An-Najah National University

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Feature Extraction of EEG Signal to Classify Epileptic Signal Using Neural Network

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Dedication

To my mother, father, wife aseel, daughter rasha, sister, uncle and my brothers with respect and love.
Special thanks to Dr. Mohannad Jazzar who spent his time and efforts while writing this thesis.
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I would also thank my family members, my parents, my wife, my sisters my uncles and my brothers for their support.

الإقرار

أنا الموقع أدناه مقدم الرسالة التي تحمل العنوان:

Feature Extraction of EEG Signal to Classify Epileptic Signal Using Neural Network

أقر بأن ما اشتملت عليه هذه الرسالة إنما هو نتاج جهدي الخاص، باستثناء ما تمت الإشارة إليه حيثما ورد، وان هذه الرسالة ككل أو من جزء منها لم يقدم من قبل لنيل أية درجة أو بحث علمي أو بحثي لدى أية مؤسسة تعليمية أو بحثية أخرى.

Declaration

The work provided in this thesis, unless otherwise referenced, is the researcher's own work, and has not been submitted elsewhere for any other degree or qualification.

Student's name: **اسم الطالب: عصام معتصم جزار**

Signature: **التوقيع:**

Date: **التاريخ: 2020/9/7**

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List of Symbols and Abbreviations

Φ_{EEG}	Vector of EEG potentials
F	Frontal lobe
C	Coronal lobe
O	Occipital lobe
T	Temporal lobe
δ	Delta wave
θ	Theta wave
α	Alpha waves
β	Beta wave
FT	Fourier Transform
WT	Wavelet Transform

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Abstract

Electroencephalogram (EEG) is the electrical signal associated with the communication of the brain neural cells. It is used to evaluate and test the electrical activity of the brain. Consequently, it can be used to detect abnormalities associated with this activity such as epilepsy. Epilepsy, characterized by recurrent seizures, is one of the most common neurological disorder that affect people at all ages. It is associated with abnormal electrical activity in the brain. One way to detect and diagnose epilepsy is by using electroencephalogram (EEG) signal since it contains enough information to characterize the disease.

We designed an algorithm capable of automate the process of identifying epileptic seizures and classifying it into three classes: normal, interictal, and ictal. The four-stage pipeline consists of a preprocessing stage, a wavelet transformation stage, a feature extraction stage, and a classification stage. The wavelet transformation stage is used to process the signals in order to prepare them for feature extraction stage. Then, statistical features are extracted from the coefficients of the wavelet transformation. Nine features were extracted and used in the classification of the signals using the Artificial Neural Network.

To evaluate the performance of our model we used several measures includes: accuracy, sensitivity, and specificity. Using 300 brain signals and carrying proper calculations, we identified 144 epilepsy cases, and 156 non-epileptic cases. The accuracy, specificity, and sensitivity of our model are 81%, 80%, 84% respectively. The project provided a method to solve problems resulted from epilepsy diagnosis

Chapter One

Introduction

This chapter introduces the problems that we solved, the importance of their problems, and the main objectives of the thesis.

1.1 EEG Signals

An electroencephalogram (EEG) is a signal that carries information about the activity resulting from brain electricity generated by the cerebral cortex nerve cells [5]. Figure (1.1) below shows an EEG recording for a healthy people.

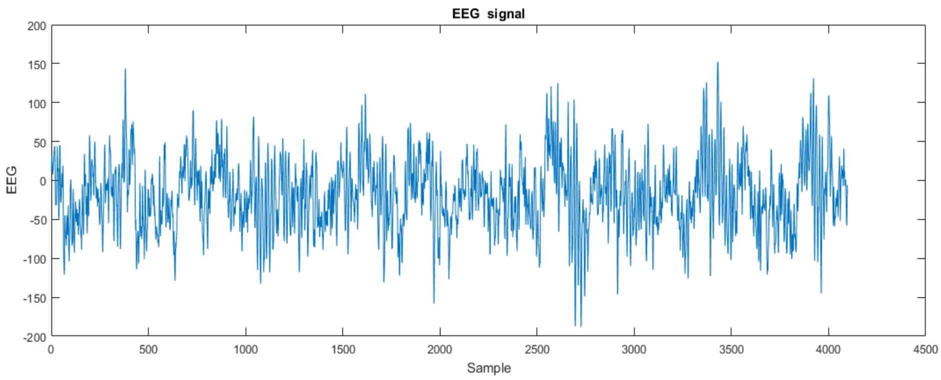

Figure (1.1): EEG Signal

It is possible to use EEG signal to detect and identify any abnormal neuronal activity which can be a guide of a neurological disorder. The EEG can be measured from the interior and exterior sides of the skull. The measurements from the exterior part are maintained by electrodes on the scalp, whereas the recordings from the interior of the skull are examined by keeping electrodes on the cortex of the brain [6]. Using signal processing techniques, recent research extracts information that can be used as an indicator of epilepsy [7].

EEG signals are classified into four basic waves [7], Delta wave, theta wave, alpha wave, and beta wave.

1.2 Epilepsy

Epilepsy is one of the most common neurological disorders. About 3% of the world's population is infected. It appears to affect people at different ages in their life [1]. It is a sudden brain failure where the disease disposes the function of neurons within the brain. Seizures can occur randomly and repeatedly disrupting the brain's function [2].

Epilepsy is a common disease with an estimated 65 million patients worldwide [3]. There are 0.5 patients infected with the disease and at least 5% have one seizure during their lifetime. Approximately 30% of epileptic patients do not respond to medication. This may lead to major complications for the patients such as sudden falls on the ground and sometimes rapid death due to lack of rapid treatment [3].

Seizure is an excess increase in brain electricity. The seizure can last for several seconds to a few minutes. Epileptic seizures are caused by a temporary defect in the activity of brain electricity and approximately one in every 100 Patient will experience a seizure at some point in their life [4]. Seizures are divided into two types: Partial seizures and generalized seizures. Partial seizures affect part of the brain leading to temporary paralysis, whereas, generalized seizures affect the entire brain and cause loss of consciousness [4].

Diagnosis is one of the most difficult stages of epilepsy patients for two main reasons: First, the patient may have seizures without the occurrence of any obvious symptoms, such as convulsions, and the absence of awareness, as epileptic seizures may occur at the brain level without the appearance of seizure symptoms on the patient. The second reason is that, if the patient has an epileptic seizure does not necessarily make him an epileptic patient. Many people may experience a one-time epileptic seizure in their lives. Thus, epilepsy needs to be diagnosed accurately and early in order to reach the appropriate treatment plan for the patient, to improve his life [1].

The EEG record can be classified into four classes: inter-ictal (between seizure), pre-ictal (before the seizure), ictal (during seizure), and post-ictal (after seizure and before return normal brain state).

1.3 Problem Statement

Epilepsy is a sudden electrical brain failure occurring randomly and repetitively, so seizures are surprising and, sometimes occur without any symptoms indicating the seizures. It may cause embarrassment to the patient especially if it is in a meeting or job interviews etc., if there is a seizure, the patient sometimes accompanied by some physical damage, such as fractures, or head bulge as a result of falling to the ground.

Repeated seizures often damage the brain cells, then the seizures recur throughout the day, so the patient's life becomes nil. In this study, we focused on brain signals to analyze them, and extract features that help detect epilepsy to help patients avoid seizures.

1.4 Objective of the Study

The main goal of this study is to apply machine learning algorithm to EEG signals to automate the process of identifying epileptic seizures and classify them into three group: normal, ictal, and inter-ictal. This can be useful in preventing the seizure from happening through medication. However, preparing the EEG signals through noise removal for features extraction is complicated and can result in a major error. Therefore, we will propose and test a method for feature extraction from EEG signal.

1.5 Benefits of the Study

- The most important benefits of this project is that it has become possible to identify and classify epileptic seizures to normal, ictal, and inter-ictal.
- Detection of seizure helps in the use of an appropriate medication to prevent seizures, but if the seizure is not properly detected, the number of seizures may increase and become more dangerous.
- Brain electricity is very important for epilepsy detection, because it contains a large amount of data that can be analyzed to detect patterns associated with epilepsy. So we analyzed this signal and used it in the analysis process to form support for the decision of the specialist doctor.

1.6 Structure of the thesis

This thesis consists of seven chapters that include theoretical project principles as well as the practical stages of the project ending with the appendix containing the script. We have mentioned in the first chapter

(Introduction) the reasons that led us in this direction, the importance of the project and the benefits of the project and from where we got the data. In the second chapter we have discussed some of the previous researches and studies, what methods were tried and how the methods of treatment and work algorithms were developed. As the third chapter deals with the project algorithm in its entirety, in addition to what each phase and its objective included, as well, the results obtained after each process. The fourth chapter discussing the methodology and the pipeline of the project. In the fifth and sixth (practical section) we have explained the technical aspect and the tools used from the software platforms and the instructions needed to access the classification genie. As chapter seven and eight included the results and recommendations.

Chapter Two

Literature Review

2.1 Introduction

This chapter provides a brief review of the literature on the diagnosis of epilepsy and the algorithms used in the diagnosis process. Also, we present a brief review about the brain waves and EEG signal as a background.

2.2 Related Work

EEG signals have been studied and diagnosed in recent years. Artificial Neural Networks have been widely used in the diagnosis process of neurological disorders due to their rapid processing, analysis, time reduction, and accuracy [20]. The related works in the literature is presented as follows:

Neural network method:

J. Gotman et al. 1979, J. Gotman, 1982, J. Gotman, 1999, Koffler et al. 1985, and Qu et al., 1993 used sharp wave recognition technology to analyze EEG signals [21-22].

Subasi 2001, used discrete wavelet transform, a new method in the process of wave analysis, he also classified the waves by ANN method using DB4 filter to get 5 levels[23].

Wang et al. 2001, extracted features using an entropy based wavelet method and k-nearest neighbor (KNN) classifier in training phase [24].

Wang et al. 2001, extracted features using an entropy based wavelet method and k-nearest neighbor (KNN) classifier in training phase [24].

Suba et al. 2005, neural networks were used and developed to classify epilepsy from EEG recordings. Inputs were EEG signals and two types of output (epileptic seizure and nonepileptic seizure). The algorithm provided high accuracy in the classification [27].

Tzallas et al. 2008, analyzed segments of EEG signals using TF, they used features as inputs of ANN. They obtained 99% accuracy in classification of the EEG signals [32].

Guo et al. 2009, develop an ANN-based analysis of EEG signals using relative wavelet energy. The accuracy rate classification was (95.2%) [33].

Guo et al. (Guo et al., 2010) They used neural network classifier (NN) and discrete wavelet transform (DWT) to classify the line length of EEG signal and they achieved the accuracy of 97.77% for all (ABCD-E) dataset [36].

Tezel and Ozbay. 2011, they used several models of neural networks with adaptive activation function to detect epileptic seizures. All models were trained to find the best model and obtained an average sensitivity of100% for all models [37].

Swami et al. 2016, used all statistical factors such as larger, smaller, standard deviation, entropy, and energy, they also applied general regression neural network (GRNN). The accuracy for non-seizure vs. seizure was 99.18%, whereas, the accuracy for normal vs. seizure was 98.4 % [40].

Statistical method:

Hojer Adeli et al. 2002, used a new technique to detect epileptic seizures, he also used the wavelet chaos methodology to analyze and perform different electrical brain waves: delta, theta, alpha, beta, and gamma waves, and applied the algorithm to several categories for healthy people and epileptic subjects during seizure [25].

Akın et al. 2004, developed an algorithm to diagnose epilepsy and applied wavelet transform to EEG signals and developed an algorithm for neural networks that diagnosed the disease. The diagnostic accuracy rates obtained were 97% for epilepsy, 98% for health, and 93% for pathological records [26].

Kannathal et al. 2007, used Entropy as input to adaptive neuro-fuzzy inference system (ANFIS). The classification accuracy obtained was about 90% [28].

Guler and Ubeyli. 2007, used the support vector machine (SVM) to diagnose epilepsy, and use neural networks, probabilistic neural network (PNN), and multilayer perception neural network (MLPNN), to find the best classification of the disease, which was the probabilistic neural network (PNN) and support vector machine [29].

Polat and G¨une¸s. 2007 used Fast Fourier Transform and decision tree to classify epileptic seizures from EEG signals. They obtained 98.72% classification accuracy [30].

Subasi. 2007, used wavelet Transform (WT), and classified it using ANFIS method. He obtained specificity 93.7%, and sensitivity 94.3% classification accuracy [31].

Hasan Ocak, 2009, used discrete wavelet transform and approximate entropy (ApEn) for the analysis of EEG signals, he was able to detect epilepsy up to 96% accuracy [34].

M. Akin, M. Arserim, M.K.Kiymik, I.Turkoglu, 2010, used a new technique to detect epilepsy where he extracted the frequencies theta, alpha, beta, and gamma by using wavelet transform. The accuracy of the neural network output was 97% for epilepsy [35].

Gandhi et al. (Gandhi et al., 2011) they used data on the German University of Bonn site classified for 5 levels of ABCD-E and used standard deviation, entropy and energy features from EEG signals using discrete wavelet transform, accuracy 95.44% [38].

Acharya et al. 2012, used entropy with several different classifiers, the best classifier was Fuzzy Sugeno classifier. Where the worst performing classifier is Naive Bayes Classifier [39].

Previous studies aimed to diagnose epilepsy from EEG recordings and classified them into epileptic, and non-epileptic seizures quickly and accurately. Whereas, the use of several applications and algorithms was to help in the detection of the disease quickly and accurately.

Chapter Three

Biology of the Brain

1.3 Introduction

In this chapter, we reviewed the anatomical and physiological profile of the brain, the brain circuits, and some neurological brain diseases. We also present a short review about epilepsy.

3.2 Brain anatomy

The nervous system is divided into two parts: the central nervous system (CNS), and the peripheral nervous system (PNS). CNS is made of brain and spinal cord, the brain is present within the cranial cavity of the skull, and the spinal cord is present within the vertebral cavity of the vertebral column, whereas, the PNS refers to the nervous system outside the CNS. PNS divided into autonomic nervous system and somatic nervous system. Autonomic nervous system is divided into sympathetic and parasympathetic [41].

The involuntary human actions, such as the heartbeat, breathing, and digestion, are controlled by the brain subconsciously by the autonomic nervous system. However, voluntary movements such as thinking and reasoning are controlled consciously by Somatic nervous system [41-43].

The brain weight is about 3 pounds (1.4 kg). It is one of the largest organs of human body in which it consists of neurons (about 100 billion cells) that are connected to each other through neural synapses that store information, where the brain can store approximately 10^ 97 of information. The brain consumes about 15% percent of the blood circulation. The heart pumps 7200 liter daily in which 1080 liter daily flows to the brain and consumed [41-43].

The human brain is divided into three main sections :**Prosencephalon (**It consists of two parts: Telencephalon and Diencephalon), **Mesencephalon**, and **Rhombencephalon** (It consists of two parts: Metencephalon and Myelencephalon).

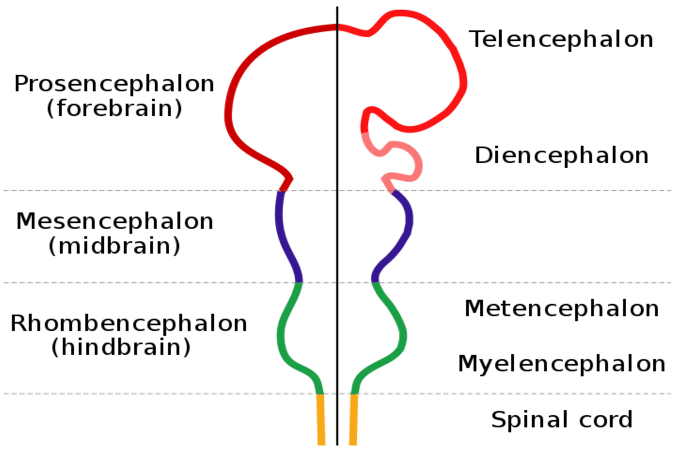

Figure (3.1): Human brain section [42]

3.3 Telencephalon

It constitutes 85 % of brain weight. It is divided by a longitudinal section called the longitudinal incision that divides brain into two parts, the right hemisphere and the left hemisphere. Each half is divided into four lobes: Frontal lobe, Parietal lobe, occipital lobe, and temporal lobe.

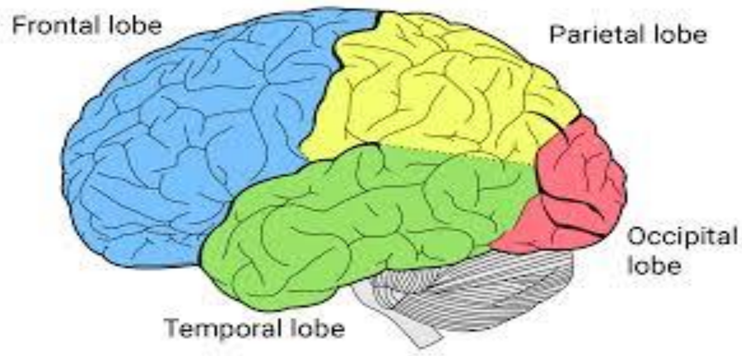

Figure (3.2): Human brain parts [42]

3.4 Diencephalon

Contains major controlling centers in body.

3.5 Cerebellum

Is the part of the brain responsible for balance, stability and movement coordination, it consists of a large mass of brain cells**.**

3.6 Brain stem

It is the part that connects the brain to the spinal cord, it contains nerve centers that control breathing, heart beat and many of the body's vital processes [42].

3.7 Brain Cells

Contains (10~ 100) billion neurons, all these neurons are presents during the first months of birth. The performance of all mental and physical functions depends on the existence and preserving of neural networks. The person's habits and skills, such as nail biting (onychophagia) and musical sense, are embedded in the brain within the neural networks [41-43].

3.8 Protection of the Brain

The brain is protected by the skull – a thick and hardened skeleton - from strikes that may cause serious injury. In addition, the brain is covered by three protective membranes called the meninges, also it is cushioned and protected by cerebrospinal fluid [41-43].

3.9 Electroencephalography

The brain contains (20) billion nerve cells that work side by side and producing nerve impulses in neuron synapses. Where these neurons works simultaneously, their neural conductivity (amplitude) is measured by in micro volts (where the brain signal amplitude does not exceed 300 micro volts). The frequency of its electrical signal is measured in Hertz. Those two factors: amplitude and frequency are the distinctive traits of brain waves.

These weak electrical signals can be measured from the surface of the scalp by electrodes placed on the crust of the scalp and with the help of a conveyor material (special ointment) [44]. After amplification of this signal by amplifiers, it can be entered into the computer where it is analyzed and obtains its capacity and frequency. This is called electroencephalography or EEG.

3.10 10-20 system

This system is named by 10 – 20 System, because the distance between any two adjacent electrodes is 10-20% of the total distance between two reference points. The distance between the electrodes is used rather than the fixed distances due to skull size variation from person to person. For each electrode (according to the system of the global electrode placement system (10 – 20) a special name defined by a letter that expresses the name of the region –on which the electrode is located – and a special number. For example, the electrodes located in the frontal lobe are expressed as F, while the electrodes extending along the upper region of the head, mid coronal plane, are represented by the letter C, while the electrodes located in the mural area are represented by the letter P, the electrodes in the occipital region are represented by the a letter O and the temporal electrodes are represented by the letter T [18].

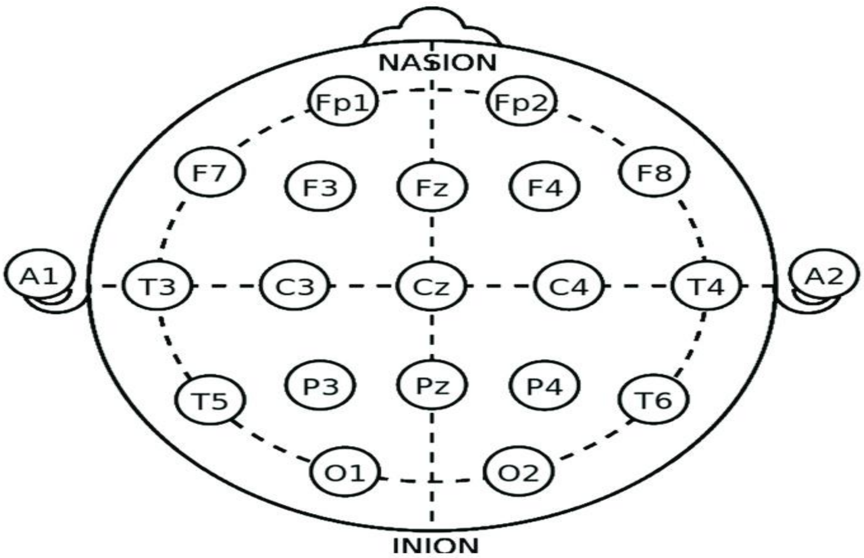

Figure (3.3): Distribution of electrodes according to the global system 10-20[19]

3.11 Brain waves

EEG signals are classified into basic waves [7]. These waves are shown in Figure (3.4) and described below:

1) **Delta wave (δ):** Frequency of 0.5 to 3.5 Hz, is present in the frontal area of adults and in the posterior area of young children and in serious organic brain diseases. It is characterized by high amplitude (Wavelength), and it is more active in children and in deep-seated sleep in adults [45-47].
2) **Theta wave (θ):** They contain frequencies between 3.5 and 7.5 Hz. These waves occur mainly in the parietal and temporal areas in children. Sometimes they occur at emotional stress, especially during periods of frustration, depression, and drowsiness
3) **Alpha waves (α):** They contain frequencies between 7.5 and 12 Hz. Located in the back of the head, it is higher in the back and side. It appears and increases during the rest and sleepiness, and also in the case of drowsiness while eyes are closed, these waves are in all normal persons and are also in the relaxed and rest states. Alpha waves are recorded from the parietal and frontal regions of the scalp.
4) **Sensory Motor Rhythm – Wave (SMR):** Frequency of 12 – 15 Hz appear in cases of attention, concentration and working conditions [45-47].

5) **Beta wave (β):** It has frequency of 15 – 30 Hz, it's located on the side of the head but it is clearer in the front of the head, and characterized by low amplitude (Wavelength) and appears in the case of attention, work, and focus and in deep thinking [45-47].

6) **Gamma wave:** Has a frequency of 20-40 Hz, appears in learning situations [45-47].

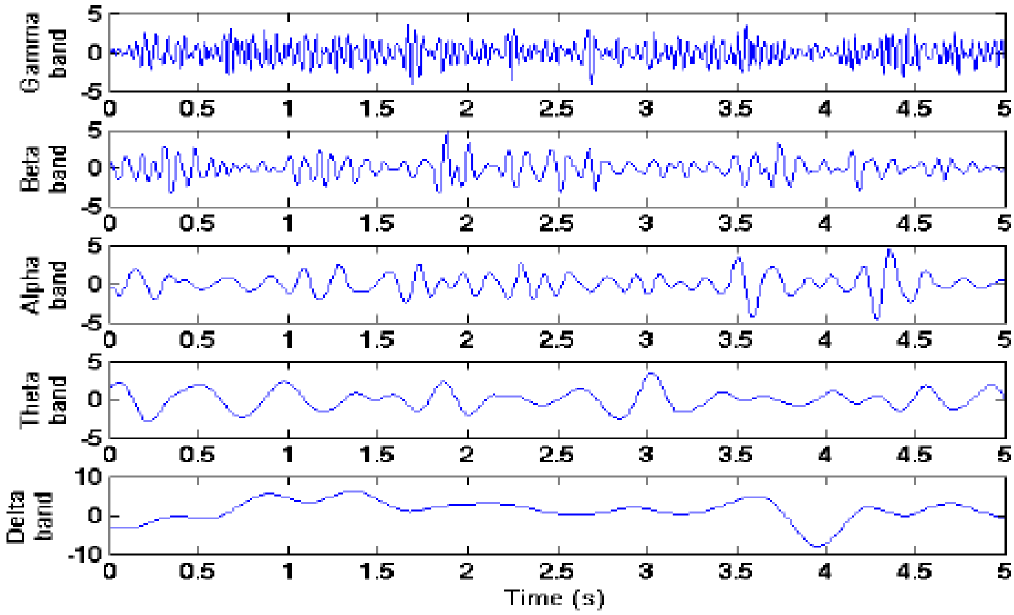

Figure (3.4): The five frequency bands of EEG signal

3.12 Brain Disorders

Injuries, diseases and inherited traumas can damage the brain, but the risk of damage depends more on the affected area than the cause. Disorders, that destroys brain cells for example, are very dangerous; because the body cannot compensate for the infected cells, but sometimes the areas that have not been damaged may perform some of the functions of the damaged areas [48-50].

Modern devices and techniques have enabled doctors to diagnose brain Disturbances early and more accurately than in the past. The EEG device, measures the patterns of electrical activity generated by the brain. Differences in the normal patterns of the brainwave diagram may indicate brain damage and may help determine the area of injury [49].

The computer-aided brain-electric scheme can monitor and organize large amounts of electrical data and can also measure the brain's response to certain visual, auditory and tactile effects. Scientists can diagnose the trajectories by comparing these results with the average results from a large number of people [49].

Brain disorder types:

1) **Genetic disorders:** Genes (the genes that are inherited in cells) carry the orders of growth of the body, including the brain. These commands are very complex, so errors may occur and may lead to a malfunction in the composition of Brain functions. Some babies have mental retardation at birth, because of errors in Genetic factors led to abnormal growth of the brain during pregnancy. In Down syndrome, for example, there is a redundant chromosome (chromosomes are bodies within the nucleus of the cell containing genes) in which it causes mental retardation and physical defects [48-50].
2) **Multiple Sclerosis:** Multiple sclerosis occurs when the axes of the brain or spinal cord lose the myelin membrane. As a result, the axon cannot carry the nerve impulses. Acute areas of the affected brain may vary,

and may include loss of balance, double vision, and weaken arm or leg. There is no cure for this disease, but some drugs may alleviate some of the symptoms, and some may slow the loss of myelin [48-50].

3) **Parkinson's disease:** It is characterized by slow motion, muscle stiffness and tremor. These conditions result in the destruction of nerve cells [48-50].

4) **Epilepsy:** Victims of epilepsy suffers from bouts that occur when many nerve cells -in a particular area of the brain- produce unusual nerve impulses. These seizures cause temporary nobility to control muscle movement and loss of consciousness [48-50].

3.13 Definition of epilepsy

Is a temporary obstruction or disruption of the intensity, speed and flow of electrical signals in the brain that results in partial or total obstruction of the brain's electrical processes. Therefore, it causes the response of some physical organs to random or erroneous contact, resulting in temporary seizures that the body cannot control or stop (non-recurrence). These seizures are known as epileptic seizures [48-50].

3.14 Rates of infection

The ratio of active epilepsy among the general population at a given time ranges from 4-10 per 1,000 populations. Some studies in developing countries indicates that the proportion of people infected with the disease ranges from 10 to 1000 per person. There is around 50 million people are infected all over the world [49].

The rate of new annual cases in developed countries ranges from 4 to 70 per 100,000 population among the general public [48-50]. In developing countries this rate is almost double because of the high risk of disease that can lead to permanent damage to the brain. The developing regions incidence of about 90% of the cases of epilepsy which are recorded all over the world [48].

3.15 The epileptic seizure

Is the occurrence of temporary obstruction in a function of the brain (Or several combined functions), in which it happens suddenly and usually for a specified period of time (may last for minutes), then ends abruptly, as the beginning and the end of it have no clear limits, and the EEG shows people with epilepsy abnormal electrical traction. At some point in the brain or circulating on all parts of the brain, these abnormal electrical impulses lead to dysfunction of the brain or a small part of it. This cycle leads to convulsive convulsions with different forms [50].

3.16 Type of epilepsy

Epilepsy can be classified into two types: general epilepsy (30% of cases), and partial epilepsy (70% of cases). What happens during the epileptic seizure is fundamentally different in each type? In some seizures, the patient has only sudden loss of consciousness. It may be accompanied by severe muscle seizures in the hands, feet or all muscles of the body [48-50]. Or the patient may pass hallucinations, or have visual tricks or appear to have intense emotions without reason, these symptoms can occur together [48-50].

3.16.1 General Epilepsy

It is also called as major seizures or tension, that is characterized as the spread of the activity of the armpit to include the brain as a whole and in which the patient loses fully consciousness, and may be accompanied by urination, and increase in salivary secretions. Symptoms of general seizure: loss of consciousness and fall, spasm, salivary secretions, Coma and muscle relaxation may occur with urination, vomiting, Confusion when awake, and the period of the seizure is (3-4) minutes but sometimes it is possible to wait (20) minutes before returning to the original condition [50].

3.16.2 Partial epilepsy

It is also called partial epileptic seizure, in which the activity of the thyroid is limited in the center of the brain without covering the brain as a whole. The partial epilepsy is manifested in a specific area of the brain. The symptoms vary according to the affected area. Sometimes it is difficult to know that this is an epileptic seizure. Partial epileptic seizures are either simple or complicated depending on the condition of the patient if he maintains contact with his surroundings or not. The patient can return into a general epileptic seizure, where the electrical storm begins in a specific area of the brain, then spreads to the rest of the brain. Symptoms of partial epilepsy are: the patient maintains contact with reality, suffers from various problems (difficulty speaking properly, cramps and trembling of organs, distortion of audio and visual), sensory problems (different smell and taste), stomach problems, sense of mine and fear. The duration of the shift extends from two to three minutes [48-50].

3.17 Causes of epilepsy

There are many mysterious aspects about the causes of seizures. Epilepsy was not known to modern knowledge of medicine, therefore, all the causes of the disease where not reached, some causes were known, but the rest of these reasons were unknown, as so as the drugs up to date. The followings are some of epilepsy causes [48-50]:

1) **Organic cause**

Which leads to damage to some brain cells causing fibrosis, the incidence rate to 25% of cases of epilepsy and these factors:

- Lack of oxygen during childbirth
- Brain Injuries from Accidents
- Brain hemorrhage
- Inflammation of the brain or meningitis
- Disturbances in brain tissue

2) **Epilepsy has no organic cause**: it is called self-epilepsy occurs in about 50% cases
3) **Inheritance**: The disease is common in the families of one third of people with epileptic seizures
4) **Unknown reasons**.

3.18 Diagnosis of Epilepsy

The subject of diagnosing epilepsy can be divided into several interlocutors that may be combined or separated as follows:

1. **Clinical examination:** Clinical history and clinical examination by the brain and neurologist, including hearing the story of what happened exactly from a witness -not the patient- who was present at the time of the incident. This is because the patient is often unconscious such as when the seizures began, the patient's condition any unusual actions he has performed, and also the doctor reports the health history of the patient's family [48-50]**.**
2. **EEG Test:** The doctor performs an electrical drawing of the brain by means of a device that accurately records the electrical activity of the brain by means of wires that are fixed on the patient's beds. The electrical signals of the nerve cells are recorded in the form of electrical waves. This procedure is repeated to monitor the episodes of the disease and the electrical waves during the epileptic nucleus. The doctor in the detection of the disease, the result may be that the situation is normal because the abnormal electrical activities occur at a deeper distance in the brain, that is, deeper than the possibility of imaging. Many people who do not have epilepsy have epileptic activity when electrocardiograms are drawn. This does not necessarily mean that they have seizures [48-50].

3.19 Protection

Epilepsy is a disease that cannot be prevented, but protection can be provided to reduce epilepsy. Protection can be provided via:

- Protect the head from bruising.
- Provide health care during childbirth to reduce the risk of childbirth.
- Provide appropriate medication to reduce epileptic seizures.

Chapter Four

Background and Material

4.1 Introduction

The brain signal processing area is one of the most vital areas and draws attention to the importance of brain electricity. It contains a lot of information about the activity of the brain, and all the disorders it may have. Brain planning is the first step in detecting epilepsy. And support medical supervision. In this chapter, the evolution of the methods of treatment in this field to the current development.

4.2 Signal Processing

In signal processing, the Fourier Transform (FT) has always been the first step in addressing any single or two-dimensional signal. Despite Fourier transform is capable to transmit signals from time domain to frequency domain and vice versa, however, it is limited to provide information about time and frequency only [50].

Short Time Fourier Transform (STFT), has been a tremendous advance in obtaining information on both frequency and time. Despite its progress, Fourier transform give a specific point related to time and frequency. So, Wavelet Transform (WT) came. So, in our project, we have studied the effectiveness of wavelet transform in the processing of brain electrical signals to obtain accurate information that can be analyzed and extracted from them for use in advanced diagnostic applications.

As computational analytical methods are getting more advanced, the method of brain signal processing becomes varied and more data are obtained from them. Most methods relied on the analysis of brain electrical signals by converting wavelets to main brain waves that is: alpha, beta, theta, gamma, and Sensory Motor Rhythm (SMR). This information provide certain characteristics associated with epilepsy disorder. The obtained characteristics could be an intelligent system through which we can detect normal from abnormal signal.

4.3 Use wavelet transform to get brain waves

Wavelet Transform is a process of signal decomposition to be analyzed and processed, and a small wave change with the change of demands of this wavelet and its location on the signal [8]. Wavelet transform provides a clear and accurate picture about certain signal frequencies and about time of these frequencies and their association with used wavelet.

We will explain the reason for the use of Fourier transform of short time, to obtain information about the signal at time and frequency levels on the same time, where fourier transform was not able to do so [51].

4.3.1 Fourier Transform

It is a way to represent the periodic signal using the sine and cosine series, then developed the non-periodic signals. Therefore, Fourier transform transfers the signal from time domain to frequency domain and vice versa [51].

$$x(f) = \int_{-\infty}^{+\infty} x(t).e^{-jwt}.dt \qquad (4.1)$$

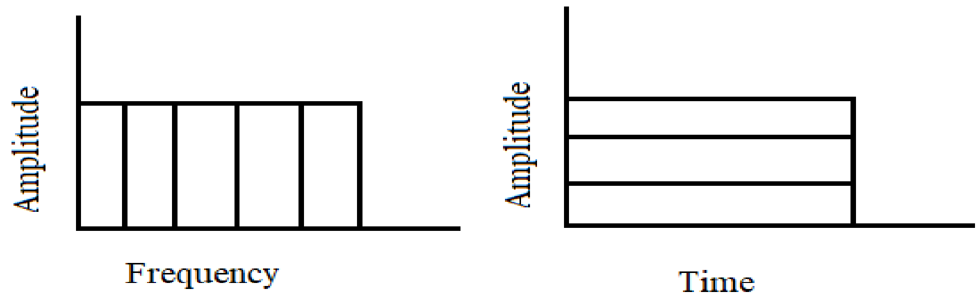

Figure (4.1): Frequency signal representation b: time signal representation [58]

But the problem is that Fourier transform becomes ineffective for discrete signals, because it does not give any information about time while monitoring frequency. For this reason, Short Time Fourier Transform (STFT) was developed [58].

4.3.2 Short Time Fourier Transform (STFT)

This Transform solves the previous problem by using a fixed width window where it represents the time and frequency of the signal on the basis of its time and frequency accuracy in accordance of the type of windows used [58].

The window is moved along the signal via multiplying the signal by windows factor along time series, and the conjugate number transfers signal from time domain to frequency domain.

The problem with this transformation is time and frequency losses. When using a small window, high precision is obtained for elements that change rapidly, while this resolution is not high for slowly changing elements, and the opposite happens when a large window is used [58]. Although, a short-time Fourier transform gave an idea about the characteristics of the signal processed at the time and frequency level, it gave an approximate, and inaccurate picture. When using a similar application in processing brain power signals that contain a lot of information, it was the wavelet transform that gave more accurate better result [52-53]. Thus wavelet transformation was developed.

4.3.3 Wavelet theory

It is a mathematical analytical method used to process signals for many practical applications, the basis of this theory is the product of Fourier's work, knowing that a lot of development has been done on the basic theory.

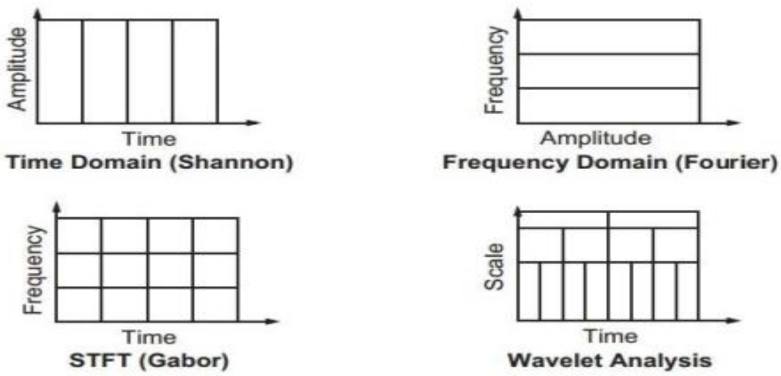

Figure (4.2): Comparison of FT, STFT and Wavelet analysis of a signal [58]

By using this transform, the problem of short-time Fourier transform (mentioned in previous paragraph) was solved, as this transform was developed to use a variable width window instead of using a fixed width window, the width of the window is changeable to obtain information of different frequency along the wavelength. Therefore, wavelength constants, whose frequency varies depending on the width of the window, were used. As figure (4.3) shows.

Figure (4.3): Variable width wavelet window [58]

The small window produces a compressed wavelet that contains high-frequency elements, known as detailed factors. The large window produces an extended wavelet that contains low-frequency elements, known as approximate factors.

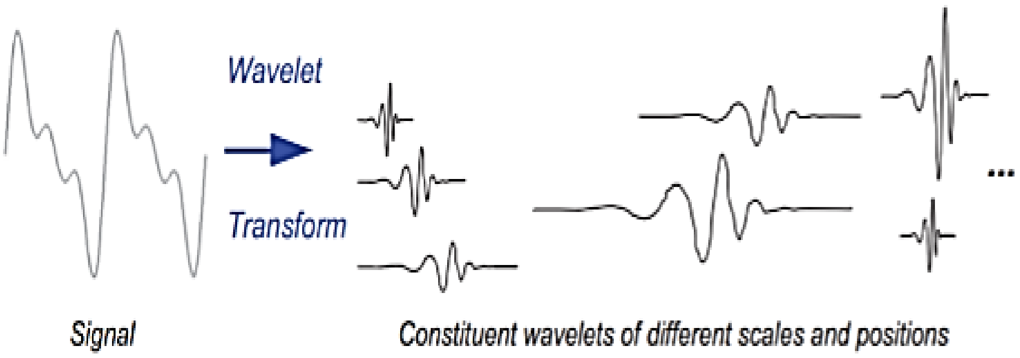

Figure (4.4): Wavelets with different levels and positions of the signal [58].

A wavelet can be defined as a time-limited signal with an average value of zero, the following figure shows examples of a few wavelets used

.

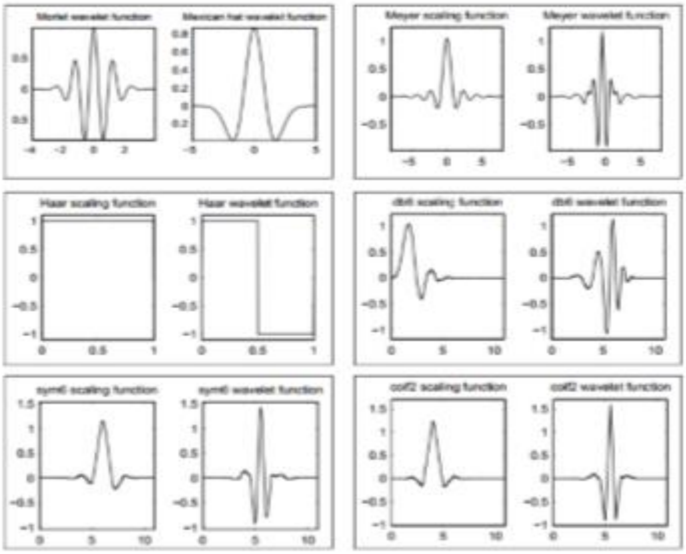

Figure (4.5): Different wavelet types [58]

There are two kinds of wavelet transforms: continuous wavelet transforms and discrete wavelet transform.

4.3.4 Continuous Wavelet Transform (CWT)

Wavelet transform also known as continuous wavelet transform, mathematically expressed by the following equation (4.3):

$$w(a,b) = \int_{-\infty}^{+\infty} x(t)\psi_{a,b}\,(t)dt \qquad (4.2)$$

$$\psi_{a,b}\,(t) = \frac{1}{\sqrt{a}}\psi(\frac{t-b}{a}) \qquad (4.3)$$

Where (a) $\psi a, b$ called mother wavelet, and it is a continuous function in both the time domain and the frequency domain called the mother wavelet and the over line represents operation of complex conjugate. The main purpose of the mother wavelet is to provide a source function to generate the daughter wavelets which are simply the translated and scaled versions of the mother wavelet. To recover the original signal x (t) the first inverse continuous wavelet transform can be exploited [58].

The analysis is performed in a manner similar to STFT, where the window is shifted along the signal for a specific gradient (window width), and the process is repeated for different gradients.

The problem of this technique is the massive number of wavelets produced due to the use of all gradients in analysis process, and huge amount of information produced due to the same reason, therefore, the processing procedure required a very long time. This problem has been solved by developing Discrete Wavelet Transform (DWT).

4.3.5 Discrete Wavelet Transform (DWT)

The main difference between DWT and the continuous wavelet transform is that it uses a specified number of gradients rather than conducting the transform for all gradients. This is done by selecting, time intersections in signal, thus it produces enough information to adjust a little time of calculation and maintain the basic information that described the signal (i.e. without losing important information from the signal) [58].

The mathematical difference between the DWT equations, CWT is in the mother wavelet expressed in the DWT conversion

$$\Psi j,k\ (t) = \frac{1}{\sqrt{a_0^{-j}}}\Psi\left(\frac{t-ka_0^{-j}b_0}{a_0^{-j}}\right) \qquad (4.4)$$

Mother wavelet in DWT, Were:

j,k are Integers

a_0 Is the degree of delay and it's a constant value. $a_0 > 1$

b_0 Is the displacement factor and it's a constant value $b_0 > 0$ and according to Shannon's theory a_0 is equal to (2) and b_0 equal (1).

Table (4.1): Comparison between CWT and DWT

CWT	DWT
A lot of information about the need	Little and sufficient information
Many wavelets are redundant	Wavelets are few and sufficient
Large computation time	Small computation time
Used for infinite energy reference	Used for all signals

Studies have shown that continuous wavelet transform takes a very long time, and large computer processors to perform the required operations. While discrete wavelet transform deals with the electrical signal of the brain, as a digital signal with a specific rate of cutting and then provides all the information needed in a small time and a few computer processors [54].

4.3.6 Wavelet types:

4.3.6.1 Haar wavelet:

It is one of the easiest wavelets, which were defined by the Hungarian researcher Haar in 1909. The equation is known as:

$$\Psi(t) = \begin{cases} 1 & if\ 0 \le t < 0.5 \\ -1 & if\ 0.5 \le t < 1 \\ 0 & otherwise \end{cases} \tag{4.5}$$

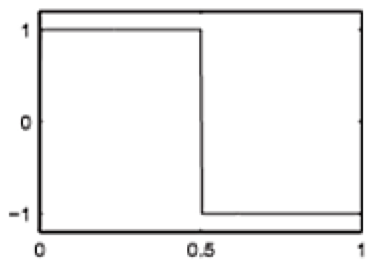

Figure (4.6): Haar wavelet [58]

4.3.6.2 Mexican Hat:

It the negative normalized second derivative of a Gaussian function, used in WT.

$$\Psi(t)= (1-2t^2)e^{(-t^2)} \tag{4.6}$$

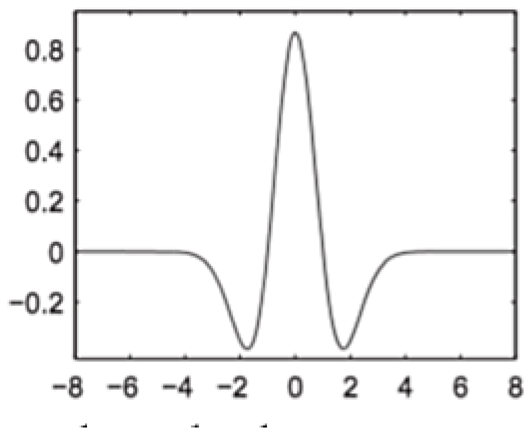

Figure (4.7): Mexican hat wavelet [58]

4.3.6.3 Daubechies wavelet

Daubechies Wavelet widely used in solving a wide range of problems such as Properties of subjective similarity or repetition problems, signal interruptions, etc.

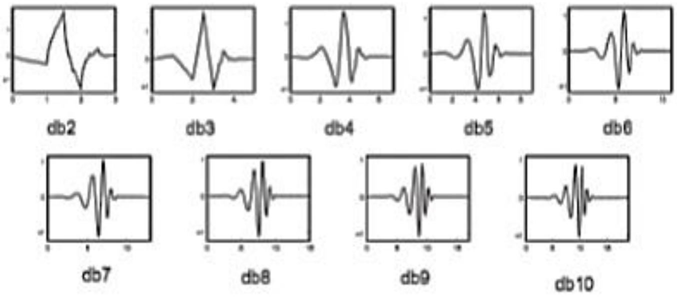

Figure (4.8): Group of wavelets of a Daubechies family with different windows [58].

In this thesis we will use discrete wavelet transform, because it provides a sufficient information from signals.

4.3.7 Signal decomposition and reconstitution

Signal decomposition is the division of the signal into approximate and detailed coefficient. These coefficient (approximate and detailed) form the wavelengths produced by multiplying the studied signal by the mother wavelength. Since wavelengths have different frequency spectrum from the original signal, they are carried out by inserting it into filters.

Sequential sets of low-pass filters and high-pass filters are used. A high-pass filter produces detailed coefficient, while a low-pass filter (with a scale factor) produces approximate coefficient, (The scaling function is used to obtain the detailed coefficient from the approximate coefficient until we reach the required level of analysis.

At each analysis stage, a half-beam pass filter (high and low) produces signals with a frequency range equals half of frequency domain of the original signal. This doubles the frequency accuracy of the signal, which means that more signal details can be obtained at each analysis stage, as shown in Figure (4.9).

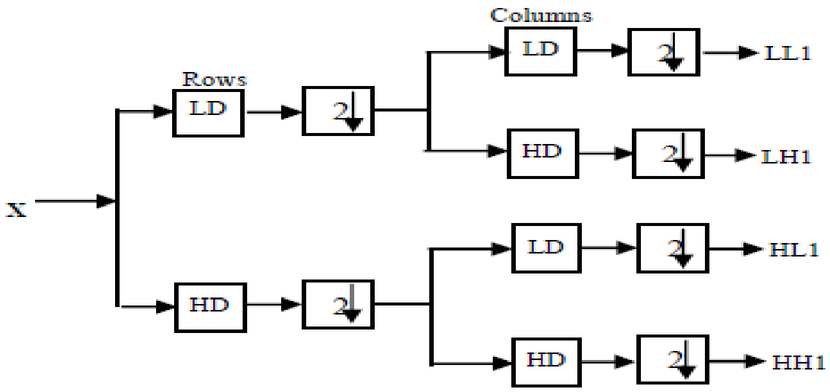

Figure (4.9): Wavelet Filter bank for one-level Signal Decomposition [58]

The original signal is obtained by sequential aggregation of all previously generated factors (approximate and detailed coefficient) starting from the last analysis phase.

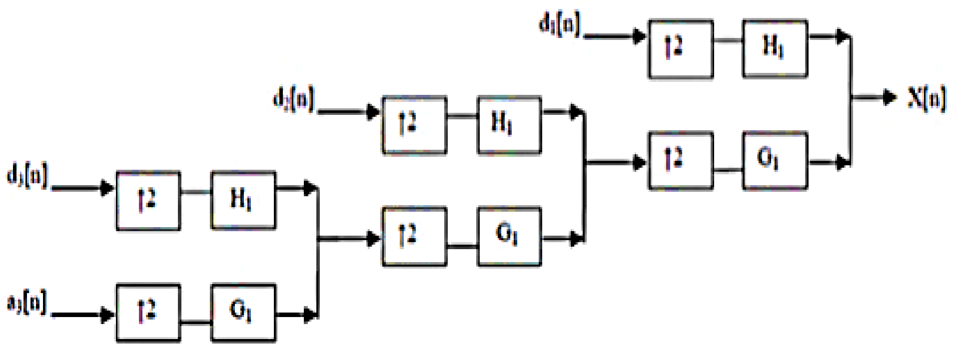

Figure (4.10): reconstitution the original signal from approximate and detailed coefficient [58]

The recombination process is carried out by inserting the above factors into the low and high pass synthesis filters and then aggregating. This process continues with the same number of stages of analysis until the original signal is obtained.

4.4 Feature extraction from EEG signal

All previous studies based on features extraction resulting from wavelet transform, where the transform divides the signal into two parts; detailed coefficient, and approximate coefficient, the transformation parameters are then adopted as feature of their characteristics and as input to the neural network [55] [56].

Recent studies also based on the statistical extraction of features, such as finding maximum and minimum values, and standard deviation. This method provided additional information about the signal and the accuracy of the system. These features gave good signal information, but using these features are not enough to get a good diagnosis sometime, because these features are linear whereas the brain signal is nonlinear [55].

4.5 Using neural networks to build a system capable of recognizing abnormal signals

The artificial neural network imitate human brain in data processing, and neural networks are one of the most important artificial intelligence techniques in use today, and are the result of the attempts of scientists and researchers to imitate, and simulate the work of the brain in the processing and interpretation of data. It has many applications ranging from classification, pattern recognition, grouping [55].

The human brain contains a huge amount of neurons. Neuron are connected to each other, creating a complex network of neurons intended to transmit signals. Each cell collects inputs from all other neurons associated with it, and if it reaches a certain limit, it indicates all the cells are connected to it.

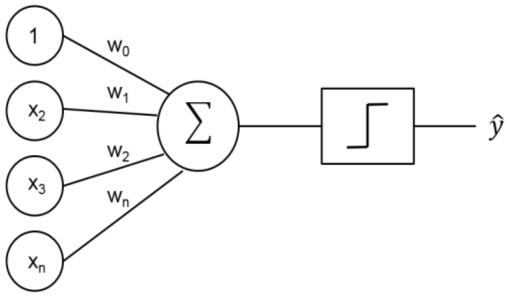

Figure (4.11): A graphical representation of a simple perceptron. Here y is the output signal, Φ is the activation function, n is the number of connections to the perceptron, wi is the weight associated with the ith connection and xi is the value of the ith connection[17].

When writing an ANN, this is imitation by using a”perceptron” as the basic unit instead of the neuron. The perceptron can take several weighted inputs and summarize them, and if the combined input exceeds a threshold it be activated and send an output. The output sent is determined by the activation function and is often chosen to be between 0 and 1, or −1 &1. As shown in figure (4.12), it’s a very simple design, and its strength can be shown when several perceptron's are combined and work together. The perceptron's are often organized in layers, where each layer takes input from the previous, applies weights and then signals to the next layer if appropriate[56].

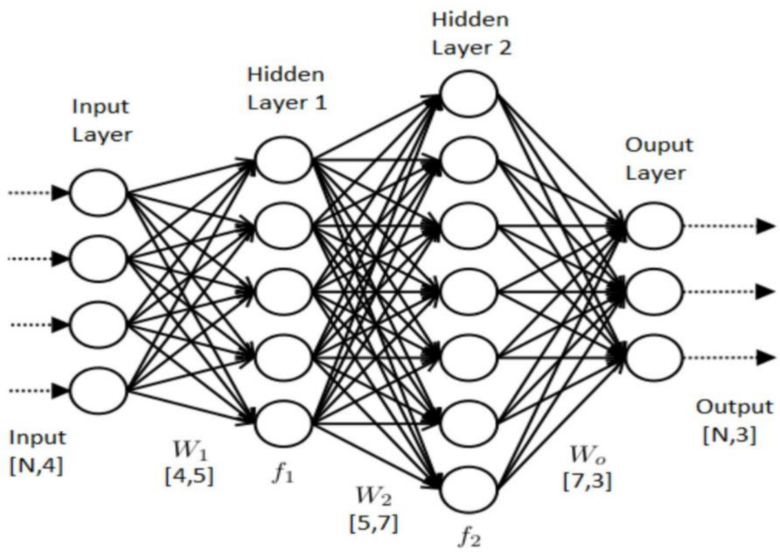

Figure (4.12): Neural networks with input layer and output layer and hidden layer [57]

As shown in figure (4.12), neural networks must be able to learn from examples and adapt, for ANN, this is achieved by updating the weights associated with the connections between the layers. There are several methods of doing this, and most involve initializing the weights and fed the network an example. The error made by the network at the output is then calculated, and feed backwards through a process called "back-propagation”. This process is then used to update the weights, and by repeated use of this process, the network can learn to distinguish between several different classes. The exact equations involved vary from case to case.

Neural networks and statistical pattern recognition methods are used in detection of epilepsy patients, because traditional methods of detecting disease such as reading EEG records are tedious, time-consuming, and error-tolerant. So, many systems have been developed to detect epilepsy in recent years. Similarly, different Artificial Neural Network (ANN) based classification systems for epileptic diagnoses have been suggested by several researchers. ANN method includes: features, nominal, average EEG amplitude, average EEG duration, coefficient of variation, dominant frequency, relative spike amplitude, average power spectrum, periodogram, spectral entropies, autoregressive (AR) features, as inputs to different types of ANN like, adaptive structured neural network, learning vector quantization (LVQ) Elman network (EN) and probabilistic neural network (PNN) [9-16]. The advance Artificial Intelligence (AI), machine learning, pattern recognition algorithms, and classification were employed to detect patterns associated with the disease, through artificial neural networks.

Scientific advances and methods have been evolved in building diagnostic systems. Where there is scope to always improve the performance and development of the built-in system, previous and current studies to change the details, and then compare the results with the previous to determine which should be followed in future research. The goal is to access an integrated system and high reliability that identifies epilepsy through treatment brain electrical signals, and identification of the characteristics of the disease, especially when the person does not pass an epileptic seizure and during seizure [57].

Finally, it became easy to recognize (ictal) signals during seizure. So, the challenge was to detect signals of epilepsy in patients who are not passes through the seizure (inter-ictal) at the moment of recording brain diagnoses .In other words, searching for subtle changes in the brain’s electrical energy that are associated with clear epilepsy features and outside the times of epileptic seizure. By doing so, we will be able to classify a group of random signals to of three groups: healthy, ictal and interictal.

Chapter Five

Methodology

The Computer Aided Diagnosis (CAD) [62] is a method used to help to increase accuracy of the doctor's diagnosis, and achieving early detection and diagnosis of pathological lesions. These techniques help in detecting diseases and obtaining the correct diagnosis before the doctors makes the final diagnosis, So, in thus study, we offer a computer-based method to diagnose epilepsy invasively which can be used in pre-surgical planning.

In this chapter, we present a four-stage pipeline that we used to diagnose patients with epilepsy from EEG data recordings. The four-stages are: 1) preprocessing, 2) wavelet transformations, 3) feature extraction, and 4) classification. The four-stages pipeline is summarized in a block diagram shown and each stage described below.

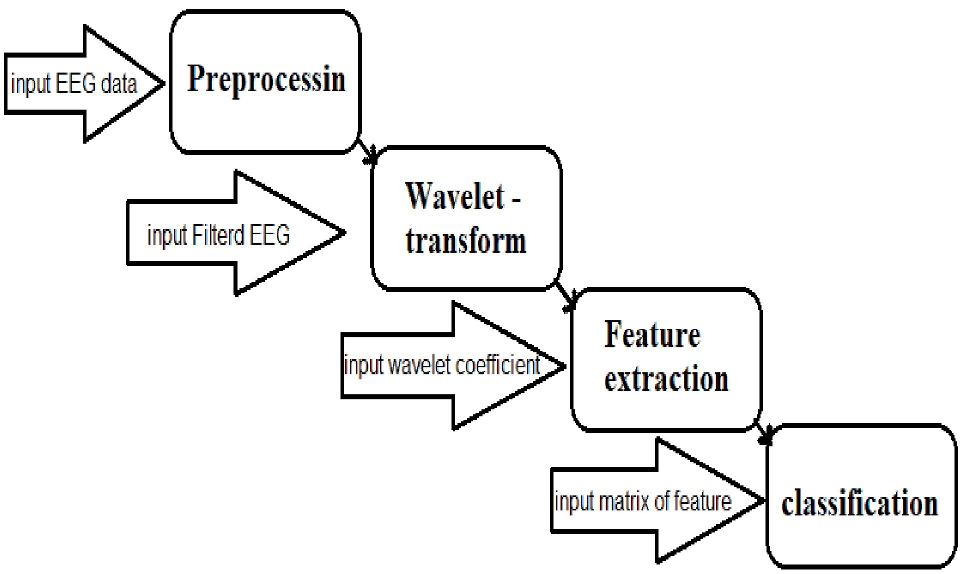

Figure (5.1): a four-stage pipeline (methodology) that we used in our model

5.1 Preprocessing

In this stage, noise removal filter is applied to the EEG signal to remove noise and a band pass filter (BPF) is applied to keep frequencies in the range of 0.5 – 40 Hz which is the range where epilepsy occurs.

Our research and data collection is based on the data and research work done by Dr. Andrzejak [18].

The data presented contains five sets of data (A, B, C, D, E) for healthy and diseased signals. Group A and B contain normal EEG data (group A with eye open, group B with eye close). Group C and D contain interictal activity, and EEG signals recorded from the hippocampal formation and the epilepsy region. Only group E has the area of the epileptic activity, group C, D and E carrying data from patients with epilepsy.

Data are obtained using 19 surface electrodes placed in accordance with the international 10-20 system. Each subset of this dataset contains 100 text files for the split EEG signals. The length of each signal is 23.6 seconds, and a total of 4097 samples at a sampling rate of 173.61 Hz.

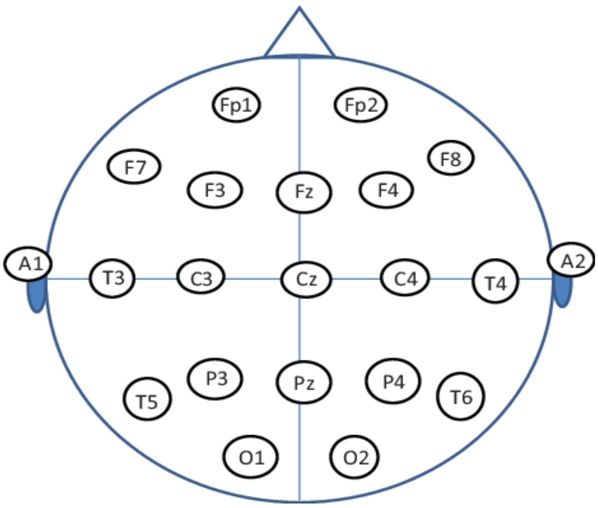

Figure (5.2): Electrodes position and 10–20 system (EEG) [19]

5.2 Wavelet Transform

Purpose of using wavelet transform is to get features in the frequency to be used in machine learning classification. The processing of a signal by Fourier transform (which transmits the signal from time domain to frequency domain and vice versa) is ineffective for discrete signals, because it does not give any information about the time in the frequency domain. This is why the Short Time Fourier Transform (STFT) was developed. However, STFT methodology has a problem in loosing time and frequency, because it depends on using fixed windows, therefore wavelet Transform has been developed in which it uses a variable width window [58].

5.3 Feature Extractions

Wavelet coefficients extracted from the EEG signal representing (frequency-time) for signal. Some statistical features can be extracted from wave coefficients, these extracted features are used to represent (Frequency - time) of EEG signal:

5.3.1 Mean

Calculates the mean or arithmetic mean by adding the values of the elements of the group to find their mean, and divides the sum by the number of elements.

$$\bar{x} = (\Sigma x_i) / n \tag{5.1}$$

4.3.2 Median

The median is the middle number in a sorted, ascending or descending, list of numbers and can be more descriptive of that data set than the average.

$$X_m = X_n \frac{n+1}{2} \tag{5.2}$$

5.3.3 Mode

Calculates the most frequency value of the signal.

5.3.4 Maximum and Minimum Values

Find the largest signal and the smallest signal

5.3.5 Range

It is the difference between the maximum and minimum value of the data.

5.3.6 Standard Deviation

A standard deviation is a measure of dispersion based on finding the difference between the values of each point individually, and the arithmetic mean of the sum of points. The standard deviation process requires several processes, which are summarized by the following mathematical law.

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - x)^2} \tag{5.3}$$

Were: σ is standard deviation $, n\ no. of\ point , x\ mean$

5.3.7 Absolute Deviation Median and Mean

The absolute deviation of the median in statistics is a measure of sample variation from quantitative data. The absolute mean deviation is a measure of statistical dispersion. Both the absolute and median deviations are calculated by the following equations.

$$y1 = \text{median}\ (|x - \text{median}(x)|) \tag{5.4}$$

$$y0 = \text{mean}\ (|x - \text{mean}(x)|) \tag{5.5}$$

5.4 Classification

There are several ways to classify the signal according to the characteristics extracted after being analyzed. The most famous of them are Neural Networks (NN) and Support Vector Machines (SVM). So in this thesis we want to use neural networks in Matlab tool using (nntool).

Neural networks are an information processing system inspired from the human central nervous system, especially the brain. Neural networks are developed such as human biological cognitive processes. In other words, teaching computer to think and solve problems [57] [17].

The neural network consists of a large number of processing units called neurons. Where each neuron binds to other neurons with connections. Each connections or link has a weight; each neuron has a mathematical function attached to it called Activation function. Each neuron sends the resulting output to the rest of the neurons through the communication links, after multiplying the resulting output by the link weight [57] [17].

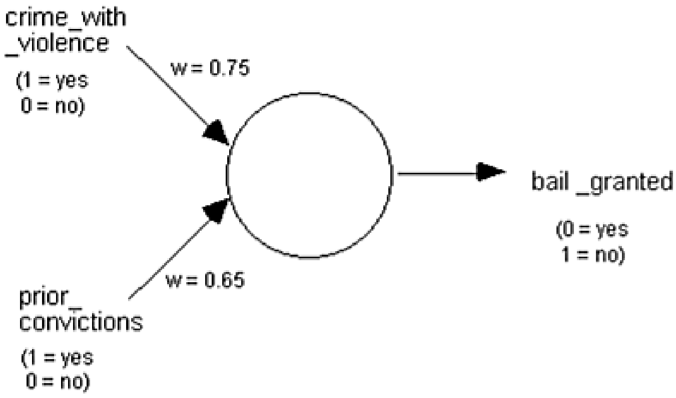

Figure (5.3): A representation of a neuron from the neural network that has two inputs with different scales and gives one output [57].

Chapter Six

Procedure

6.1 Introduction

This chapter describes the computational environment and the main computational tools that we used in conducting this research. In this thesis, we used Matlab software and its wavelet transform and machine learning tool boxes. First, we loaded the EEG signals, and then we used the wavelet transform toolbox to transform the signal from the time domain to the time-frequency domain. Then, the several features of the time-frequency transformed signal are computed. These features are used to train a machine learning algorithm.

6.2 Computational Environment

MATLAB is a popular computational environment that allows performing complex calculations and simulates various systems easily. It has various toolboxes that can be used in science and engineering. It is also used in developing algorithms, simulation and designs various systems. Also, it supports 3D visualization.

We chose Matlab environment because it is the easiest and one of the most productive computing environment for scientists. The Matlab language is the only programming language that is dedicated to scientific computing. Matlab arranges data in matrix form, as it has a rapid response, so it can be used to solve most complex arithmetic problems easily and in a short time.

Matlab includes a collection of libraries, where each library is called toolbox. A toolbox allows the user to handle specialized applications. In the following subsection we describes the toolboxes and the main functions that we used in this project.

Wavelet toolbox

The wavelet toolbox provides a set of functions shown in Figure (6.1). These functions can be used within a script or other matlab functions. The toolbox provides tools for analyzing and synthesizing signals and images, as well tools for statistical applications.

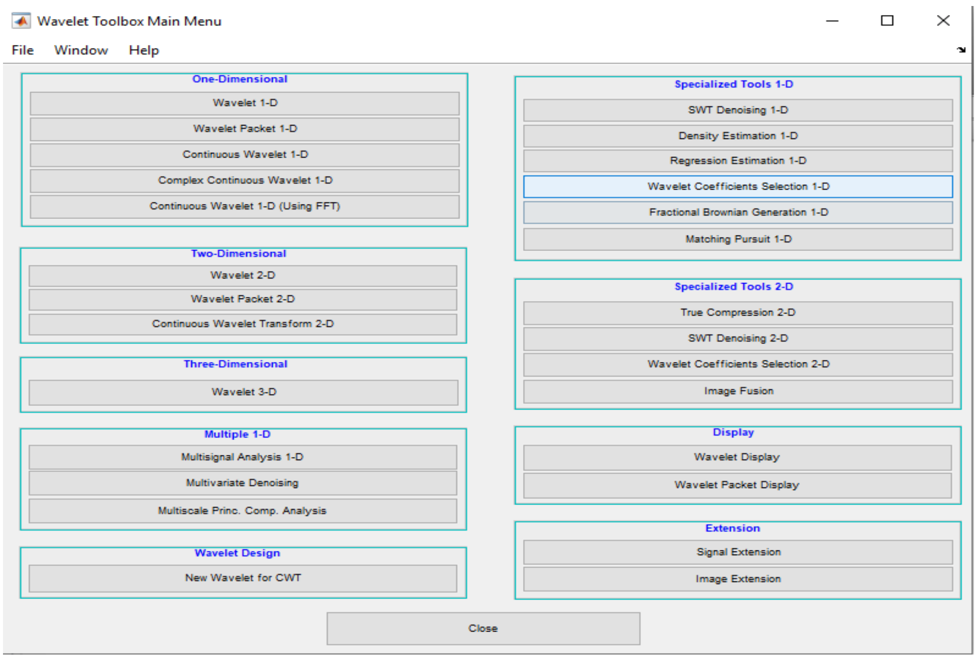

Figure (6.1): Wavelet toolbox menu

6.3 Reading EEG signals

The first step in this project is to obtain and load the EEG signal to the computer program. For this project, we used EEG records provided by University of Bonn database [63]. The data sets consist of five groups (A, B, C, D, E). Each group contains 100 records of brain signals for a particular kind of subjects. Each record spans a 23.6 seconds. Groups A and B contain signals obtained from the surface of the cerebral cortex of five healthy volunteers. Groups C and D contain EEG records of patient subjects between seizures. Group D contains EEG signals recorded from the epileptic region (epileptogenic zone) while the signal in group C is recorded from hippocampal in the opposite half of the epilepsy area. Finally, group E contains signals of a patient subject that includes seizure activities.

All signals are recorded with an amplified system (128 – channel). All signals were converted from analogue to digital using 12-bit analog-to-digital converter. The sampling frequency is 173.61 Hz.

The data set is available in text format, where each group consists of 100 text file. Each text file that contains the 23.6 seconds EEG recording. The following figure shows the first 500 samples of brain signals (Ictal, Interictal, healthy):

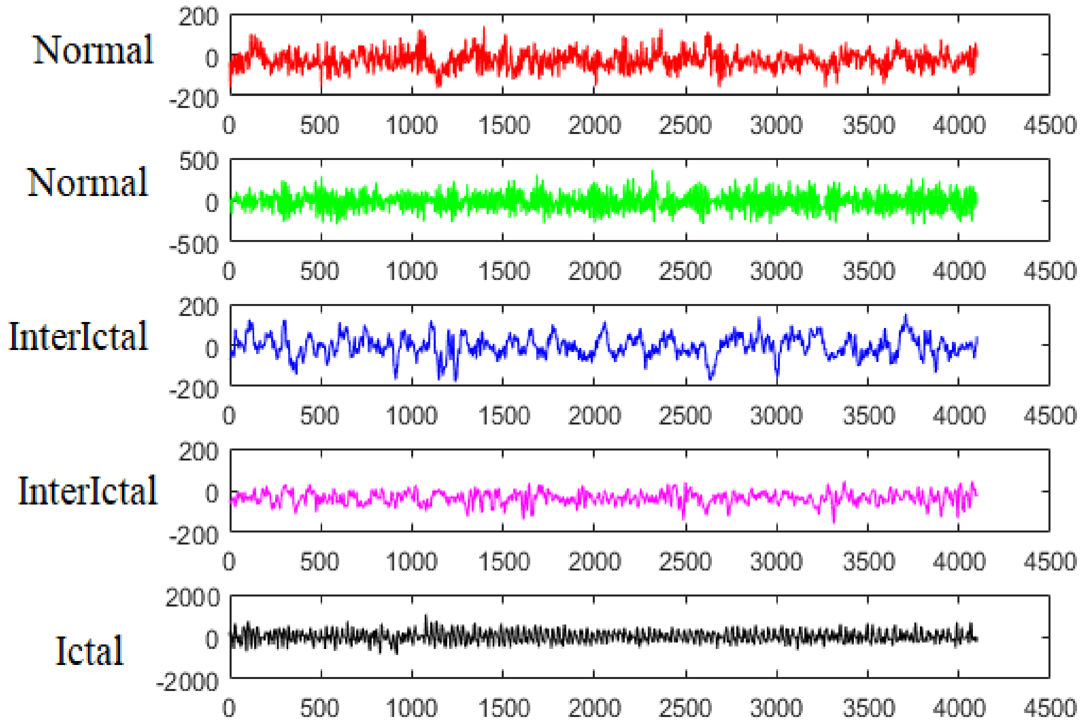

Figure (6.2): brain signal for (Ictal ‹Interictal ‹healthy) people

In this project, three EEG groups were selected from the five available groups as shown in Table [6.1].

Table (6.1): EEG Database Group

Group	Group Description
A	Signals of healthy subjects (**healthy**)
D	Signals of subjects with epilepsy recorded between epileptic seizure(**Interictal**)
E	Signals of subjects undergoing seizures **(Ictal).**

To read electrical brain signals, we use the following function:

<u>Load (filename):</u> This function loads data from the (filename) into (workspace) as matrix type (double).

```
%%% matlab code

>> sig = load ('EEG.txt');
```

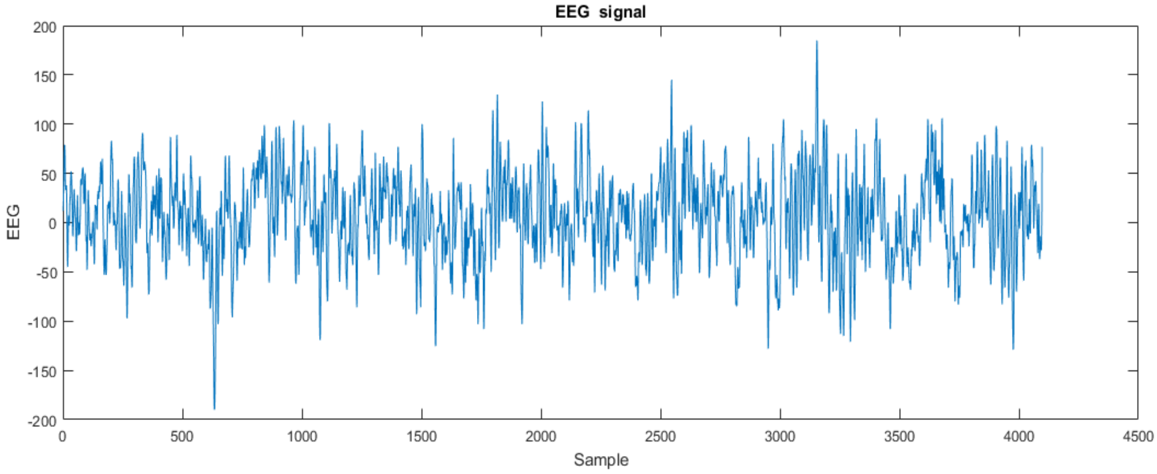

Figure (6.3): plotting EEG signal for healthy people

6.4 Filtering frequencies

The first stage of brain signal processing is filtering EEG signal by using a band pass filter (BPF) by passing it through frequencies between 0.53 Hz and 40 Hz, because we obtain the epilepsy signals between these frequencies.

Since the previously data is in time domain, signals must be converted to frequency domain to use the frequency filter, by using fourier transform calling the following function.

fft (x): This function calculates the fast Fourier transform of x signal.

ifft (y) : This function calculates the invers fast Fourier transform of y signal.

```
x = x(1:4097);

fs = 173.61; % Sampling frequency

order    = 1;
fcutlow  = 0.53;
fcuthigh = 40;
[b,a]  = butter(order,[fcutlow,fcuthigh]/(fs/2), 'bandpass');
y  = filter(b,a,x);

freqz(b,a,1000,fs)

figure;
plot(x);
hold on
plot(y);
hold off

xlabel('Time (s)')
ylabel('Amplitude')
legend('Original Signal','Filtered signal ')
```

The following figure (6.4) shows the original EEG signal and filtered signal where original EEG signal contain all frequency, shown in blue line and filtered signal contain filtered frequency between 0.5 - 40 Hz, plotting in red line.

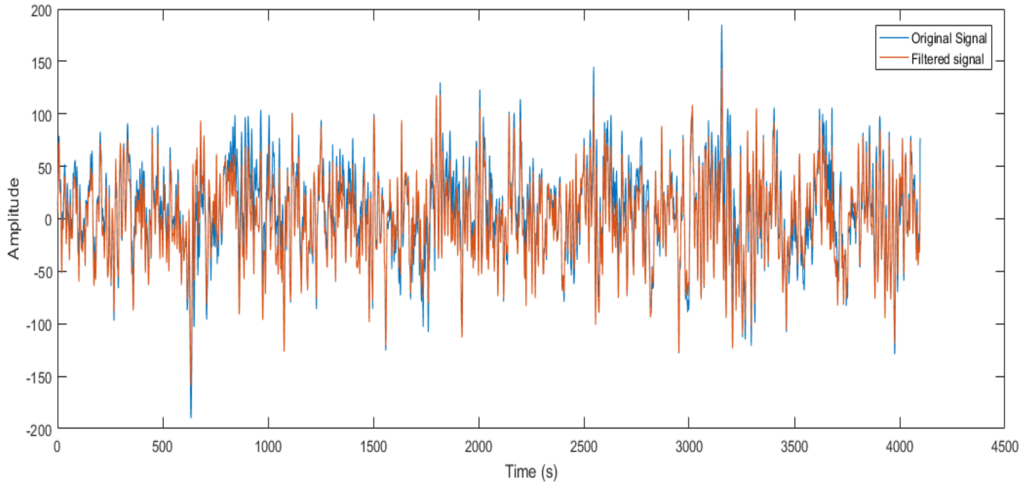

Figure (6.4): plotting original EEG signal and Filtered signal

6.5 Wavelet Transform

Once the EEG signal is filtered and only frequencies in the bandwidth .5 to 40Hz are kept. The EEG signal is analyzed using the Discrete Wavelet Transformation (DWT). The number of levels of analysis is chosen depending on the important frequency components of the signal. And that the chosen levels correspond to the frequencies necessary to classify the signals. We used DB2 (Daubechies order 2 wavelet transform) on EEG signal with three level. Wavelet analysis toolbox is used to transform each signal from the time domain to the time-frequency domain. Then, extraction of several features is done in the time-frequency domain for classification using machine learning algorithms.

6.5.1 Perform wavelet transform for the signal

We used the following functions from the wavelet toolbox in this project.

([c, l]=wavedec(s, n, 'wname') : This function performs the wavelet decomposition up to level n to the one-dimensional signal s. The output of this function contains the signals (c) and the length of the signals (l) for each coefficients.

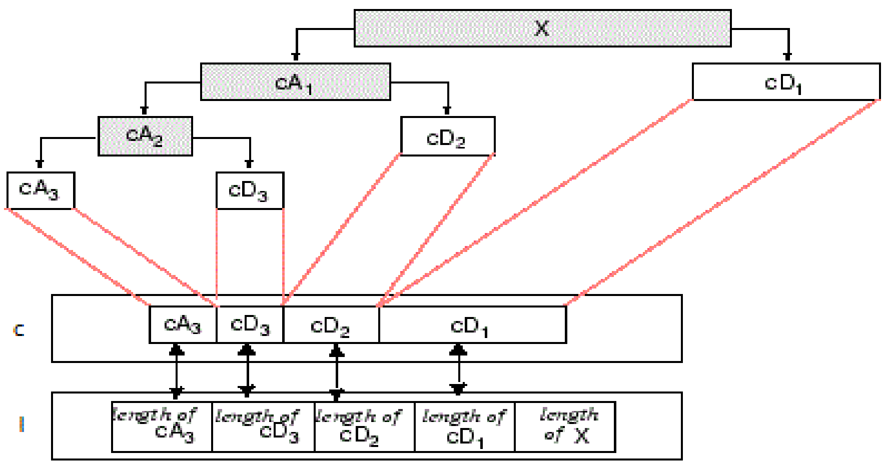

Figure (6.5): multi-level wavelet decomposition [58]

```
%%% matlab code
>> w = 'db2';                      % name wavelet
>> lv = 4;                         % level
>> [c ,l] = wavedec (s,lv,w);      % where c is a vector & l is a length of
each component
```

6.5.2 Approximate and detail coefficients

Signal decomposition are reconstructed from coefficients one-dimensional wavelet using the following function:

<u>Wrcoef ('type', c, l, 'wname', n)</u> <u>:</u> This function rebuilds the parameters based on the results of the wavelet analysis (c&l), name of wave ("wave") in level (n) with input ("type") who determined approximate coefficient ('type' = 'a') or detail coefficient ('type' = 'd') .

```
%%% matlab code

Approximations

>> A1 = wrcoef ('a',c,l,w,1);

>> A2 = wrcoef ('a',c,l,w,2);

>> A3 = wrcoef ('a',c,l,w,3);

Details

>> D1 = wrcoef ('d',c,l,w,1);

>> D2 = wrcoef ('d',c,l,w,2);

>> D3 = wrcoef ('d',c,l,w,3);

%%% To show the signal analysis in three level

>> dt = 1/Fs;

 >> t = L*dt;

 >> t = 1 : 1 : t*Fs;

>> figure;

 >> subplot (4,2,1); plot (t,s(t),'r'); title ('Orig. signal and approx 1 to 3.');

>> subplot (4,2,2); plot (t,s(t),'r'); title ('Orig. signal and details 1 to 3.');

>> subplot (4,2,3); plot (t,A3(t),'b');
```

```
>> subplot (4,2,5); plot (t,A2(t),'b');
>> subplot (4,2,7); plot (t,A1(t),'b');
>> subplot (4,2,4); plot (t,D3(t),'g');
>> subplot (4,2,6); plot (t,D2(t),'g');
>> subplot (4,2,8); plot (t,D1(t),'g');
```

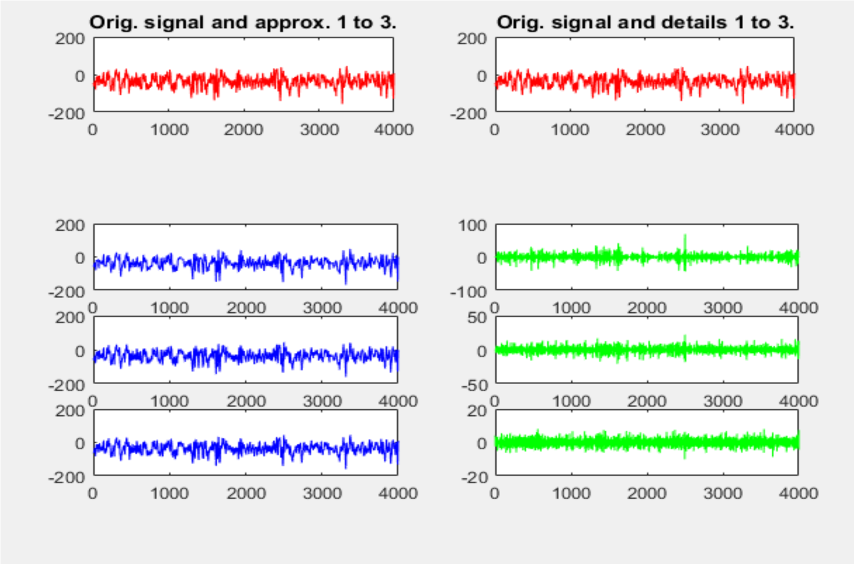

Figure (6.6): The original signal and the approximate and detailed signal within three levels

6.6 Feature extraction

The wavelet coefficients that is extracted from the EEG brain signal provides a time-frequency decomposition of the signal. Some statistical features can be extracted from these coefficients and be used in machine learning. The following statistical attributes are used to represent the time-frequency distribution for EEG signal:

1. **(Mean)**: To find the mean value for the approximate coefficient, as one statistical parameter is resulted from this attribute.

The (mean) in matlab environment is calculated by the following function.

```
%%% matlab code
    >> mean_A1 = abs (mean (A1));
```

The same way is followed to calculate approximate coefficient.

2. **(Median):** To calculate approximate coefficient, statistical parameter from this attribute is resulted.
3. **(Mod):** To calculate the most frequent value of the signal frequency for approximate coefficient were, one statistical parameter is resulted.
4. **(Maximum and minimum values):** max(x) & min(x) functions are used to calculate the maximum and minimum of approximate coefficient, two statistical parameters resulted from this step.
5. **(Range):** It is the difference between the maximum and minimum value of the data, in which we get one statistical parameter.

```
%%% matlab code
>> range_A1 = max(A1) – min(A1);
```

6. **(Standard Deviation):** Standard deviation in matlab is calculated by the function **(std(x))**, in which we also get one statistical parameter form approximate coefficient.
7. **Absolute Deviation Median and Mean (mad):** To calculate the two following attributes in matlab we use the function mad(x, 0) that calculates the absolute deviation for median, and function mad(x, 1) that calculates the absolute deviation for the mean. For each approximate

coefficient, we get one statistical parameter for each function, i.e. we get two statistical parameters.

6.7 Classification

Depending on the features extracted from the previous stages, machine learning algorithms were used to Classify brain signal into three classes: Healthy, Epileptic with no seizure, and Epileptic with a seizure. These classes correspond to healthy, ictal, and interictal.

Then, these features are used to classify the EEG signal into the above three classes using Artificial Neural Networks. In this thesis, we used the matlab toolbox (nnstare), and we used the (nprtool and nntool) functions from toolbox.

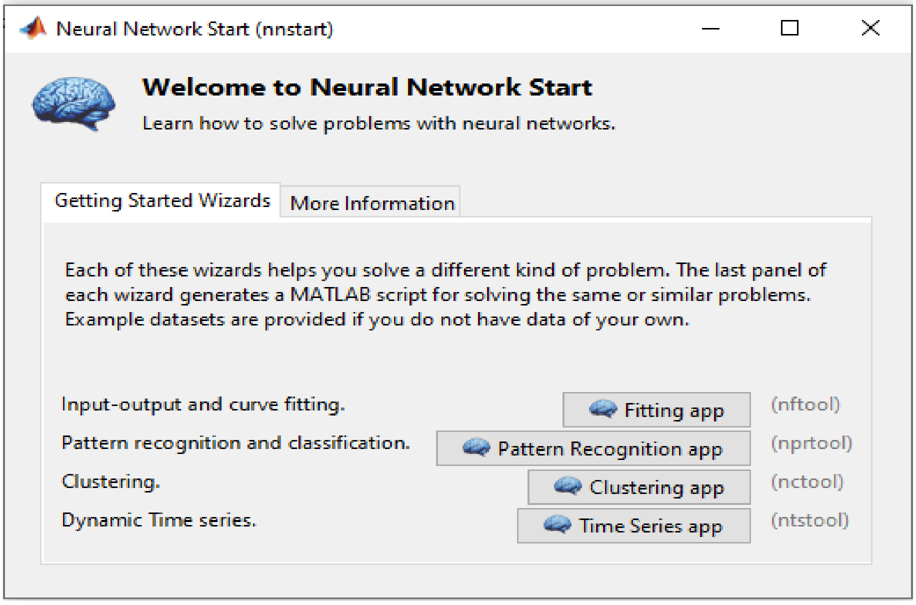

Figure (6.7): Neural network start toolbox

Chapter Seven

Results

7.1 Introduction

In this chapter we present the main results of this thesis. This includes, the results of the preprocessing stage, the feature extraction stage using the wavelet transform and the classification of the EEG signal into epileptic and normal signals.

7.2 EEG signal pre-processing

Three groups, each consists of 100 EEG signal recordings as explained in Chapter five are used in the classification process. All signals are filtered using band pass filter to keep only the relevant frequencies between 4 and 40 Hz in each signal. The results are saved in a matrix of dimension 300×1.

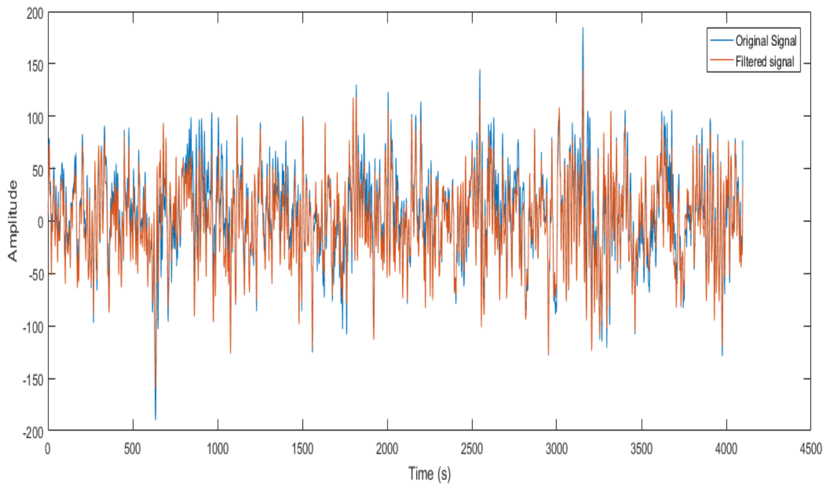

Figure (7.1): plotting original EEG signal and Filtered signal

7.3 Apply wavelet transform

After obtaining the signal matrix, discrete wavelet transform using daubechies mother wavelet was applied to each signal. Three level decomposition scheme was used, we obtained 3 sub-levels of the signal. As a result of applying wavelet transform, three approximate coefficients: cA1, cA2, and cA3 and three detailed coefficients: cD1, cD2, and cD3, were obtained. A plot of these coefficients for a particular signal is shown in the Figures (7.2), (7.3).

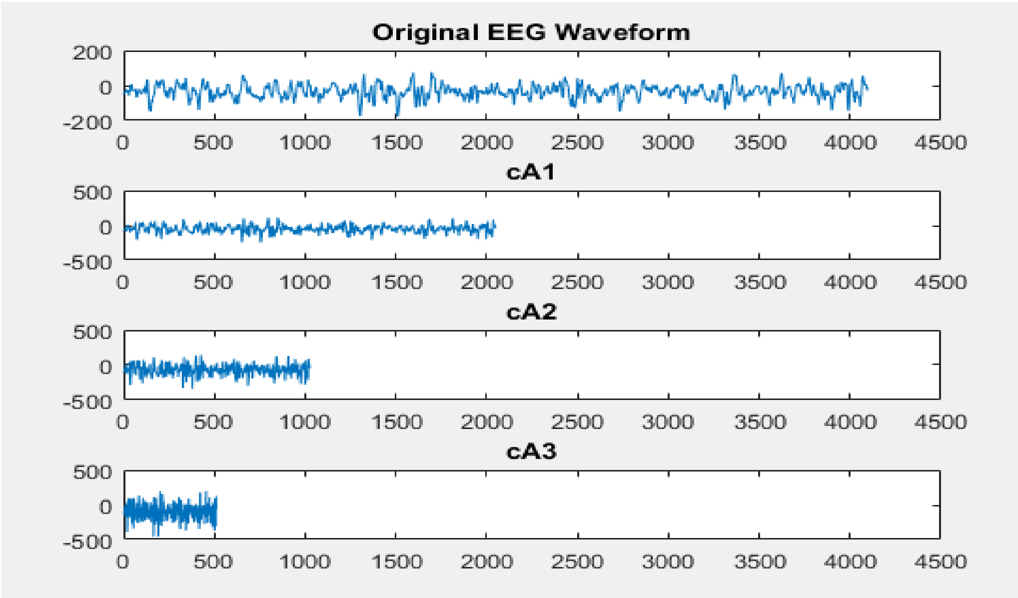

Figure (7.2): Signal decomposed into approximate coefficients

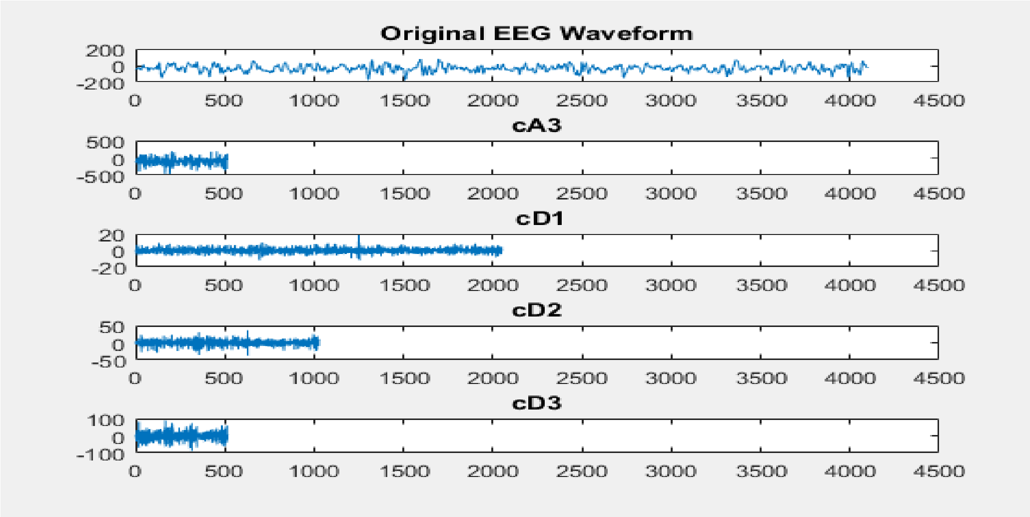

Figure (7.3): Signal decomposed into approximate coefficients at level 3 and detail coefficients at level 1, 2, and 3.

7.4 Feature Extraction

After applying the initial pre-processing stage and the wavelet transform stage, the features were extracted from each transformed signal. The results are the 9 features: mean, median, mode, maximum, minimum, range, standard deviation, absolute Mean Deviation, and absolute median deviation, for approximate coefficient at level three because it contain all important information in signals.

After getting the matrix, we added a header row at the beginning of the matrix and a column at the end. The added column contains a label for each signal with a value of 1 (healthy), -1 (ictal), and 0 (interictal).

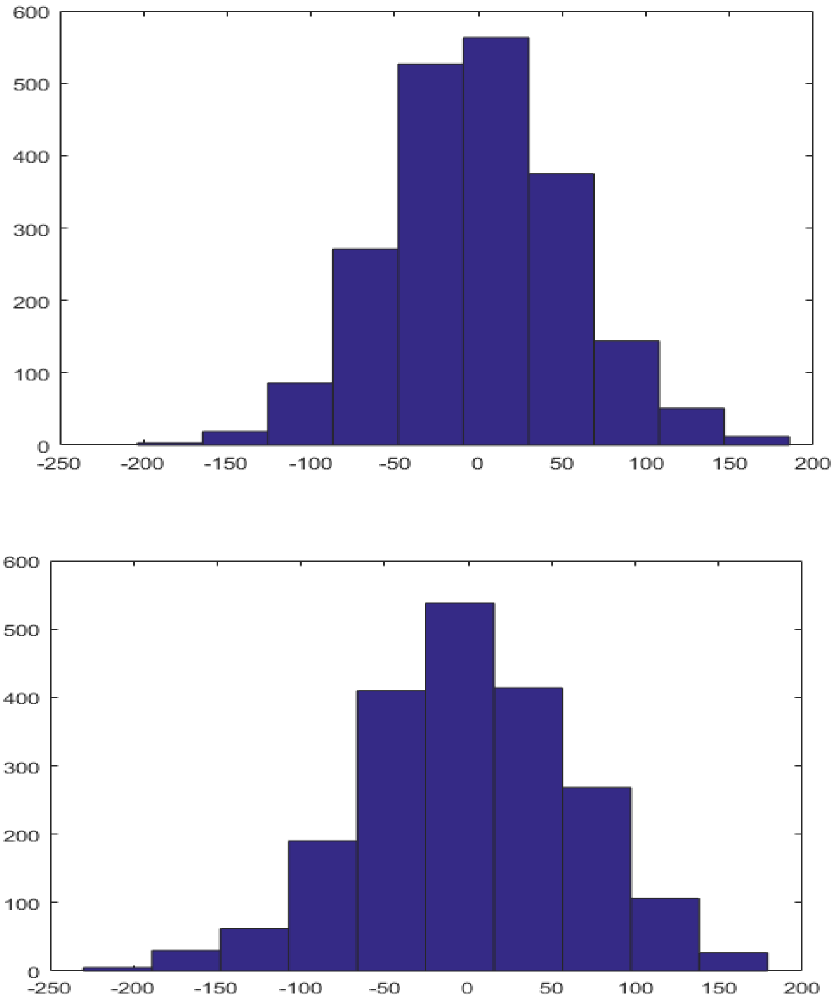

Figure (7.5): Histogram for inter-ictal signal

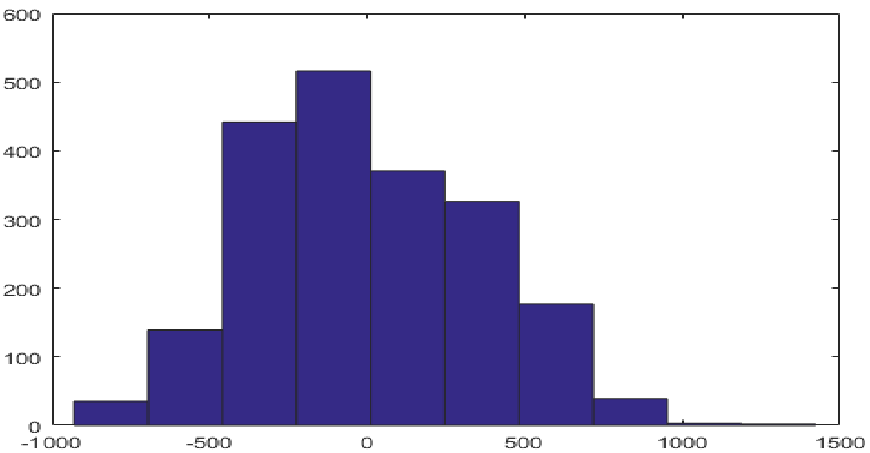

Figure (7.6): Histogram for ictal signal

Table (7.1) shows these features. The dimension of the features matrix is 300×9, in which, each row represents a signal, and the columns represents features.

Table (7.1): Feature extract from one signal

Max	Min	abs(max – min)
201.360629349128	-220.076285848540	421.436915197668
abs(mean)	median(A1)	mode
0.114700155351565	1.45029149709344	-220.076285848540
Stander deviation	AMeD	AMdD
55.5839576959615	43.8832017573105	36.3408060233012

7.5 Classification

After obtaining the features matrix, we used the matlab machine learning toolbox to classify the brain signal into three classes, healthy, ictal, and interictal. We got a matrix of 300 row × 9 column dimension, however, in matlab the matrix, must be flipped, where, the row turns into a column and the column into a row before starting the classification process, so that, the dimensions of the matrix become 9×300. In this thesis we used the Artificial Neural Network for classifications.

The features matrix was split into two sets: a features attributes set and a target set for each signal. In the target data set, we have imposed the following symbols: 1 for ictal, 0 for healthy, and -1 for interictal, as shown in Figure (7.7).

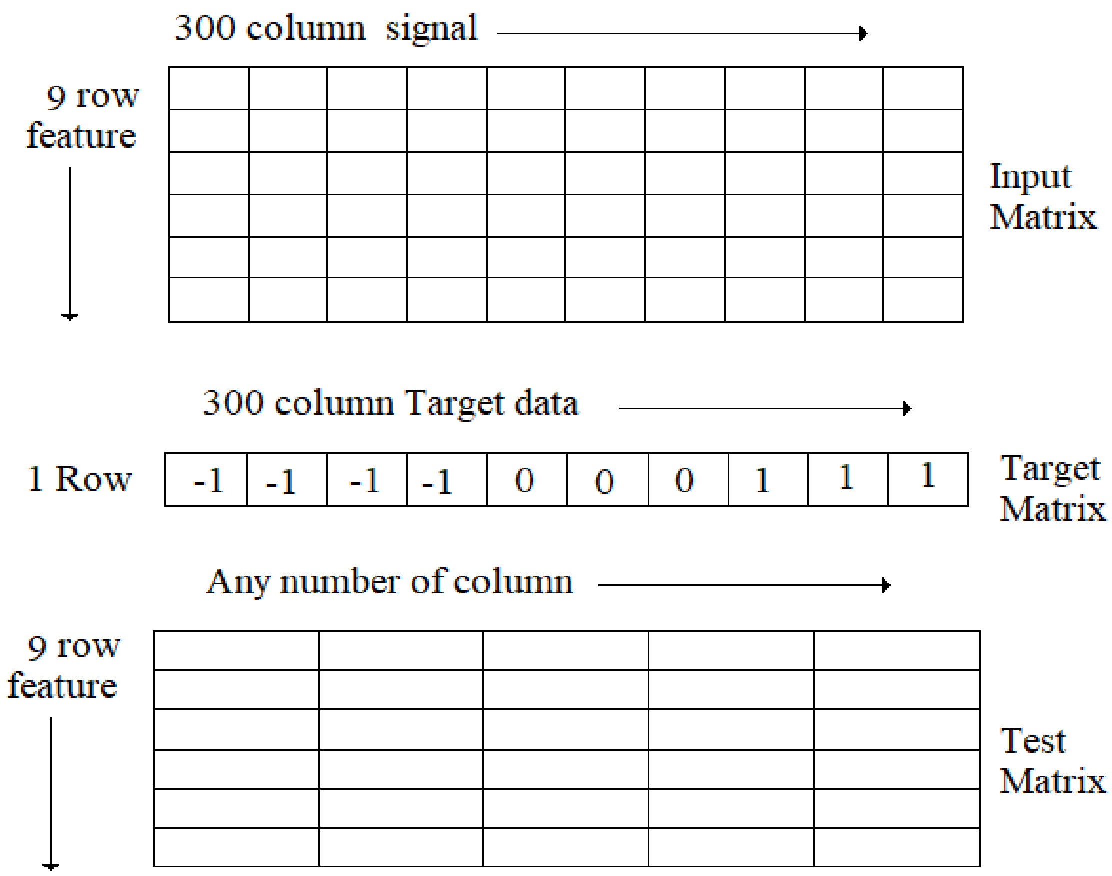

Figure (7.7): Matrix signal for input, Target and Test

7.5.1 Training the neural network

As discussed before, we used the matlab neural network toolbox to classify the EEG signals into the three classes: healthy, ictal, and interictal. The classification is based on the features extracted from wavelet transformation coefficients. We used default neural network properties such as Feed-forward back-prop for network type, number of neutrons 10, hidden layer 10 and transfer function is TANSIG.

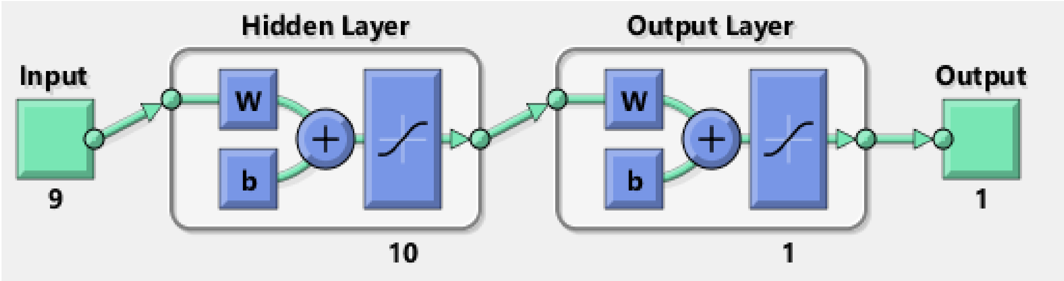

Figure (7.8): Neural networks

Figure (7.9) shows a plot of the mean square error versus the number epochs used in the training: As the figure shows, the optimal number of epochs is 62. Also, the figure shows that the training error is the smallest as expected and the validation error and the testing errors are similar which indicates that the model doesn't over fit. If the testing error increased significantly compared to the validation error, then it is possible that the model over fitting, we split the data between training set, validation set, testing sets as followed: 210 sample for training, 45 sample for validation and 45 sample for test.

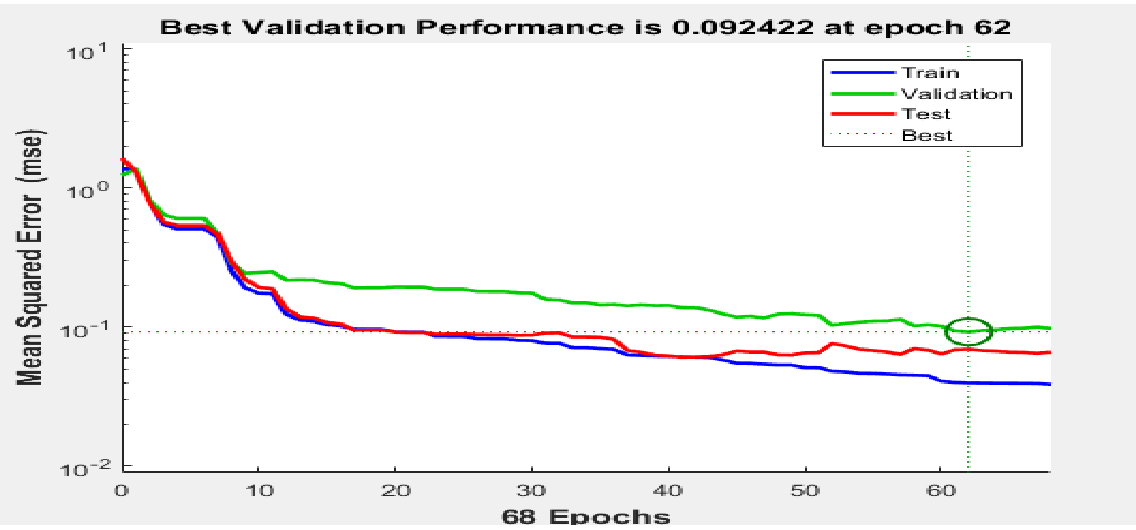

Figure (7.9): Best validation and performance

Figure (7.10) show regression: This curve showed the distribution of data over four plots that is: training, validation, test, and all data.

The dashed line in each plot represents (perfect result – outputs = targets) and, the fixed line represents the best fit line regression between outputs and targets. The R value shows if their a relationship between the outputs and targets, here, if R=1, it indicates that there is an exact linear relationship between outputs and targets, while, if R is close to zero, then there is no linear relationship between outputs and targets.

This figure shows that the training, validation, and testing data indicated good results. We noted that data were arranged accordingly to distribution categories in the classification process, and the data were arranged vertically not scattered, because the scattered plot shows that certain data points have poor fits.

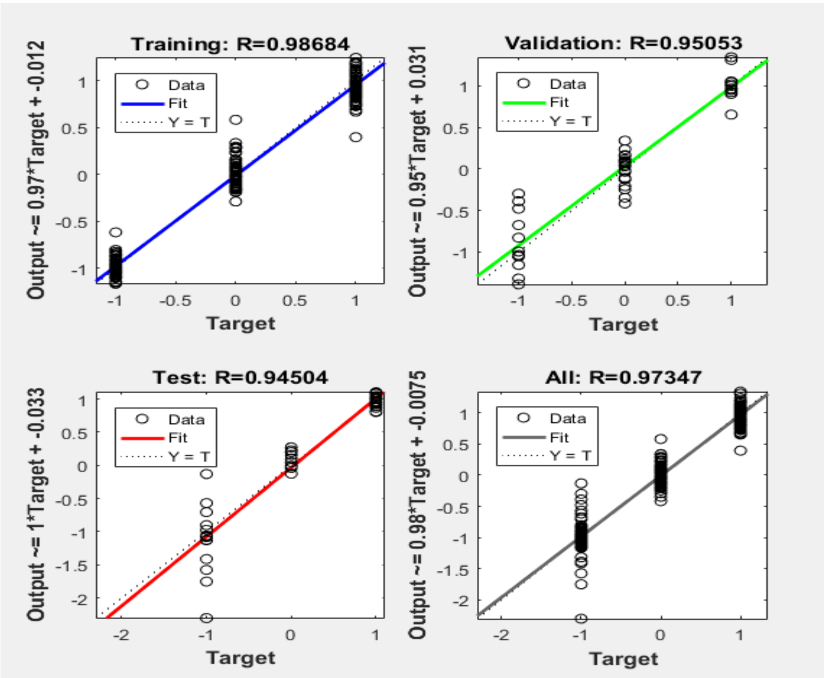

Figure (7.10): Regression

7.5.2 Evaluations

1. **Confusion Matrix:** The confusion matrix expresses all the amounts previously reported that is: sensitivity, accuracy and specificity. The values of positive cases that are correctly categorized, as well as negative cases that are correctly categorized, and positive cases that are incorrectly categorized, and negative cases that are incorrectly categorized are all expressed by confusion matrix [61].

   On the confusion matrix plot, the rows represent (Output Class), and the column represents (Target Class). The diagonal cells show the observations that are correctly classified. Both the number of observations and the percentage of the total number of observations were shown in each cell. The column on the right of the plot shows the percentages of all the examples predicted belong to each class that are correctly and incorrectly classified. These scales are often called as the positive predictive values. The row at the bottom of the plot shows the percentages of all the examples belonging to each class that are correctly and incorrectly classified. These scales were often called as the true positive rate. The cell in the right bottom of the plot showed the overall accuracy.

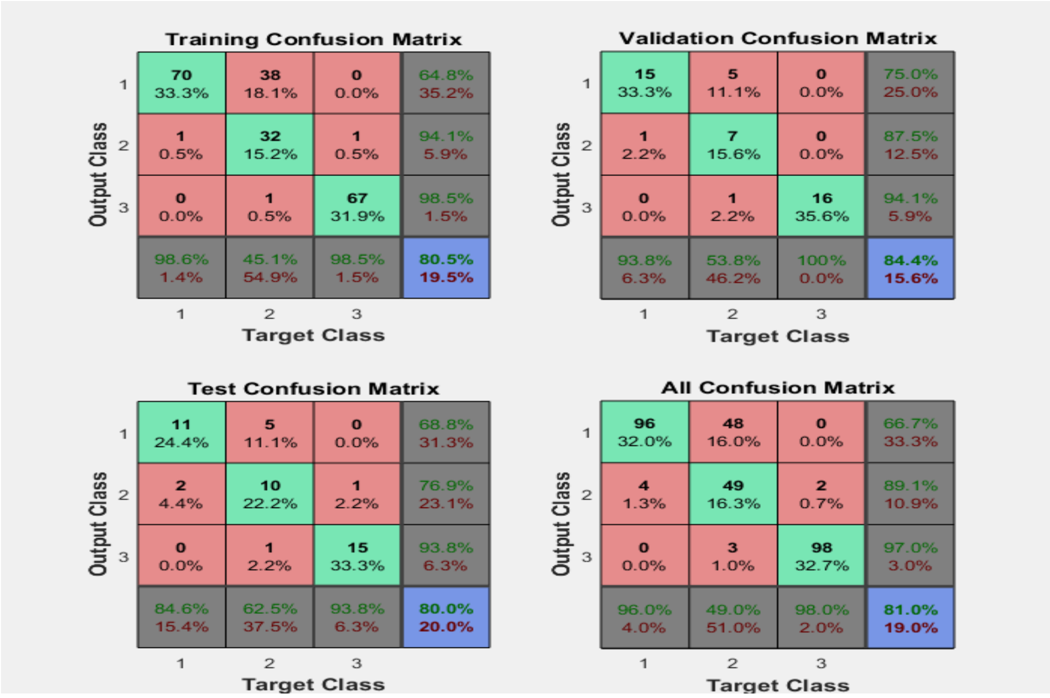

Figure (7.11): Neural Network Training Confusion matrix

2. **Accuracy:** It is used as a statistical measure of the success of classification test [60]. It is the ratio of correct results (positive or negative) to the total number of cases examined, the accuracy in our model was equal to 81%.

$$\text{Accuracy} = \frac{\text{ratio of correct results}}{\textit{total number}}$$

3. **Sensitivity:** It is the number of signals that have been correctly categorized positively, over the number of signals correctly categorized positively, plus the number of signals categorically misconfigured negatively, the sensitivity expresses the idea of how many times the test will be positive if a person has the disease, (the correct classification rate for positive cases). In other words, if the test is sensitive and the test

result is negative, this means that the patient is not infected with a high rate [60]. In our model the value of sensitivity was 84%.

$$\text{Sensitivity} = \frac{\text{Number of signals that categorized Correctly positively}}{\text{no. sig that categorized Correctly positively} + \text{no. sig that categorized incorrectly negatively}}$$

4. **Specificity**: It is the number of negative signals correctly categorized over the number of correctly categorized negative signals plus the number of positive signals incorrectly categorized [60], in our model the value of specificity was 80%.

$$\frac{\text{Number of negative signals}}{\text{no. sig that categorized Correctly negatively} + \text{no. sig that categorized incorrectly positively}}$$

For performance evaluation we considered the following parameters:

Positive: affected patients, negative: unaffected patients, true: correct prediction, and false: incorrect prediction.

Accuracy: is used to measure the performance of the technique used in the system. = TP+TN/TP+TN+FP+FN

The higher the accuracy the better the performance of the system.

Table (7.2): Parameters Considered

Epilepsy	Prediction	Results
Yes	Yes	TP
Yes	No	FP
No	Yes	FN
No	No	TN

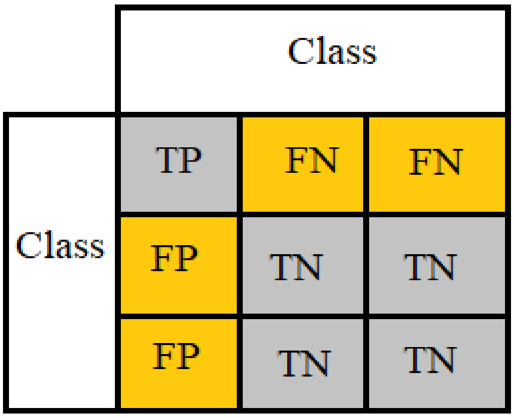

Figure (7.12): Confusion matrix showing the distribution of predictions to true positives, false negatives, false positives, and true negatives for a classification model prediction for three classes [59].

For analysis of the obtained results a total of 300 samples were considered. 144 out of these samples had epilepsy (by adding TP+FN), while 156 samples did not have epilepsy (by adding FP+TN), as shown in table (7.3) [60]

Table (7.3): Cases Diagnosis

Cases Diagnosis	Epilepsy	Not-Epilepsy
300 Sample	144	156

Table (7.4): Results Obtained From Confusion Matrix

Results	Values
TP	96
FN	48
FP	4
TN	152
Sensitivity	84%
Specificity	80%
Accuracy	81%

The our computer model specification is 8.00GB RAM, Intel (R) Core (TM) i5-4210U CPU 1.7GHz 240GHz processor and 64-bit Operating System ,x64-based processor system type.

The total time required to find best solution using element-by-element matrix is 3.774139 seconds. By using a pair of tic and toc where tic works with the toc function to measure elapsed time. The tic function records the current time, and the toc function uses the recorded value to calculate the elapsed time.

7.7 Conclusion

The machine learning algorithm provided a model with accuracy, sensitivity, and specificity, which is reliable while designing a system of classifying healthy signals from abnormal signals. Classification accuracy in our project was 81% which is considered a good result.

Chapter Eight

Conclusion

8.1 Difficulties of the project

- The difficulty of cooperating with hospitals and communicating with doctors to discuss methods used for treatment, due to the lack of neurological departments to diagnose epilepsy patients in Palestinian hospitals.
- The types of electrical signals in the brain differ according to the signal source, which requires additional treatment to reach the unification of specifications between signals.
- Difficulty of obtaining EEG brain data from Palestinian hospitals, as so we used an open source data.

8.2 Conclusion

Epilepsy is one of the most common neurological diseases worldwide, and is considered as a sudden electrical brain failure, where the disease disposes the function of neurons within the brain. The traditional way of diagnosing epilepsy is by reading EEG records. In this project, we designed an algorithm to process the brain signal and extract features from it, with the aim of using it to classify the epileptic signals from non-epileptic signals.

We designed an algorithm model to reach the desired results, in which wavelet transform was used to process the signals in order to prepare them for feature extract stage, then statistical features were extracted. Nine features from all statistical features of the study were obtained. The nine features along with 300 brain signals were input as a matrix in neural network. The accuracy, sensitivity, specificity, and confusion matrix were calculated. Following input of 300 brain signals and carrying proper calculations, we got 144 epilepsy cases, and 156 non epileptic cases. The accuracy, specificity, and sensitivity percent were 81%, 80%, 84% respectively.

The importance of the project and the implementation steps can be summarized by the following points:

1. The possibility of detecting cases with epilepsy that does not go through a seizure "interictal ", as all diagnostic methods in the health sector depends only on reading the patient's previous records. Therefore, this project provided good progress in the methods of diagnosis and early detection of epilepsy.
2. Machine learning algorithms were used in the classification process especially machine language, and neural networks, which provides huge potential for development, and diagnosis.
3. The filtering process that was performed on signals before processing improved the computing process by providing a large amount of processing that did not provide any information for the project, when passing the signals through a band pass filter between 45-5.0 Hz gave all the necessary frequencies related to epilepsy.
4. The matlab gave appropriate primary treatment, as well as, the application of wavelet transforms and feature extract, provided a several graphical tools to accelerate and facilitate the treatment.

8.3 Recommendations

1. The possibility of implementing the project commercially

The accuracy that the program offers and the ability to detect epilepsy is very important. Therefore, the program could be provided to neurological clinics, which might be a helpful for the doctor, and provides important support for doctor's decisions. It is also possible to integrate this algorithm with the EEG monitor that reads the electrical brain signal, as the EEG device can be linked with dedicated devices that filter, classify and give results directly.

2. Improved the used algorithm

We recommend to reduce number of features and search for the best features to increase accuracy.

At the end, we hope that we have presented a clear and comprehensive study of the principle and steps of wavelet transform, processing electrical brain signal, and extracting features from signal for adoption in classification, with the aim of building a system capable of classifying brain signals within three categories: healthy, interictal, and ictal. This field of study is very wide, and interesting and also has a major impact on people suffered from the disease, and those who have not been diagnosed yet. Because, as we mentioned earlier, epilepsy can be diagnosed even in the absence of traditional symptoms.

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جامعة النجاح الوطنية

كلية الدراسات العليا

استخراج سمات من إشارة كهربائية الدماغ لتصنيف إشارة الصرع باستخدام الشبكة العصبية

إعداد

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قدمت هذه الأطروحة استكمالا لمتطلبات الحصول على درجة الماجستير في الحوسبة المتقدمة بكلية الدراسات العليا في جامعة النجاح الوطنية، نابلس، فلسطين.

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الملخص

مخطط كهربية الدماغ (EEG) هو عبارة عن إشارات كهربائية مرتبطة بتواصل الخلايا العصبية في الدماغ، ويستخدم لتقييم واختبار النشاط الكهربائي للدماغ. وبالتالي، يمكن استخدامه للكشف عن المشاكل المرتبطة بهذا النشاط مثل امراض الصرع. الصرع ، الذي يتميز بالنوبات المتكررة، هو أحد أكثر الاضطرابات العصبية شيوعًا التي تصيب الأشخاص في جميع الأعمار. يرتبط بنشاط كهربائي غير طبيعي في الدماغ. تتمثل إحدى طرق اكتشاف الصرع وتشخيصه في استخدام إشارة مخطط كهربية الدماغ (EEG) لأنه يحتوي على معلومات كافية لوصف المرض. الهدف الرئيسي من هذه الرسالة هو تصميم نموذج قادر على تصنيف إشارات الدماغ إلى إشارات مصابة بمرض الصرع وغير مصابة بمرض الصرع من خلال تطبيق أربعة خطوط أنابيب هي: المعالجة أولية، وتحويل المويجات، واستخراج السمات ، والتصنيف ، لأتمتة عملية تحديد نوبات الصرع و تصنيفها (سليمة، بين النوبتين، مصابة بالصرع). للقيام بذلك، تم استخدام تحويل المويجات لمعالجة الإشارات من أجل إعدادها لمرحلة استخراج السمات، ثم تم استخراج السمات الإحصائية من معاملات تحول المويجات. تم استخراج تسعة ميزات واستخدامها في تصنيف الإشارات باستخدام الشبكة العصبية الاصطناعية. تم إدخال السمات التسعة إلى جانب 300 إشارة الدماغ كمصفوفة في الشبكة العصبية. تم حساب الدقة والحساسية والنوعية ومصفوفة الارتباك. بعد إدخال 300 إشارة دماغية وإجراء الحسابات، حصلنا على 144 حالة صرع، و156 حالة سليمة. كانت الدقة والنوعية والحساسية 81٪ و80٪ و84٪ على التوالي. قدم المشروع طريقة لحل المشكلات الناتجة عن تشخيص الصرع. على الرغم من أن النتائج تجاوزت 80٪ من الدقة، فإننا نوصي بتقليل عدد السمات والبحث عن أفضل الميزات لزيادة الدقة.