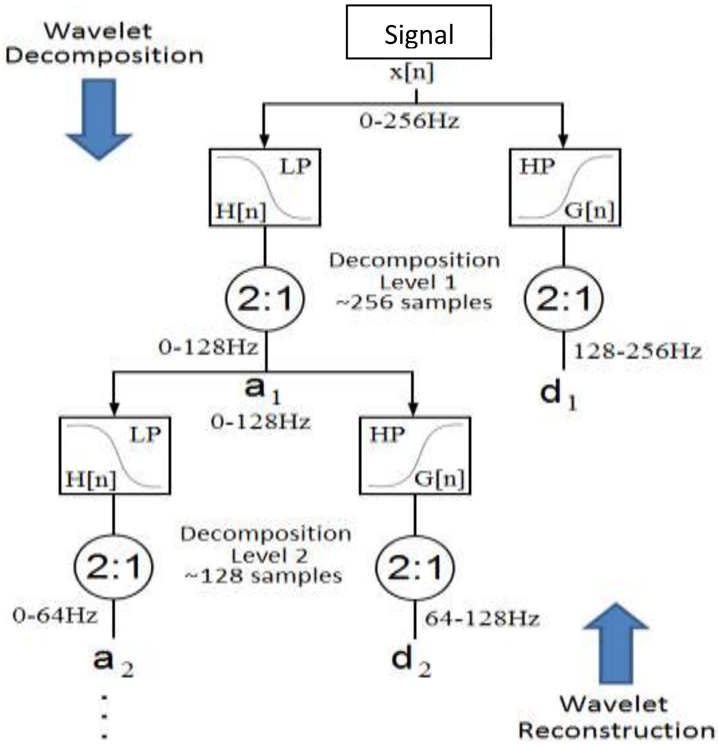


Figure (4.3) Representation of the Wavelet Analysis (decomposition of discrete wavelet transform implementation)

Such a signal level decomposition may not always separate out all the desired features, Therefore, the low resolution components are further decomposed into low and high resolution components after a second level of decomposition and so on , his process form multi resolution analysis where the original signal examined at different levels with multiple resolution.

The EEG signals can be considered as a superposition of different structures occurring on different time scales at different times. One purpose of wavelet analysis is to separate and sort these underlying structures of different time scales. It is known that the WT is better suited to analyzing non stationary signals, since it is well localized in time and frequency. The property of time and frequency localization is known as compact support and is one of the most attractive features of the WT.

In order to analysis EEG signal need a raw data to import it in matlab, After that need to do some preprocessing to remove noise from it.
Then extract feature from this signal and select the best of this feature. Now the signal is ready to be classified.

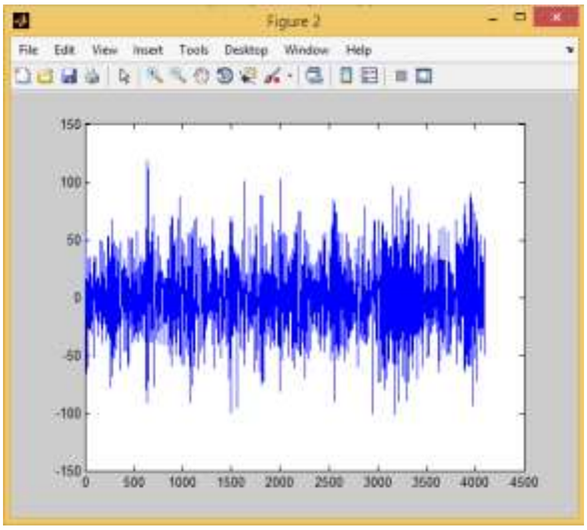
4.3.1 Data Preprocessing

This data is usually not clean so some preprocessing steps are needed. These often include the application of filters.

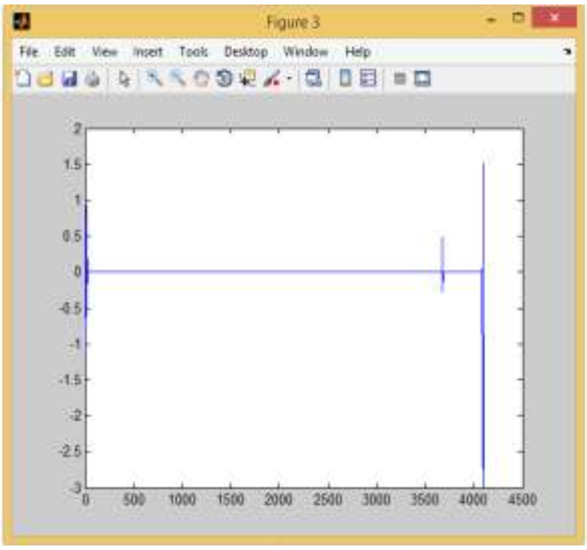
The data used has already gone through the pre- processing steps. It was cut out from continuous multichannel EEG recordings after visual inspection for artifacts due to muscle activity or eye movement.

4.3.2 Filtering EEG signals using the denoising method:

The denoising method is a resource used in the decomposition process of the Wavelet Transform. This method is used to filter the signal through the manipulation of its coefficients in the Wavelet domain, before the reconstruction of the signal. Once the full decomposition process was done from a particular Wavelet function it is possible to alter any of the coefficients in the transformed signal before performing the inverse transform Figure (4.4).



(A)



(B)

Figure (4.4) Denoising method to filtering EEG signals. **(A)** Original signal and **(B)** the decomposed signal in the Wavelet domain.

To demonstrate the behavior of a signal processed by denoising method was used an event Abnormal signal decomposed into four levels, generating the levels A4 and D4, D3, D2, D1 (figure (4.5)). For better visualization the original signals and the processed signals were superimposed, as a way to contrast the changes made between them. In (figure (4.5)) is presented the first form of filtering selecting a given level of decomposition. The level A4 was removed from the decomposed signal, setting zero values to the corresponding coefficients (Eliminating this level of approximation, the lower frequency of the signal will also be eliminated after its reconstruction. The signal resulting from this process compared with the original signal shows a reduction of low frequency oscillations, highlighting the peak of the Abnormal signal.

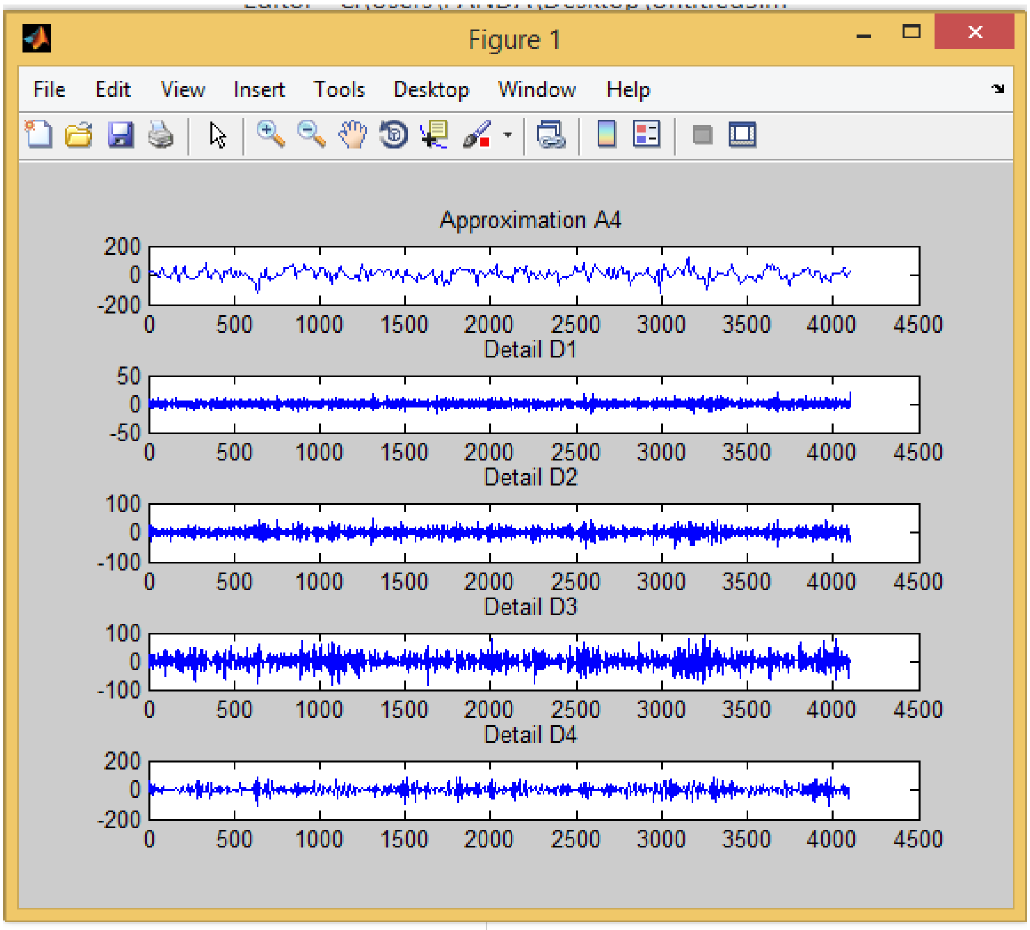


Figure (4.5) EEG signal decomposed into four levels, generating the levels A4 and D4, D3, D2, D1

4.3.3 Proposal for a filter to processing EEG signals using the wavelet transform: An interesting feature of the Wavelet Transform, observed through the experiments, is that this tool when used properly has the capability to act as a digital filter. Through Figure (4.5) can be observed the stages of decomposition and reconstruction of a signal. In this research, the signal is decomposed and reconstructed into 4 levels, generating an approximation level A4 and four levels of detail, D4, D3, D2 and D1. The decomposed signal contains all frequency components of the original signal, grouped by level of decomposition.

When a signal is reconstructed from a specific level of approximation or detail, only the frequencies that covers this level in particular will be used to generate this signal. In other words, we have specific bands of the original signal; fragmented in secondary reconstructed signals (A4, D4, D3, D2 and D1).Performing the sum between the reconstructed signals, the original signal is obtained. On the other hand, performing the difference between them, a signal without specific frequencies is obtained. Based on these considerations a digital filter was designed using the Wavelet Transform for preprocessing the EEG signals, which may be used in the localization and identification process of abnormal events.

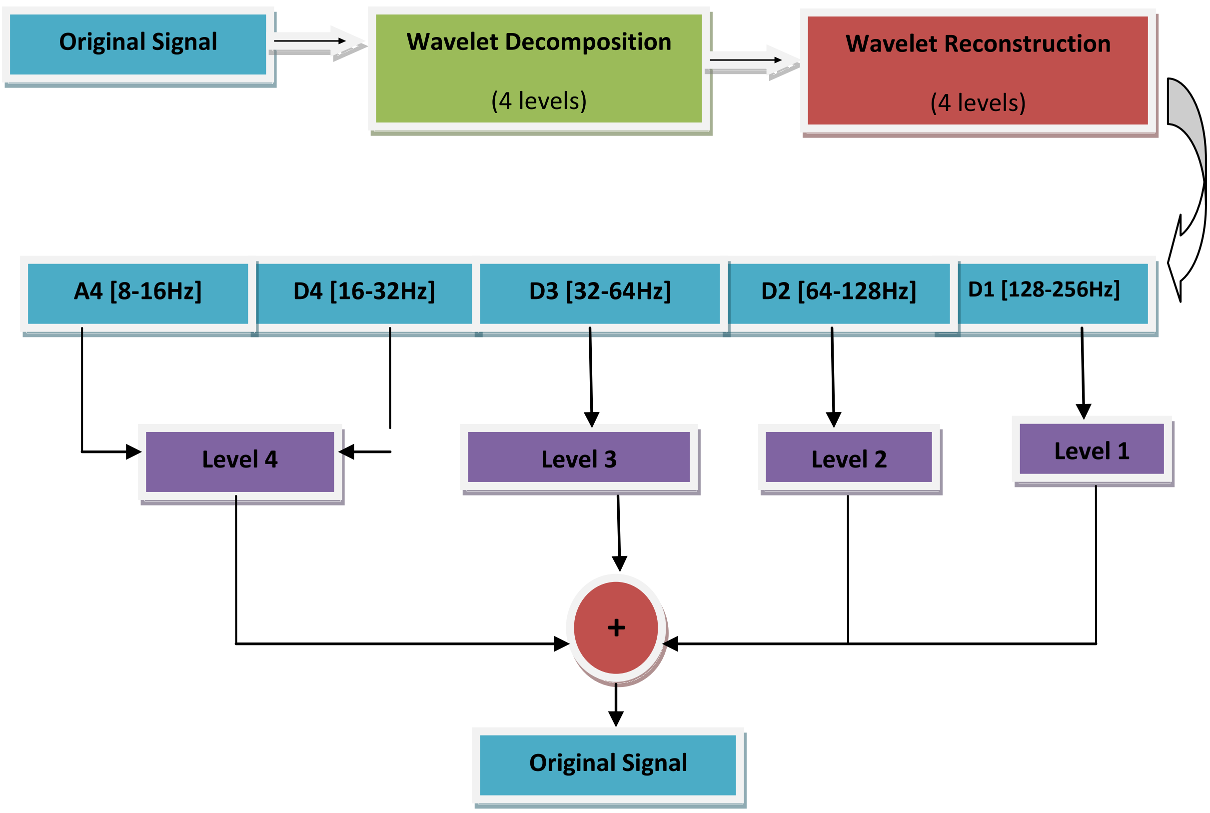


Figure (4.6) Process of decomposition and reconstruction of a signal.

4.4 Feature Extraction:

The next step could be considered the most important one **feature extraction.** EEG signals are complex, making it very hard to extract information out of them. In this research, selection of appropriate wavelet and the number of decomposition levels is very important in analysis of signals using the WT. The number of decomposition levels is chosen based on the dominant frequency components of the signal. The levels are chosen such that those parts of the signal that correlate well with the frequencies required for classification of the signal are retained in the wavelet coefficients. In this study, the number of decomposition levels was chosen to be 4. Thus, the EEG signals were decomposed into details D1–D4 and one final approximation, A4. The smoothing feature of the Daubechies wavelet of order 2 made it more suitable to detect changes of the EEG signals. Therefore, the wavelet coefficients were computed using the Daubechies wavelet of order 2.

Wavelet analysis of a normal EEG:

DWT applied to EEG normal data record from 20 children.

EEG sample ate 256 Hz for sampling rate of 1/256 = 0.0039 second or 3.9 m sec. 2end order Daubechies wavelet transform was applied to the EEG signal.

The computed detail and approximation wavelet coefficients of the EEG signals were used as the feature vectors representing the signals. The EEG signals were decomposed into time–frequency representations using discrete wavelet transform and statistical features were calculated to depict their distribution.

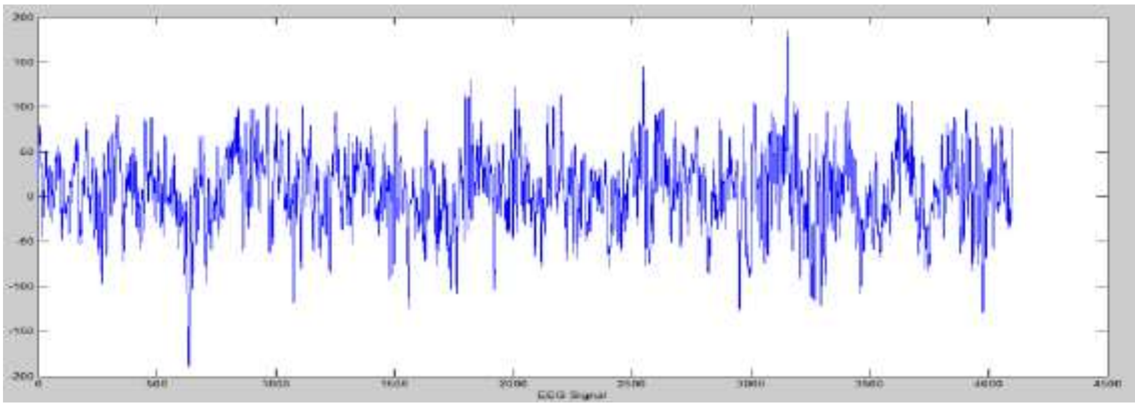


Figure (4.7) EEG signal for normal patient

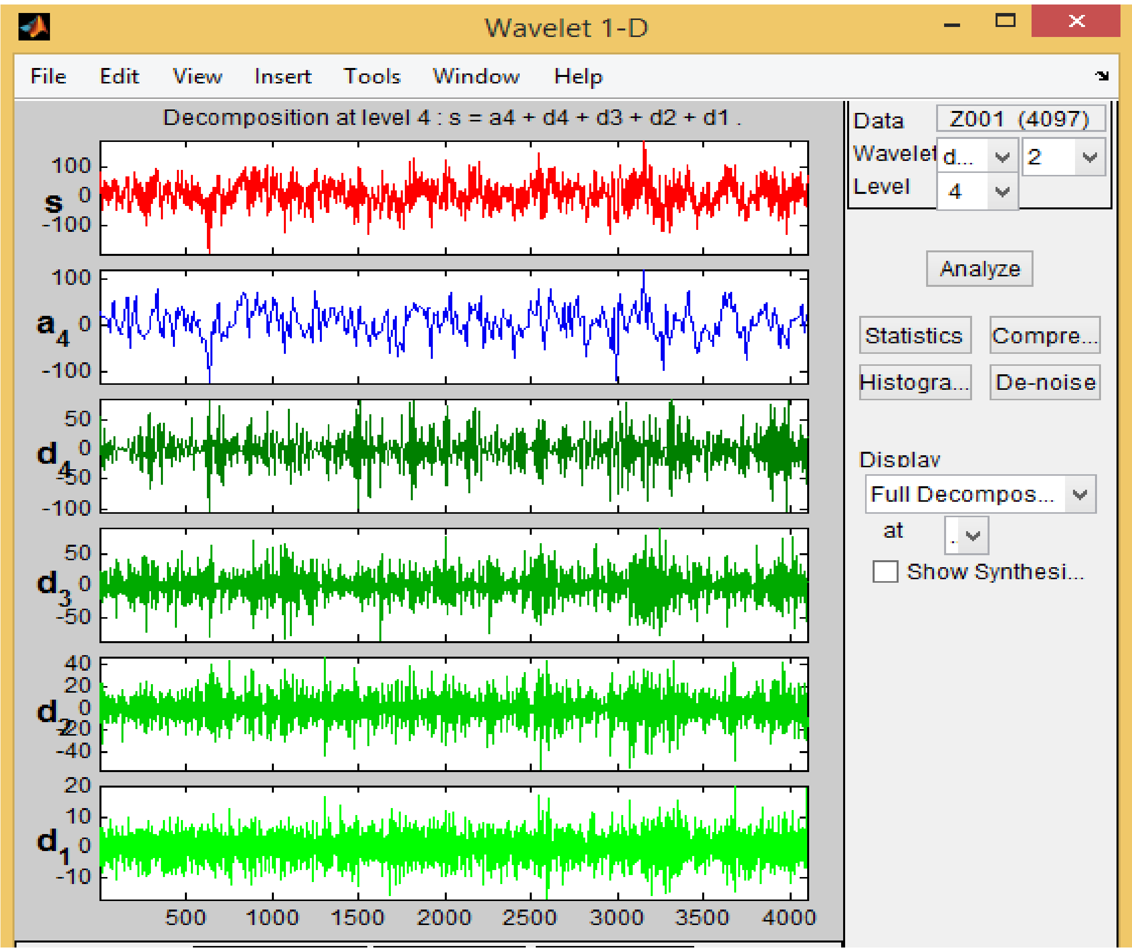


Fig (4.8) Represent the EEG signals were decomposed into details D1–D4 and one final approximation, A4

In order to reduce the dimensionality of the extracted feature vectors, statistics over the set of the wavelet coefficients were used. The following statistical features were used to represent the time frequency distribution of the EEG signals :

1. Maximum of the wavelet coefficients in each sub band where the Maximum is positive EEG potential values.
2. Minimum of the wavelet coefficients in each sub band where the Minimum is negative EEG potential values.
3. Mean of the wavelet coefficients in each sub band where the mean gives the average intensity value .Since the sum of (positive and negative) EEG potential is usually in the order of a few microvolts when The analysis time is not too short, the Mean Is essentially a constant, although of small value. Any shifts In values of the mean, therefore, are indicative of changes in potential that are of technical origin, such as amplifier drifts, etc.[15]

$$M= \sum_{i=1}^{n}(x/n)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \qquad (4.3)$$

Since:

M=mean, x=variable , n=number of variable.

4. Standard deviation of the wavelet coefficients in each sub band where in statistics and probability theory, shows how much variation or dispersion from the average exists. A low standard deviation indicates that the data points tend to be very close to the mean (also called expected value); a high standard deviation indicates that the data points are spread out over a large range of values. The standard deviation of a random variable, statistical population, data set, or probability distribution is the square root of its variance.[15]

After extraction of this feature for each signal, arrange this feature to represent the signal. To make sure to get better result, this feature was extracted also for sub signal so we have 20 features each 4 features represented one of the five sub signal.

4.5 Artificial Neural Network model

Are computation models of learning that are aspired by the biology of the human brain ANNS mimic the learning abilities of the brain and can ideally, by trained to recognized any gives set of inputs by adjusting the synaptic weights most common application to ANNs is supervised classification and therefore requires separate training and testing data.

The learning is usually performed with the training data, the mathematical formalization is based on the training data. The input training matrix for the classification is denoted by F_R and the desired output vector is O_R.

For building neural network model there are two main steps:

1. Create the neural network.

2. Train and test the neural network.

4.5.1 Create Neural Network:

MATLAB is a good programming toolbox package of version 7.14, provides functional software environment for creating neural network. The main goal of this package is to provide users with a set of integrated tools neural networks to create models of biological and simulate them easily, without the need of extensive coding.

The data was input to the neural network from the work space. Data were randomly divided into a training sample (20 cases) and a test sample (40 cases).

4.5.2 Training and Testing of ANN Network:

Feed Forward Back propagation Network:

Insert EEG signal in Feed Forward Back propagation Network with tow hidden layer and 10 nerouns to training the ANN applied it for 20 EEG normal signals after that testing the 40 EEG signal.

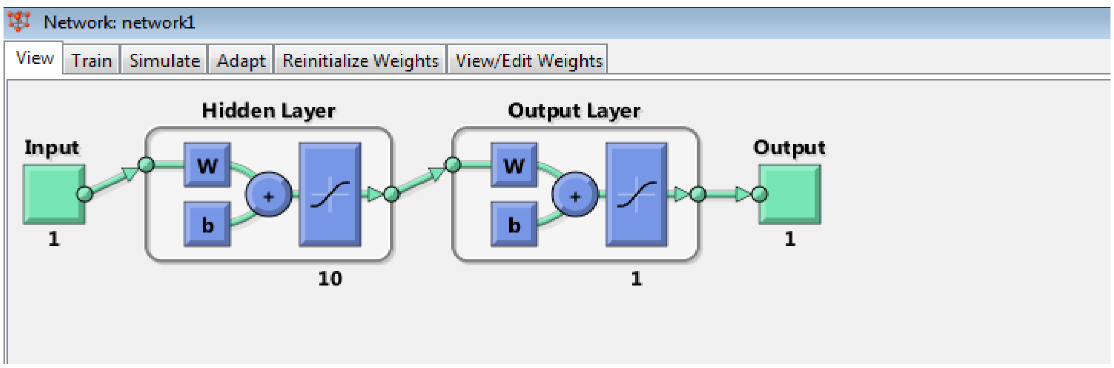


Figure (4.9) Training of Feed Forward Back propagation Network

Cascade Forward Back propagation Network:

Insert EEG signal in Cascade Forward Back propagation Network with tow hidden layer and 10 nerouns to training the ANN applied it for 20 EEG normal signals after that testing the 40 EEG signal.

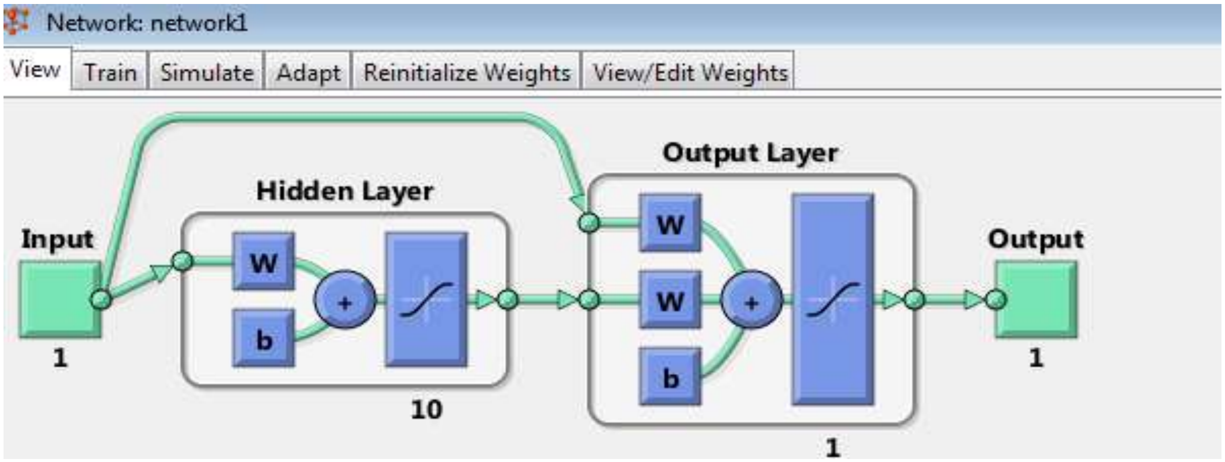


Figure (4.10) Training of Cascade Forward Back propagation Network

The performance of cascade forward back propagation and feed forward back propagation were evaluated. The data set having input and one target is divided as training and testing as 20 used for training and 40 for testing to develop different models in Feed forward back propagation and Cascade forward back propagation. The results are in the next chapter.

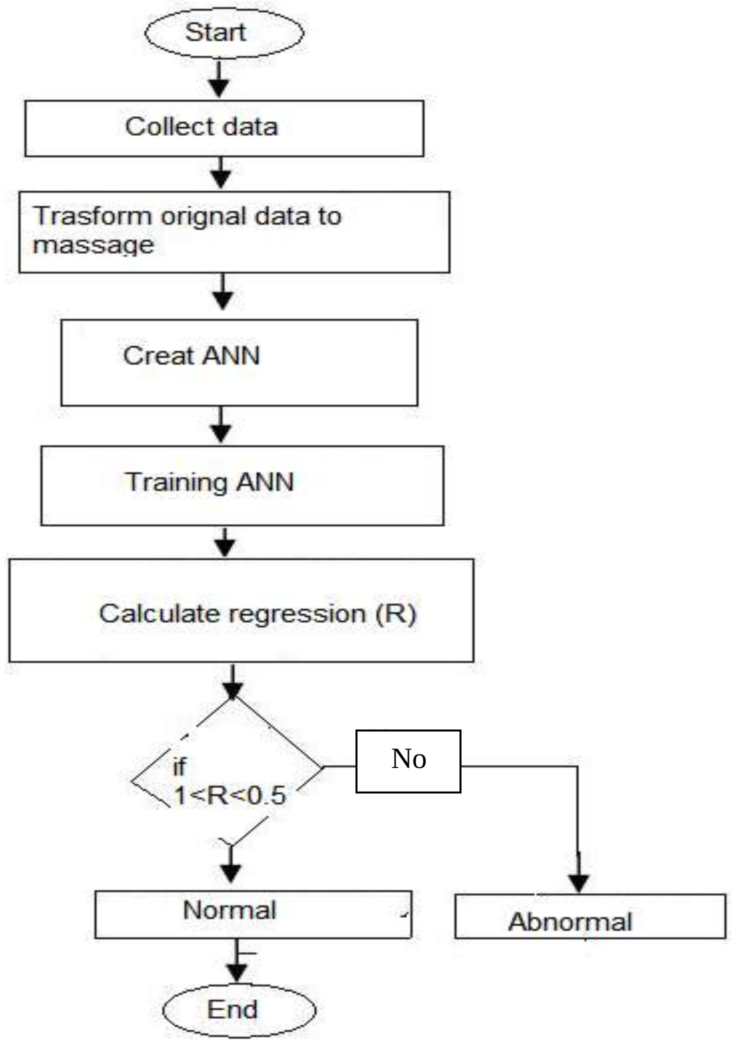


Figure (4.11) Flow diagrams for creating and training of a neural network

4.6 Classification

The algorithm uses artificial neural network (The word network in the term 'artificial neural network' refers to the inter–connections between the neurons in the different layers of each system) using feed-forward back propagation network type. The schematic representation of neural network with 'n' inputs, 'm' hidden units and one output unit. The selected features are considered as input to the neural classifier. A neural network is a set of connected input/output units in which each connection has a weight associated with it. The neural network trained by adjusting the weights so as to be able to predict the correct class. The classification process is divided into the training phase and the testing phase. During training, the features are extracted from the signal is known. After training is over, the trained networks are stored to be used in the algorithm. Whenever a signal is taken as input in the algorithm, it is simulated with the trained net-works and goes for testing the data. The accuracy, sensitivity, specificity of the classification is depends on the efficiency of the training [10].

4.7 Test work

In order to test work calculate accuracy, sensitivity and specificity. Using four categories output which are true positive (TP), false positive (FP), true negative (TN) and false negative (FN).

4.7.1 Accuracy

The accuracy of a measurement system is the degree of closeness of measurements of a quantity to that quantity's actual (true) value

$$\text{Accuracy} = (TP + TN) / \text{The number of data} \ldots\ldots\ldots \qquad (4.4)$$

4.7.2 Sensitivity: The sensitivity tells us how likely the test is come back positive in someone who has the characteristic. Among all people that have the characteristic, what proportion will test positive?

$$\text{Sensitivity} = TP / (TP+FN) \ldots\ldots\ldots\ldots\ldots \qquad (4.5)$$

4.7.3 Specificity: The specificity tells us how likely the test is to come back negative in someone who does not have the characteristic. Among all people without the characteristic, what pro-portion will test negative?

$$\text{Specificity} = TN / (FP+TN) \ldots\ldots\ldots\ldots\ldots\ldots \qquad (4.6)$$

Where:

- True positive: abnormal signal correctly diagnosed as abnormal
- False positive: normal signal incorrectly identified as abnormal
- True negative: normal signal correctly identified as normal.
- False negative: abnormal signal incorrectly identified as normal.

Through application wavelet decomposition of low frequency component are accurately capture and localize in both frequency and time using DWT the objective is to create or established a system for continuous EEG based monitoring of pediatric ICU patients and automatic detection of translate state change on EEG signal. The system may serve of provide supporting data in case of monitoring and dermi stration during delivery system.

CHAPTER FIVE

RESULTS AND DISCUSSION

5.1 Results of Neural networks:

In this research there were three stages to get results. The first stage included importing data to matlab then preprocessing to remove artifact from each signal and extract the feature from the signal by using wavelet (WT). The second was the feature selection. Finally, the classification by using neural network. The ANN was trained with inputs. After successful training, the system was able to diagnose the unknown cases and make prediction.

5.1.1 Data Set for Normal patients:

The extracted features for normal patients is as shown in table (5.1). The original data is transformed (massaged) using the simple equation(5.1):

(original value -lower bound)/(upper bound – lower bound + 1)………. (5.1)

The massaged value was used to train the system since it's in the format recognized by the system. Figure (5.1) shown the regression of normal patient is equal to 0.96. Which the range of normal patient is between (0.5 to 1). Table (5.2) describes the regression of 20 normal people as the table show there are a few patient have not classified will by the neural network.

Table (5.1): Extracted Features for Normal patients:

extracted features	wavelet sub bands				
	D1	D2	D3	D4	A4
R	-0.0158	0.003	0.0012	-1.98E-04	2.66E-06
SD	0.453	0.2852	0.1065	0.0092	4.98E-05
X	3.8864	6.6871	4.3992	0.1067	9.98E-04
N	-14.0236	-12.4974	-1.2656	-0.2772	-5.55E-04
R	-0.0182	0.0034	0.0014	-2.22E-04	2.96E-06
SD	0.6851	0.322	0.1203	0.0104	5.41E-05
X	24.1901	7.556	4.9727	0.1206	0.0011
N	-15.8173	-14.1118	-1.4305	-0.3134	-5.47E-04
R	-0.016	0.0031	0.0012	-2.21E-04	3.08E-06
SD	0.489	0.3032	0.1134	0.0099	6.55E-05
X	4.1865	7.0832	4.6625	0.1131	0.0012
N	-14.8127	-13.2238	-1.3413	-0.2939	-9.75E-04
R	-0.0091	0.0014	6.69E-04	-6.09E-05	5.52E-07
SD	0.2752	0.124	0.0466	0.0042	3.64E-05
X	6.2311	2.8698	1.8896	0.0459	6.36E-04
N	-5.9944	-5.3554	-0.5436	-0.1191	-7.61E-04
R	0.0034	-3.20E-04	-2.13E-04	-1.12E-05	4.08E-07
SD	0.079	0.0328	0.0137	0.0021	4.08E-05
X	3.0746	1.1983	0.2628	0.0416	9.77E-04
N	-0.8113	-0.7722	-0.4603	-0.0579	-8.16E-04
R	2.21E-04	-6.63E-05	-2.85E-05	4.64E-06	-6.29E-08
SD	0.0079	0.0069	0.0025	2.13E-04	1.22E-06
X	0.3662	0.3083	0.0295	0.0064	1.53E-05
N	-0.0575	-0.1592	-0.1026	-0.0025	-2.30E-05
R	0.0101	-0.0014	-7.35E-04	1.86E-05	2.81E-07
SD	0.2103	0.1167	0.0432	0.0011	6.60E-06
X	5.2382	4.6908	0.5284	0.0324	1.31E-04

N	-1.5314	-2.5172	-1.5972	-0.0122	-1.09E-04
R	0.0023	-1.62E-04	-1.36E-04	1.09E-07	2.14E-08
SD	0.0759	0.0294	0.0129	2.49E-04	1.88E-06
X	3.2182	1.2542	0.3384	0.0041	4.51E-05
N	-0.8492	-0.8083	-0.4777	-0.0087	-3.77E-05
R	-0.0091	0.0017	7.07E-04	-1.18E-04	1.61E-06
SD	0.2658	0.1666	0.0622	0.0054	3.14E-05
X	2.2792	3.9011	2.5669	0.0623	5.83E-04
N	-8.1739	-7.2883	-0.7384	-0.1618	-4.02E-04
R	-0.0023	4.24E-04	1.63E-04	-3.05E-05	4.33E-07
SD	0.0713	0.0405	0.0153	0.0014	9.82E-06
X	0.6424	0.947	0.6266	0.0152	1.88E-04
N	-1.9313	-1.7515	-0.1802	-0.0396	-1.57E-04
R	-0.0092	0.0018	7.27E-04	-1.31E-04	1.84E-06
SD	0.2867	0.1787	0.0668	0.0059	3.99E-05
X	2.4381	4.1703	2.7441	0.0666	7.29E-04
N	-8.7372	-7.7911	-0.7894	-0.173	-6.09E-04
R	-0.0188	0.0031	0.0014	-1.62E-04	1.83E-06
SD	0.4543	0.2795	0.1046	0.0091	5.10E-05
X	3.9598	6.5557	4.3186	0.1048	9.81E-04
N	-13.6591	-12.2221	-1.2423	-0.2724	-7.38E-04
R	0.0102	-0.0021	-8.16E-04	1.61E-04	-2.34E-06
SD	0.343	0.2117	0.0793	0.0071	5.72E-05
X	10.2947	9.1803	0.9302	0.2038	9.71E-04
N	-3.6578	-4.914	-3.2335	-0.0784	-0.0012
R	-0.0095	0.0016	7.20E-04	-8.54E-05	9.74E-07
SD	0.2316	0.1455	0.0543	0.0047	2.54E-05
X	1.9913	3.4119	2.2449	0.0545	5.10E-04
N	-7.1503	-6.3749	-0.6458	-0.1415	-3.40E-04
R	-0.0029	3.20E-04	2.03E-04	5.96E-06	-2.99E-07
SD	0.0671	0.0308	0.0126	0.0018	3.41E-05
X	0.677	0.6444	0.3841	0.0483	6.81E-04
N	-2.5658	-0.9999	-0.2193	-0.0347	-8.15E-04

R	-0.024	0.0044	0.0018	-2.69E-04	3.47E-06
SD	0.6483	0.4048	0.1512	0.013	6.09E-05
X	5.6359	9.512	6.2619	0.1519	0.0014
N	-19.8838	-17.7555	-1.8013	-0.3948	-3.12E-04
R	-0.0122	0.0023	9.38E-04	-1.53E-04	2.07E-06
SD	0.3514	0.2185	0.0817	0.0071	3.94E-05
X	3.0395	5.1229	3.3726	0.0818	7.66E-04
N	-10.7063	-9.5617	-0.9702	-0.2126	-4.69E-04
R	0.0083	-0.0014	-6.38E-04	6.98E-05	-7.52E-07
SD	0.1967	0.1256	0.0468	0.0041	2.58E-05
X	6.1841	5.4934	0.5546	0.1214	4.41E-04
N	-1.6514	-2.9337	-1.9279	-0.0467	-4.37E-04
R	0.0081	-0.0015	-6.29E-04	9.21E-05	-1.19E-06
SD	0.2364	0.1389	0.0518	0.0044	2.08E-05
X	6.8418	6.0987	0.6177	0.1353	1.04E-04
N	-2.6539	-3.2638	-2.1473	-0.0521	-4.87E-04
R	-0.0024	6.92E-04	2.16E-04	-7.09E-05	1.16E-06
SD	0.1374	0.08	0.0304	0.0031	4.25E-05
X	3.1025	1.7593	1.1566	0.042	9.86E-04
N	-3.7014	-3.2919	-0.4645	-0.0729	-8.24E-04

Where:

R = Mean, SD = Stander deviation, X = Maximum, N= Minimum.

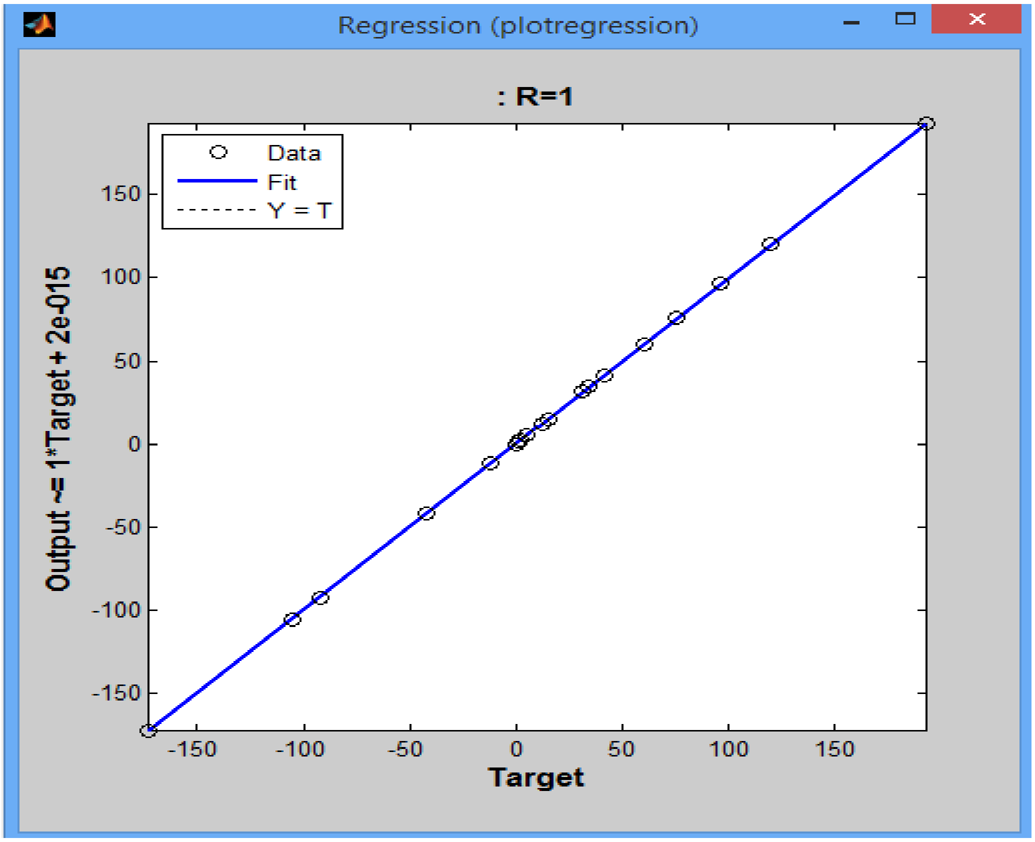


Figure (5.1): Normal patient regressions

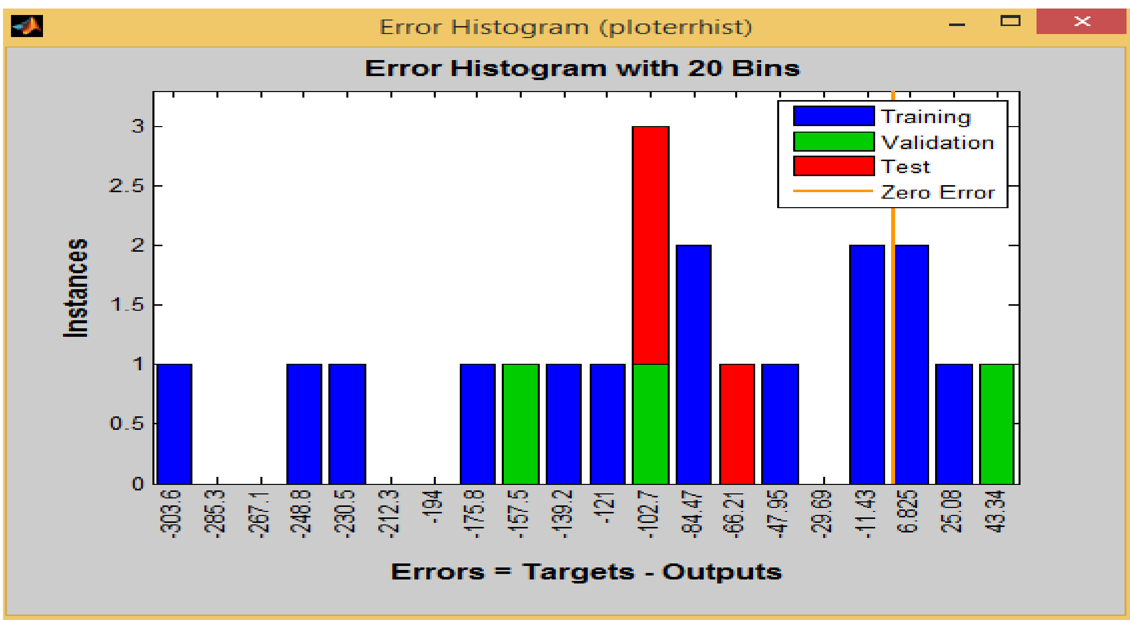


Figure (5.2): Plot mean square error normal

Table (5.2): Normal person regression

Number Patient	Value FFB Regression	Regression value CFB
1	0.8358	0.963
2	0.755	0.8528
3	0.423	0.41
4	0.1035	0.259
5	0.299	0.432
6	0.432	0.632
7	0.632	0.727
8	0.727	0.719
9	0.719	0.607
10	0.607	0.354
11	0.354	0.277
12	0.292	0.257
13	0.359	0.261
14	0.328	0.695
15	0.726	0.257
16	0.342	0.155
17	0.177	0.258
18	0.363	0.259
19	0.733	0.718
20	0.702	0.686

5.1.2 Data set for Abnormal patients:

The extracted features for abnormal patients is as shown in table (5.3). Figure(5.2) shown the regression of abnormal patient which is equal to 0.05. The range of abnormal is between (0 to 0.5). Also we got about 2 patients outside the range but have the same figure with patient inside the range.

Table (5.4) describes the regression of 40 abnormal patients. The regression values get close to 0.

Table (5.3): Extracted Features for Abnormal patients:

extracted features	wavelet sub bands				
	D1	D2	D3	D4	A4
R	5.70E-04	-5.34E-04	-1.65E-04	6.19E-05	-1.04E-06
SD	0.1024	0.0704	0.0262	0.0028	4.07E-05
X	3.4305	2.9014	0.4485	0.0605	7.95E-04
N	-2.996	-1.5022	-0.9698	-0.0406	-9.52E-04
R	0.0631	-0.0124	-0.0051	7.89E-04	-1.04E-05
SD	18.1332	1.1581	0.4325	0.0372	1.87E-04
X	112.433	50.7743	5.1473	1.1279	0.0016
N	-109.3362	-27.1875	-17.893	-0.4341	-0.0041
R	0.0093	-0.0018	-6.93E-04	1.37E-04	-1.99E-06
SD	5.2099	0.1797	0.0674	0.006	4.89E-05
X	73.4215	7.7862	0.7903	0.1732	8.32E-04
N	-38.7643	-4.1726	-2.7474	-0.0667	-9.95E-04
R	-0.0248	0.0036	0.002	-3.42E-05	-1.17E-06
SD	7.4721	0.3091	0.1213	0.0145	2.45E-04
X	52.9858	6.1491	4.0589	0.3438	0.0048
N	-60.4445	-11.4226	-1.5616	-0.2563	-0.0058
R	0.0052	-0.0014	-4.24E-04	1.56E-04	-2.60E-06
SD	14.0661	0.172	0.0658	0.007	1.00E-04
X	138.2817	6.9551	1.1047	0.1545	0.002
N	-108.0652	-3.7243	-2.4511	-0.0999	-0.0023
R	-0.008	0.001	5.69E-04	-1.18E-05	-2.94E-07
SD	13.5965	0.089	0.0347	0.0041	6.78E-05
X	111.8864	1.7931	1.1802	0.0951	0.0013
N	-114.7761	-3.3479	-0.432	-0.0744	-0.0016
R	0.4019	-0.0772	-0.0332	0.0044	-5.45E-05
SD	25.8409	7.031	2.6261	0.2251	0.001
X	396.0974	308.519	31.2953	6.8581	0.0036
N	-322.3588	-165.2634	-108.789	-2.6396	-0.0247
R	0.4132	-0.0824	-0.0344	0.0051	-6.68E-05
SD	54.7696	7.6638	2.8624	0.2458	0.0012
X	428.346	336.1549	34.0906	7.4703	0.0076
N	-354.4172	-180.0395	-118.5056	-2.8752	-0.0269
R	0.1357	-0.029	-0.0114	0.0021	-2.95E-05
SD	18.6965	2.8278	1.058	0.0931	6.54E-04
X	160.8482	123.1934	12.4803	2.7342	0.0103
N	-135.7825	-65.9354	-43.3834	-1.0523	-0.0123

R	-0.0823	0.0144	0.0063	-8.02E-04	9.62E-06
SD	2.1294	1.3042	0.4872	0.0418	2.00E-04
X	21.4813	30.6398	20.1692	0.4894	0.0046
N	-64.7164	-57.2008	-5.8021	-1.2715	-0.0015
R	0.0198	-0.004	-0.0016	2.71E-04	-3.70E-06
SD	7.7604	0.3841	0.1433	0.0124	7.26E-05
X	60.9945	16.8173	1.6997	0.3722	9.39E-04
N	-58.3345	-8.9873	-5.9084	-0.1433	-0.0013
R	0.0164	-0.0023	-0.0012	7.25E-05	-3.17E-07
SD	0.906	0.1993	0.0758	0.0075	9.36E-05
X	24.0319	8.3126	0.8462	0.1856	0.0021
N	-34.1707	-4.4629	-2.9415	-0.1271	-0.0018
R	-0.0926	0.0152	0.0069	-7.47E-04	8.01E-06
SD	2.774	1.342	0.5026	0.0439	2.81E-04
X	54.0982	31.3927	20.6761	0.5018	0.0047
N	-65.4724	-58.5484	-5.9478	-1.3038	-0.0049
R	-0.0379	0.0075	0.0032	-4.48E-04	5.68E-06
SD	9.2754	0.6882	0.2568	0.022	1.01E-04
X	62.2636	16.1699	10.6396	0.2581	0.0024
N	-77.4427	-30.2099	-3.0607	-0.6706	-2.21E-04
R	0.0633	-0.0121	-0.0052	7.01E-04	-8.67E-06
SD	6.8422	1.1038	0.4123	0.0353	1.62E-04
X	61.4485	48.4333	4.9142	1.077	3.73E-04
N	-47.6975	-25.9484	-17.0828	-0.4145	-0.0039
R	0.0892	-0.0133	-0.0077	1.82E-05	6.66E-06
SD	51.6582	1.1715	0.4646	0.0592	0.0011
X	340.8152	40.6913	6.7346	1.0667	0.025
N	-283.6317	-21.8514	-14.4042	-1.4827	-0.0209
R	-0.003	5.94E-04	2.83E-04	-2.81E-05	2.81E-07
SD	5.7664	0.0554	0.0202	0.0018	1.32E-05
X	35.2377	1.2747	0.8268	0.0199	2.14E-04
N	-44.3498	-2.4422	-0.238	-0.0517	-2.56E-04
R	-0.0337	0.0057	0.0027	-2.11E-04	1.53E-06
SD	9.9385	0.4875	0.1839	0.0173	1.82E-04
X	68.5647	11.1365	7.333	0.2397	0.0034
N	-47.1078	-20.7793	-2.1095	-0.4623	-0.004
R	-0.243	0.043	0.0202	-0.0018	1.68E-05
SD	34.0322	3.7418	1.4044	0.1267	0.0011
X	166.8221	86.6374	57.0306	1.3837	0.0189
N	-249.003	-161.7411	-16.406	-3.5952	-0.0226
R	-0.0229	0.0036	0.0017	-1.48E-04	1.27E-06

SD	20.1622	0.3115	0.117	0.0107	9.81E-05
X	104.5703	7.1842	4.7271	0.1243	0.0018
N	-78.2255	-13.4226	-1.3599	-0.2979	-0.0021
R	-0.0795	0.0156	0.0065	-0.001	-9.60E-06
SD	40.0659	1.4461	0.5399	0.0474	2.00E-04
X	216.7667	33.9726	22.3571	0.5435	0.0015
N	-277.5883	-63.4529	-6.4315	-1.4419	-0.0046
R	0.0092	-0.0019	-8.51E-04	1.02E-04	1.44E-06
SD	34.5458	0.1789	0.0648	0.0055	2.69E-05
X	202.323	7.9667	0.7711	0.1672	5.42E-04
N	-236.9313	-4.1404	-2.679	-0.0644	-2.96E-04
R	0.1003	-0.0223	-0.0083	0.0018	-2.62E-05
SD	24.5965	2.2574	0.8478	0.0771	6.98E-04
X	154.773	97.3176	9.8662	2.1618	0.0124
N	-193.9271	-52.111	-34.2965	-0.832	-0.0149
R	0.0926	-0.0182	-0.0077	0.0011	-1.39E-05
SD	7.8109	1.6805	0.6273	0.0538	2.46E-04
X	94.0454	73.7667	7.4756	1.6379	6.24E-04
N	-73.5175	-39.4901	-25.9865	-0.6304	-0.0059
R	-0.0437	-8.86E-04	0.0023	0.0011	-2.25E-05
SD	3.8668	1.0583	0.4449	0.0696	0.0014
X	56.379	26.3084	15.6816	1.9715	0.0278
N	-104.7491	-40.8236	-8.9547	-1.4183	-0.0333
R	-0.2709	0.0532	0.0218	-0.0035	4.66E-05
SD	8.526	5.0155	1.8738	0.1618	8.67E-04
X	136.5524	117.6354	77.4206	1.8783	0.0176
N	-262.5207	-219.687	-22.2717	-4.8801	-0.0095
R	0.096	-0.0192	-0.0081	0.0012	-1.52E-05
SD	14.1031	1.7861	0.666	0.0571	2.67E-04
X	126.72	78.4285	7.9354	1.7381	0.0013
N	-108.9554	-41.9425	-27.5844	-0.6689	-0.0063
R	0.0217	-0.0032	-0.0016	1.09E-04	-6.56E-07
SD	39.633	0.2737	0.1036	0.01	1.15E-04
X	267.3864	11.5556	1.1740	0.2574	0.0026
N	-255.5415	-6.1963	-4.0812	-0.1537	-0.0022
R	0.0183	-0.0041	-0.0015	3.47E-04	-3.54E-06
SD	0.7158	0.4247	0.1603	0.015	6.49E-05
X	20.2256	18.1014	1.8403	0.4035	7.78E-05

N	-10.9853	-9.7104	-6.3973	-0.1553	-0.0016
R	-0.005	7.27E-04	3.56E-04	-0.2657	1.46E-07
SD	0.1067	0.0619	0.0235	0.0023	2.62E-05
X	**0.8659**	1.4007	0.9235	0.0351	4.95E-04
N	-2.9068	-2.6075	-0.2657	-0.0583	-5.92E-04
R	0.0095	-0.0016	-7.15E-04	7.90E-05	-1.22E-06
SD	0.2257	0.1409	0.0527	0.0046	2.19E-05
X	6.8994	6.1544	0.6238	0.1367	1.20E-05
N	-1.9327	-3.295	-2.1684	-0.0526	-5.30E-04
R	-0.0071	0.0011	4.87E-04	-4.90E-05	4.90E-07
SD	0.2867	0.092	0.0348	0.0031	2.30E-05
X	12.6295	2.1511	1.4238	0.0347	3.73E-04
N	-7.2916	-3.9761	-0.4095	-0.09	-4.47E-04
R	0.0061	-0.0012	-4.71E-04	7.90E-05	-1.08E-06
SD	0.1941	0.1111	0.0416	0.0036	2.13E-05
X	5.4327	4.8567	0.4932	0.1081	2.78E-04
N	-3.4191	-2.6036	-1.7146	-0.0416	-3.89E-04
R	-0.0025	5.73E-06	1.42E-04	5.28E-05	-1.14E-06
SD	0.1298	0.0534	0.0226	0.0036	7.26E-05
X	1.4456	1.3759	0.8201	0.1031	0.0015
N	-5.4783	-2.135	-0.4683	-0.0742	-0.0017
R	-0.0104	0.0023	8.41E-04	-1.81E-04	2.69E-06
SD	0.3744	0.2303	0.0864	0.0079	7.27E-05
X	4.9001	5.3084	3.4919	0.0847	0.0016
N	-11.1385	-9.9229	-1.0045	-0.22	-0.0013
R	0.003	-5.89E-04	-2.42E-04	3.85E-05	-5.16E-07
SD	0.0867	0.0559	0.0208	0.0018	9.53E-06
X	2.7668	2.4552	0.2476	0.0542	1.01E-04
N	-0.7297	-1.3103	-0.8608	-0.0209	-1.95E-04
R	-0.0026	2.27E-04	6.17E-05	-2.64E-05	4.49E-07
SD	0.1048	0.0284	0.0109	0.0012	1.83E-05
X	1.6742	0.6017	0.3962	0.0183	4.30E-04
N	-3.0682	-1.1229	-0.2025	0.0183	-3.59E-04
R	-0.0292	0.0056	0.0023	-3.68E-04	4.97E-06
SD	0.8429	0.5262	0.1966	0.017	9.40E-05
X	7.2905	12.3359	8.1194	0.197	0.0018
N	-25.809	-23.0341	-2.3357	-0.5118	-0.0011
R	0.0028	-8.36E-04	-2.42E-04	9.14E-05	-1.53E-06
SD	0.2247	0.0999	0.0384	0.0041	5.94E-05
X	4.4841	4.0201	0.6544	0.0898	0.0012

N	-6.9321	-2.1588	-1.4231	-0.0592	-0.0014
R	-0.0299	0.0042	0.0022	-9.81E-05	-9.79E-08
SD	0.6662	0.3542	0.1356	0.0144	2.06E-04
X	6.12	7.6747	5.0534	0.2856	4.00E-03
N	-16.3108	-14.3205	-1.4537	-0.3186	-0.0048

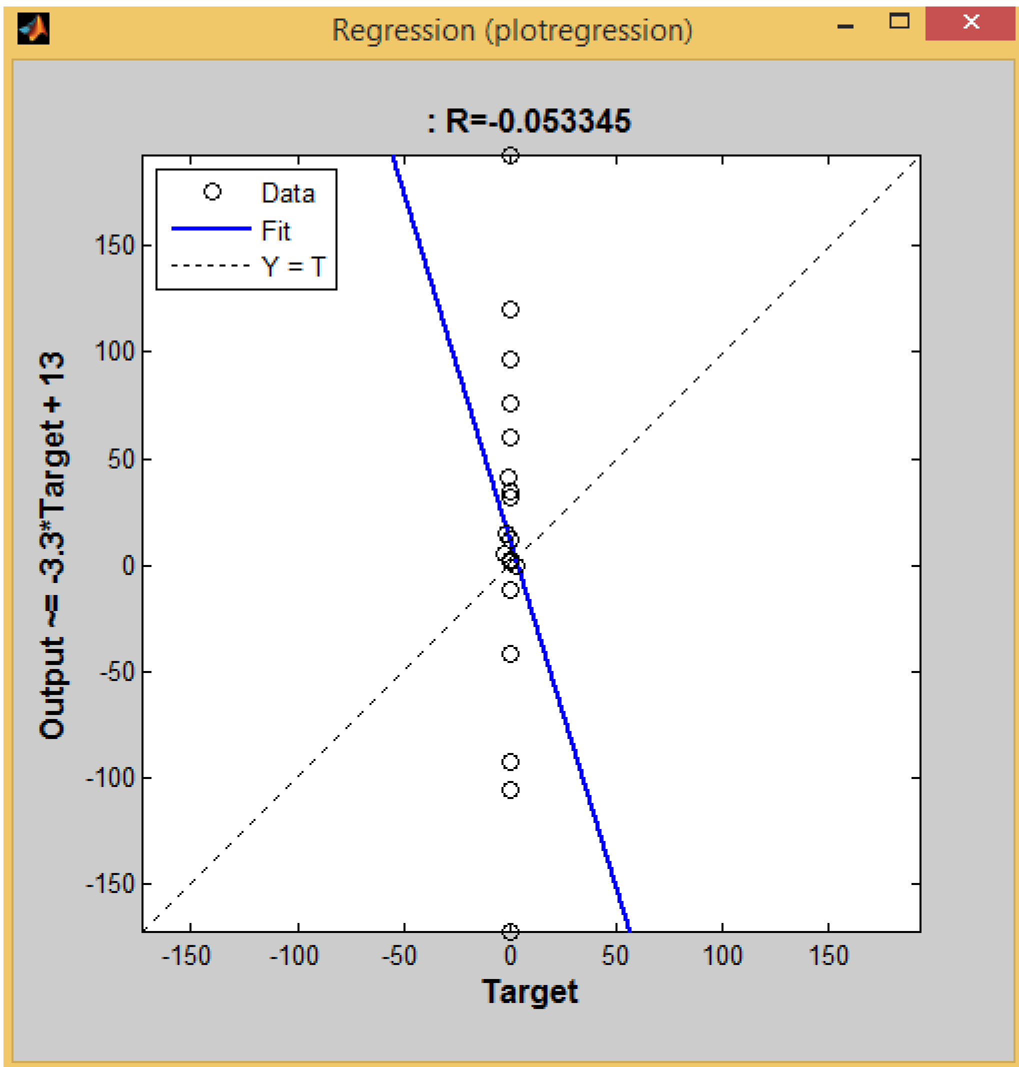


Figure (5.3): Abnormal patient regressions

Table (5.4): Abnormal patient regression

Number Patient	Value FFB Regression	Regression value CFB
1	0.407	0.374
2	0.551	0.533
3	0.457	0.42
4	0.186	0.349
5	0.31	0.224
6	0.087	0.248
7	0.597	0.173
8	0.818	0.711
9	0.789	0.731
10	0.632	0.551
11	0.534	0.267
12	0.386	0.33
13	0.144	0.201
14	0.564	0.356
15	0.341	0.271
16	0.445	0.577
17	0.358	0.404
18	0.067	0.15
19	0.229	0.387
20	0.504	0.759
21	0.46	0.329
22	0.555	0.832
23	0.242	0.796
24	0.225	0.503
25	0.783	0.643
26	0.515	0.456
27	0.735	0.716
28	0.448	0.361
29	0.641	0.615
30	0.435	0.435
31	0.706	0.291
32	0.719	0.718
33	0.212	0.17
34	0.522	0.258
35	0.536	0.378
36	0.1055	0.285
37	0.338	0.562

38	0.483	0.23
39	0.167	0.499
40	0.686	0.715

5.1.3 Performance Analysis

For checking the results the accuracy, sensitivity and specificity for FFBP and CFBP are calculated from table (5.2) and (5.4) using four categories output which are true positive (TP), false positive (FP), true negative (TN) and false negative (FN). This performance analysis is given in table (5.5).

Table (5.5): Performance analysis

Categories	FFBP	CFBP
Sensitivity	96.61%	98.31%
Specificity	100%	100%
Accuracy	95%	96.67%

5.2 Discussion:

Comparison of FFBP and CFBP Network values from table (5.2), table (5.4) and table (5.5) shows that good performance is obtained in both Feed-forward Backpropagation (FFBP) and Cascade-forward Backpropagation (CFBP) networks. The FFBP network was trained to get an overall regression, R = 0.8358, while the CFBP network with same topology gives a better performance of R = 0.963. These results were obtained after many training, validation and performance evaluations.

From the results it is evident that the CFBP network is better compared to the FFBP network.

CHAPTER SIX

CONCLUSION AND RECOMMENDATIONS

6.1 Conclusions:

In this research a method for the analysis of EEG for detection normal and abnormal signal using wavelet based features has been presented. As EEG is a non stationary signal the wavelet transform gave good results. After wavelet decomposition at level 4 using Daubechies wavelet of order 2, the four statistical features minimum, maximum, mean and standard deviation were computed over the wavelet coefficients at each level.

Minimum, Maximum, Mean and Standard deviation in a sample window are successfully used to train the neural network to detect the Abnormality in signals. The performance of the CFBP network is better compared to the FFBP networks in classifying a signal. This contribution presented a new application of the neural network classifier to detect the normal and abnormal in the EEG signal.

6.2 Recommendations:

From the results obtained it is recommended to use (CFBP) for classification to detect the normal and abnormal in the EEG signal.

For future studies it is recommended that:

1- Activating real time analysis.
2- Try it with more cases of EEG signal and Use different type of features.

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APPENDIX A

Wavelet code:

```
s=Z001(1:4097);
[C, L]=wavedec(s, 4,'db2');
cA4 = appcoef (C, L,'db2', 4);
cD1 = detcoef (C, L,'db2', 1);
cD2 = detcoef (C, L,'db2', 2);
cD3 = detcoef (C, L,'db2', 3);
cD4 = detcoef (C, L,'db2', 4);
A4 = wrcoef ('a', C, L,'db2', 4);
D1 = wrcoef ('d', C, L,'db2', 1);
D2 = wrcoef ('d', C, L,'db2', 2);
D3 = wrcoef ('d', C, L,'db2', 3);
D4 = wrcoef ('d', C, L,'db2', 4);
figure,Subplot (5, 1, 1);
plot(A4)
title('Approximation A4');
subplot (5, 1, 2);
plot(D1)
title ('Detail D1');
subplot (5, 1, 3);
plot(D2)
title ('Detail D2');
subplot (5, 1, 4);
plot(D3)
title ('Detail D3');
subplot (5, 1, 5);
plot(D4)
title ('Detail D4');
w=D1+D2+D3+D4;
figure,plot(w)
% thresholding and reconstruction
sdenoise=wden(w,'heursure','s','mln',4,'db2');
eeg=sdenoise;
figure,plot(sdenoise);

R=mean(eeg)
S=std(eeg)
```

X=max(eeg)
N=min(eeg)

MATLAB code to get the regression:

```
 net=setx(net,w);
y=sim(net,a1);
r=corrcoef(y,l);
R=r(1,2)
```

MATLAB code for data classification

```
fprintf('enter the data\n');
X=input('enter ur data as matrix');
X(1)=((x(1)-15)/(45-15+1));
X(2)=((x(2)-0.5)/(1.5-0.5+1));
X(3)=((x(3)-3.5)/(5-3.5+1));
X(4)=((x(4)-135)/(140-135+1));
X(5)=((x(5)-8.6)/(10.3-8.6+1));
X(6)=((x(6)-2.5)/(5-2.5+1));
X(7)=((x(7)-2)/(7-2+1));
net=setx(net,w);
y=sim(net,x);
r=corrcoef(x,y);
z=r(1,2)
R=abs(z)
If 1> R> 0.5
      disp('The patient is normal')
Else
      Disp('The patient is abnormal')
end
```

APPENDIX B

Data Acquisition:

The device used is EEG from SIMtechno ltd.co with specification below:

Sample-rate options: (sample rate is adjustable by user)	2048 Hz	4096 Hz	8192 Hz	16,384 Hz
Max. number of channels @ selected sample rate:	280	280	280	152
Bandwidth (-3dB):	DC - 400 Hz	DC - 800 Hz	DC - 1600 Hz	DC - 3200 Hz
Low-pass response	5^{th} order sinc digital filter			
High-pass response	fully DC coupled			
Digitalization:	24 bit, 4^{th} order Delta-Sigma modulator with 64x over sampling, one converter per channel			

To make a recording of 64 channels at 256 Hz sample rate:

- Select speed mode 4. The AD-box will sample 256 channels at 2 kHz.

- In Act View (at the right bar) select a decimation of 1/8. So the sample rate will be 2048/8 = 256 Hz.

- When saving in Act View, select to save only 'A1-B32 (64)' so Act View will save 64 channels.