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# ANALYSIS AND CLASSIFICATION OF BRAIN SIGNALS USING DWT AND SVM

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## ABSTRACT

The brain is the main dominant of the human body and any defect that occurs in the brain impact the body's vital activity. There are many diseases that affect on the brain tasks. They Infects many people worldwide. The Brain signals recorded by Electroencephalography (EEG) system are used to diagnose brain signals and classify them as normal or abnormal. Detecting and classifying of EEG signals are exhausting and difficult process and require effort by the neurologist to diagnose them. When the brain injury is severe, treatment of brain injuries become difficult and require surgical intervention, but in early detection of the injury it may be treated without surgical intervention. The purpose of this paper is to detection and analysis of the brain signals and extract the main bands of the signal by Discrete Wavelet Transform (DWT) and then to classify them by the Support Vector Machine (SVM) for early detection of brain abnormalities. The database used in this paper were collected from a group of patients at Baghdad Teaching Hospital / Medicine City by an EEG system in the form of images. The signals are extracted from the images by detecting the signal inside the image and dealing with it as a digital signal. These signals are immersed by noises to eliminate this noise the Finite Impulse Response (FIR) filter is used where low frequencies pass and block the high frequencies to obtain noise-free signals. Set of statistical measurements are measured to use as input to train the Support Vector Machine and used them in classification of the signal. The classification ratio obtained in this paper is 96.8 %.

**Keywords:** *Brain Signals, Signal Processing, Signal Analysis, DWT and SVM.*

## 1. INTRODUCTION

Research within the automated detection of brain abnormalities has started since 1970 and many algorithms have been proposed for this issue. These algorithms for automated disclosure of brain disorder depend on the recognizable of various samples like amplitude raise, activity of periodic cadence or electroencephalogram EEG flattening [1]. The brain activities can be measured by two ways: non-invasively by using EEG or invasively by using electrocorticography (ECOG). EEG signals are recorded by electrodes putted on the scalp, these electrodes can read brain activities. Currently, clinical EEG analysis is performed visually by the trained electroencephalographs to locate and detect the disorders in brain signals. Since a lot of signals are generated by many electrodes, the mechanism of brain signals processing helps to make this tedious process is quick and permitting the medical vocational to determine brain disorders quickly and precisely. EEG signal analysis is used in the diagnosis and medication of diverse neurological ailments [2,3].

Recently, there has been high attention in the techniques of machine learning applications for helping doctors for right diagnosis of brain disorder. The EEG data is utilized to detect diseases and abnormalities in the brain. With growing request of brain diseases detection, EEG help to suit this request in reasonable prices with best clinical and healthcare services [4,5].

During abnormality seizures, main changes happen in a patient’s brain signal because of the synchronous electrical activity of the neurons. One of the specific features of the brain signal abnormality is the incidence of sharp and spikes waves. The factors taken from brain waves can be utilized as useful diagnostic characteristics for automatic detection of brain turmoil. EEG waves which really carry information concerning brain abnormalities are also polluted by the noises such as deeply breathing, eye blinking and artifacts of muscle [6].

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Signal processing is one of the fields of engineering and science that has quickly developed. This fast evolution is the result of big advances in technology of digital computer and integrated circuit manufacturing. Signal processing refers to any "manual or mechanical" process that adjusts, analyzes or processes the information included in the signal. Mathematically, the signal can be described as a function of one or more independent variables. One example of a natural signal is ECG and EMG. These signals provide doctors with sufficient information on the situation of the heart and muscles [7,8]. Signal processing is the empowering innovation for the generation, conversion, and elucidation of data. Another example of the signals is the brain signals at various phases of time our brain responds differently. These signals are utilized for different aims so that they are conceivable to study the functionalities of brain appropriately by producing, conversion and elucidation the signal that are collected. This procedure is known as brain signal processing [9].

## 2. RESEARCH OBJECTIVE

EEG signals are often containing a large amount of data, including data that represents the brain activities and other data that are not useful as noise. We need to use appropriate technical methods to analyze these signals to extract information about brain activity from this large amount of data.

The analysis and classification of brain signals manually is tired, requires expert in this field and take time consuming. The fatigue and insufficient experience often leads to mistake in the diagnosis. Therefore, the need to develop systems to analyze the brain signals automatically to saving time and effort. The aim of this research is to extract, analyze and then classify the signals recorded in the medical report of the patient extracted from the EEG device.

## 3. RELATED WORK

There are many literatures used different techniques for detection and analysis brain signals, some of these works are:

Umut Orhan, Mahmut Hekim and Mahmut Ozer (2011) used Multilayer Perceptron Neural Network (MLPNN) for the classification of the brain signals. The proposal method used discrete wavelet transform (DWT) to decompose signal into a set of sub-bands through consecutive low-pass and high-pass filters of time domain. The wavelet clustered by using K-mean clustering algorithm. The clustering algorithm divides data sets into two groups: similarities or differences. This algorithm defines the centers of cluster and the items belonging to them by reducing the squared fault. The objective of the algorithm is to determine the centers of cluster far away as much as possible from others and to link each point to the closer cluster. The suggested model classified patient brain signal with open eyes with the precision of 96.67% [10].

M.Kalaivani, V.Kalaivani and V.Anusuya Devi (2014) supposed Discrete wavelet transform (DWT) the EEG signals decomposition into sub-band and the feature extraction, DWT methods are used to extract the time domain and frequency domain features of the EEG signal. In this proposed genetic algorithm are used to extract the best features by select the pertinent features by removing features with few or no prophetic information and k-means classifier to classify EEG signals [11].

T. Sunil Kumar, et al. (2015) proposed a classification system for brain disorders, proposed system is based on segmentation of brain waves using four parallel Gabor filters from particular range of frequencies. Discriminatory characteristics extraction by using from 1D-local binary patterns 1D–LBP. The processed brain wave is separated into smaller pieces and histograms of 1D-LBPs of these pieces are calculate. The features extracted used as inputs to nearest neighbor classifier (NN) for classification [12].

Ratnaprabha R. Borhade and Dr. Manoj S. Nagmode (2016) proposed a method which depends on features extraction from EEG signals. Features extraction depend on diverse methods such as DCT, DCT-DWT, SVD and IMF. To successfully distinguish brain seizures, extracting the features from EEG waves needs to hold enough power of discrimination to permit the discrimination between normal and abnormal signal. The extracted features can be classified into time domain features, frequency domain features, waveform morphology features and wavelet features. Feature selection takes relevant feature and ignores irrelevant feature. (SVM) is used to classify brain signals into normal and abnormal. SVM is usually used as a strong tool for the real data classification. (SVM) is high efficiency and simple to deal with classifiers [13].

Arjunan Kavitha and Vellingiri Krishnaveni (2016) suggested wavelet transformation with low-pass and high-pass filters for signals decomposition and pre-processing. There are 5 levels of wavelet decomposition for extracting the features of the signals. Approximation entropy method is used for feature extraction. This strategy extracts the rhythms precisely from the EEG waves. In addition to the statistical and entropy features, there are 64 features which are computed such as maximum, minimum, sum, average and etc. But only few features are chosen for classification the EEG waves seizures. Proposed approach used multi-class support vector machine (SVM) to classify EEG signals. SVM is able to train itself on any type of data without outer technical assistance. One of the main advantages of this proposed approach is that 10 scales are used for computing wavelet of the signals [14].

Farheen Siddiqui and M.P.S. Chawla (2017) proposed ways to extract the features from EEG signals and classify them. The proposed system is divided into two main sections, the first is the noise elimination to obtain a noise-free signal using Notch Filter to eliminate the unwanted frequencies and pass the required frequencies to improve performance. The band-stop filter is used to pass the required frequency band. The second part is the extraction of features, two methods were used to extract the features from signal, the first method using Principal Component Analysis (PCA) and the other method using Power Spectral Density (PSD). The PSD is used to indicate signal strength. The use of PSD can easily compute intensity of energy signal. The features extracted by the above methods feed to the neural network for classification the signals. When they suggested Feed Forward Neural Network (FFNN) in signal classification process, they obtained an accuracy of up to 96.34 [15].

Amirmasoud Ahmadi, Vahid Shalchyan and Mohammad Reza Daliri (2017) suggested a method for the analysis and classification of brain signals for the detection of epilepsy based on Wavelet Packets Transform (WPT) with using a number of features in the features extraction process. They used WPT for analyzing and decomposing the signal to multi sub-bands, where they used five levels of WPT and used the following statistical measures: root mean square (RMS) and Standard Deviation (STD) for each WP sub-band. In their proposed system, they used (SVM) in the classification of the signal with different kernel function. The proposed system was evaluated on a publicly available dataset containing sets of data with and without epilepsy. Classification accuracy from 94.38 to 99.64 was obtained when applied to different sets of data [16].

## 4. METHODOLOGY

The proposed system analyzes and classifies the brain signals recorded by the EEG system. The EEG system uses several electrodes that are placed on the brain cortex where they capture brain activities. EEG captures the brain signals that contain enough information about the brain that is used to detect diseases and brain abnormalities.

This work contains two main stages: first stages is to detecting and extracting the signal and the second stages involves preprocessing, extracting the features and classification, figure 1 show block diagram of the works.

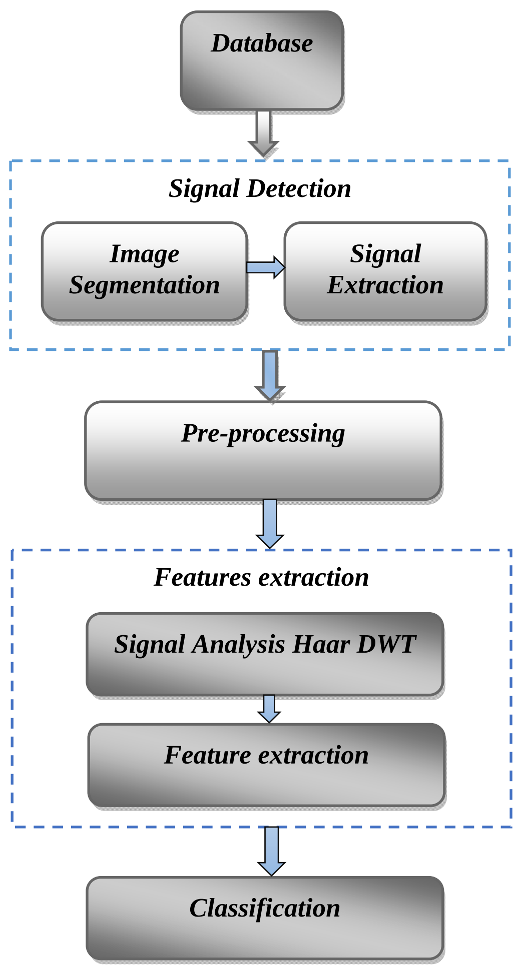


*Figure 1: System Block Diagram*

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### 4.1 Dataset

The EEG data was collected from Medical City/ teaching hospital of Baghdad/ EEG acquisition systems/ Neurophysiology laboratory. Data was collected by international 10/20 EEG and extracted on papers, these papers then scanned by scanner. The EEG system gives 16 signals from different places of brain, from the following channels (Fp2, F4, C4, P4, Fp2, F8, T4, T6, Fp1, F3, C3, P3, Fp1, F7, T3, T5). Table 1 shows all channels and electrodes names. Database was collected from 10 patients, the first were five healthy and the others were unhealthy. Database was recorded in two state, open eyes and closed eyes. So the total number of database contains 320 signals (160 normal signals in two states and 160 abnormal signals in two states).

*Table 1: Channels and Electrodes Names*

| Channel Name | Differential Electrodes |
|---|---|
| Ch1 | Fp2- F4 |
| Ch2 | F4 - C4 |
| Ch3 | C4- P4 |
| Ch4 | P4 -O2 |
| Ch5 | Fp2- F8 |
| Ch6 | F8 - T4 |
| Ch7 | T4- T6 |
| Ch8 | T6- O2 |
| Ch9 | Fp1- F3 |
| Ch10 | F3 - C3 |
| Ch11 | C3- P3 |
| Ch12 | P3- O1 |
| Ch13 | Fp1- F7 |
| Ch14 | F7- T3 |
| Ch15 | T3- T5 |
| Ch16 | T5- O1 |

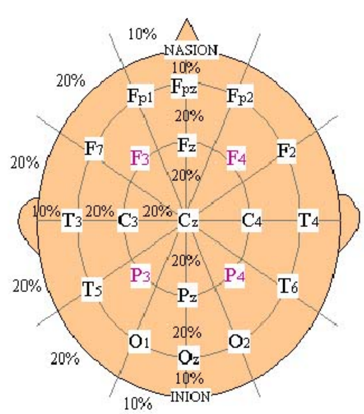


*Figure 2: International 10-20 Electrode Placement System*

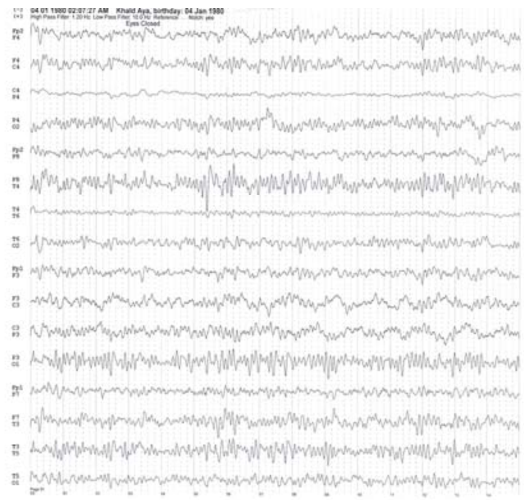

*Figure 3: EEG Signals collected*

### 4.2 Signal Detection

At this stage, all recorded signals on patient report are extracted after they have been scanned by the scanner as images. First, the images preprocessed, all images were converted to grayscale image and cropped to take the signals position only. This step consists of two steps, the first is the segmentation to remove the background from image, the second step is to extract the signals from the image and deals with them as digital signals.

*Figure 4: The cropped image*

### A. Image Segmentation

Image segmentation is one of the most important processes in techniques of image processing which segment the images into several zones. There are various algorithms that are used to segment the images into multi regions, some of them are based on segmentation into objects. The image is separated into areas called objects and

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background. Segmentation is an essential step in image analysis to extracting required objects from images and eliminating background [17]. Segmentation is a key step towards derivation of semantics from digital images. Segmentation of image indicates to the splitting of an image into multiple zones, where every zone differs from other with respect to certain features such as texture, color, space and intensity. In general, the segmentation goal is to simplify and modify the shape of an image to clearer and easier to analyze [18]. In this paper, threshold mechanism was used for segmentation the image. Threshold is one of the multi methods used for image segmentation. It is helpful for recognizing the objects from the background over choosing appropriate threshold value, the image is converted to binary image. This image contains the wanted and important information that is extracted from the original image. One of the characteristic of the binary image is that it contains less complex data and simplifies the classification process and recognition. To convert grayscale image to binary image, choosing a threshold value and any value higher than the threshold is classified as white (One) and the lower threshold is classified as black (Zero) [19,20]. By using the threshold technique, the background will have removed and get binary images containing only signals that will be extracted in next step.
Image (i,j) > threshold, then output = 1
Image (i,j) ≤ threshold, then output = 0

Image threshold g(x,y) define as:

$$g(x,y) = \begin{cases} 1 & if \quad f(x,y) > T \\ 0 & if \quad f(x,y) \leq T \end{cases} \qquad (1)$$

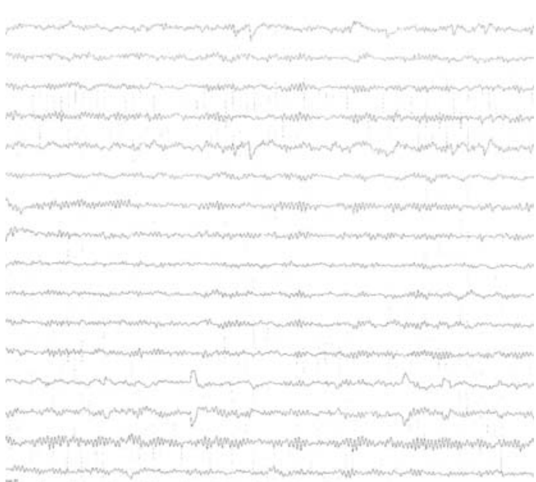

*Figure 5: Threshold Technique Result*

**B. Signal Extraction**

At this stage all signals are extracted from the images by tracking and reading the black pixels of each signal by assigning a specific range for each signal in the image and reading them separately to get 16 signals.
The signals extracted from this step contain some noise that is in the signal due to insufficient elimination of the background of the image and the noise must be removed from the signal by applying a particular filter, the Median filter was used to smoothing the signals.

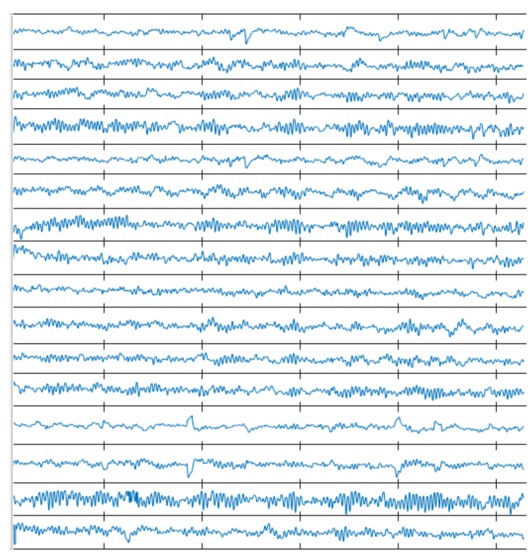

*Figure 6: The extracted Signals*

## 4.3 Pre-processing

Brain signals are very noisy and overwhelmed with large quantity of useless information generated by physiological artifacts that hide the EEG signals, filtering the signals are useful to remove this noise and unwanted data to get filtered signal [21].
So all this signals are pre-processed to remove noises caused by: deep breathing, blinking of the eyes, muscle movements, etc. The high frequency removed and filtered by low pass filter (LPF), so low frequencies will pass, that hold the original EEG signal that contain features and important data about brain activities.
The purpose of the pre-processing is to eliminate this noise and extract the original signal from this noise and to enhance the levels of signals of attention and remove undesirable signals [13]. Signal processing filters are more helpful while it comes to repressing the high frequencies in the signal, smoothing the signal, decreasing the noise or repressing the low frequencies [22].

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The filter used for high frequency removing is Finite Impulse Response (FIR).

FIR is a basic process for noise eliminating from a signal, it replaces every point of the signal by a local average that can be gained by computing the mean of the sample at n its N-1 ancestors. The most important thing of FIR filters is the ability to take a linear phase response exactly. There are some characteristics of FIR filter [23]:

1. It is inherently stable
2. It can have a linear phase
3. There is a considerable flexibility in forming their magnitude response
4. It is comfortable and simple in implementation

FIR filter is designed to pass frequency less than 64 Hz.

FIR filter for signal de-noising can be defined as:

$$y(n) = \sum_{k=0}^{N-1} b_k x(n-k) \qquad (2)$$

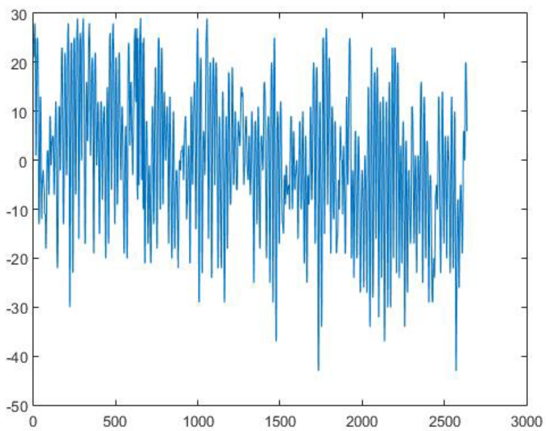


*Figure 7: Original Signal*

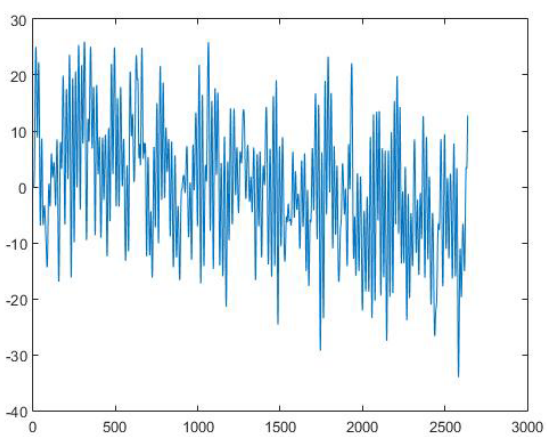


*Figure 8: Filtered Signal*

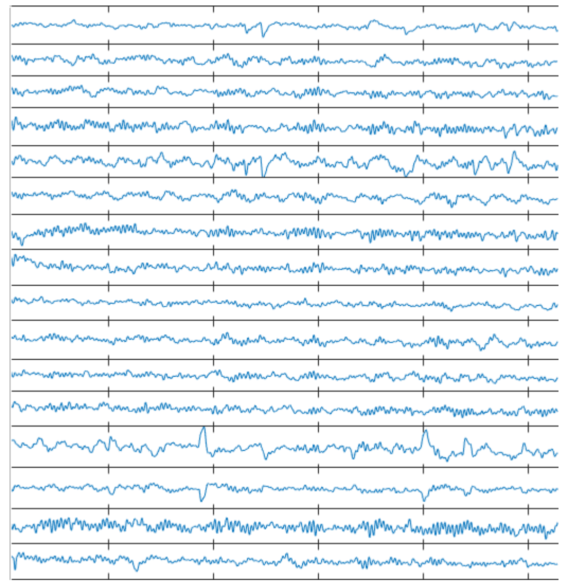

*Figure 9: Pre-processing Result for 16 Signal*

### 4.4 Feature Extraction

The method for Extraction the important features form the signal that contain information about signal to reduce the dimensional size of the signal.

The requirement of feature extraction method is to extract right features or verifying what's appropriate data that is used to classify EEG signal [24].

The basic characteristics of the signal are immersed in the noise. Therefore, in order to extract the features, the brain signals are analyzed in order to give an accurate description of the energy of the signal as a function of time and frequency domain [25].

DWT is one of signal processing tools that is adaptable. It is a successful tool in fields of brain diseases detection because it holds transient advantages in both content of time and frequency accurately. DWT method analyzes the signal in diverse frequency band, with diverse resolutions by separating the signal into approximation coefficient and detail coefficient. DWT use two sets of functions titled wavelet and scaling functions with regarding to lowpass filter and highpass filter. Analysis by using the DWT needs to select appropriate wavelet and the decomposition levels [26,27].

Discrete Wavelet Transform (DWT) method minimizes the quantity of data and holds sufficient information thus enabling the reconstruction of an excellent signal of wavelet coefficients [28].

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With expansion parameter $a=1/2^s$, translation $b=k/2^s$, where $s, k \in Z$, for the signal $f(n)$, discrete wavelet transform is defined as [28]:

$$DWT\left(\frac{k}{2^s}, \frac{1}{2^s}\right) = 2^{s/2} \sum_n f(n)\psi(2^s n - k) \quad (3)$$

DWT has a useful signal compression property. It is usable for many real signals and it is also computationally efficient. For these reasons it is used for many application including: noise reduction, image compression, pattern recognition and etc. The energy of discrete wavelet is calculated at different decomposition levels produced by DW transform [28].

$$E_n = \sum_{m=1}^{M} |T_{nm}|^2 \quad (4)$$

where n=1..., N are decomposition levels, T is the discrete wavelet coefficients, M is the number of coefficients at each level.

The most suitable kind of wavelet to be applied for a signal depends on the signal type. The simplest and oldest type of wavelet is Haar's wavelet that uses functions of square wave which can be scaled and translated to include the whole signal range [29].

Haar DWT was used in this work to analyze the signal and feature extraction. DWT hold sufficient information and thus enables the reconstruction of an excellent signal from the coefficients of the wavelet.

Haar wavelet is a procedure takes the elements mean and differences in signal, replaces adjacent pairs. Haar wavelet transform decomposes an input signal into two sub signals. In Haar wavelet applies low pass and high pass filter, low pass is performed by averaging two adjacent pixel values, high-pass filter is performed by subtracting two adjacent pixel values. From haar wavelet transform two signal are produced one has low coefficient (low band) and another have high coefficient (high band) [30].

Haar DWT decompose EEG signals into multi sub-bands waves delta, theta, alpha, beta, and gamma, figure 11 show five sub-band waves for one signal. The frequencies of the EEG waves are: delta wave varies between 0-4 Hz, Theta waves between 4-8 Hz, Alpha wave frequencies between 8-12 Hz, Beta wave frequencies varies from 12 to 30 Hz and Gamma wave have frequencies above 30 Hz [4].

Delta Rhythmic appear in deep sleep and can be present in the waking case. Theta rhythms were associated with creative revelation and deep thinking. Alpha rhythms appear during relaxation awareness. Beta rhythms are associated with a waking of brain, active attentiveness, active thinking, involved in issues solving, appreciation and decision-making. Gamma rhythms are fastest waves that processes information in different areas of the brain simultaneous [31].

$$a_i = \frac{(S_i + S_{i+1})}{\sqrt{2}} \quad (5)$$

$$d_i = \frac{(S_i - S_{i+1})}{\sqrt{2}} \quad (6)$$

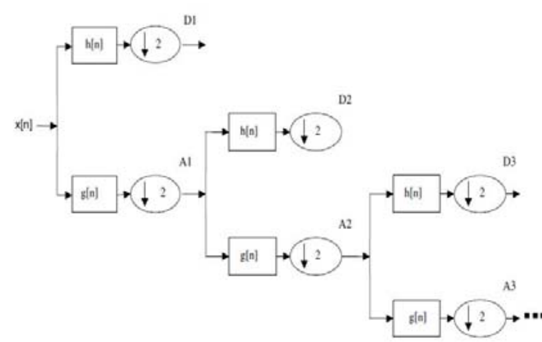


*Figure 10: DWT Sub-band decomposition*

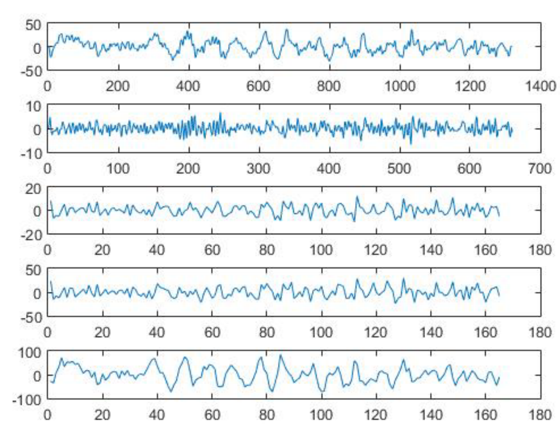

*Figure 11: five EEG Sub-bands*

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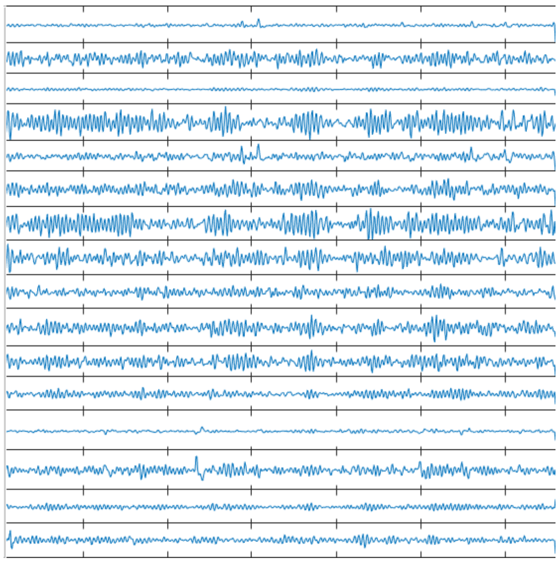

*Figure 12: Beta Sub-band for 16 signal*

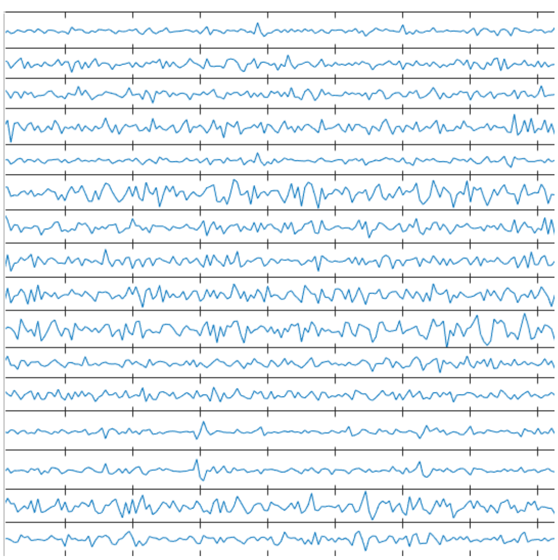

*Figure 13: Alpha Sub-band for 16 signal*

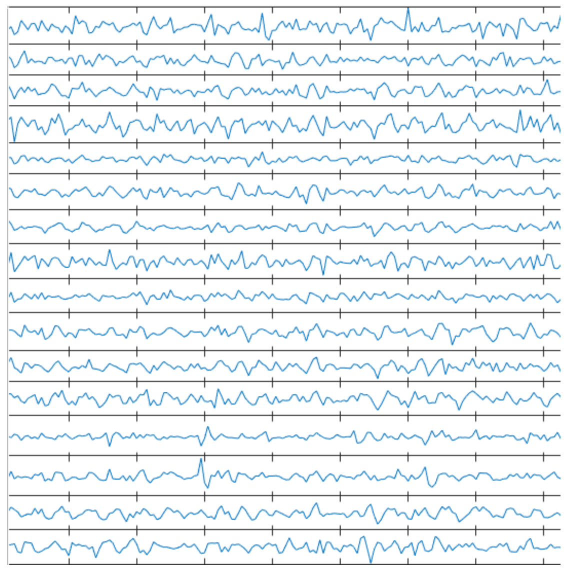

*Figure 14: Theta Sub-band for 16 signal*

In this paper we used three sub-bands (beta, theta and alpha) to extract the features. The following statistical measurements was measured for each sub-bands:

1. Mean Absolute Value (MAV)
2. Standard Deviation (SD)
3. Band Power (BP)
4. Maximum value
5. Minimum value

So, fifteen features from each signal are used to train the network.

Mean Absolute Value equation is:

$$MAV_i = \frac{1}{N}\sum_{n=1}^{N} S_i^2(n) \tag{7}$$

Standard Deviation (SD) equation is:

$$SD_i = \sqrt{\frac{1}{N}\sum_{n=1}^{N} (S_i(n) - \mu)^2} \tag{8}$$

Where μ is mean value of the signal.

Band Power (BP):

$$BP_i = \frac{1}{N} SVD(S_i)^2 \tag{9}$$

Where N is number of element in signal, and SVD is singular value decomposition.

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*Table 2: Features from Normal Data for One Person*

| MAV | STD | BP | Max | Min |
|---|---|---|---|---|
| Beta Sub-band | | | | |
| 1.42 | 2.78 | 5.59 | 6.38 | -41.64 |
| 1.68 | 3.13 | 6.82 | 8.23 | -39.61 |
| 2.14 | 3.92 | 10.54 | 12.6 | -43.06 |
| 1.95 | 3.47 | 8.08 | 9.11 | -35.18 |
| 2.02 | 3.57 | 8.51 | 7.73 | -40.34 |
| 1.82 | 3.26 | 7.17 | 9.02 | -34.61 |
| 2.24 | 4.08 | 11.43 | 10.74 | -42.51 |
| 2.82 | 4.71 | 14.02 | 12.94 | -29.55 |
| 1.58 | 2.66 | 4.50 | 6.88 | -21.58 |
| 1.47 | 2.65 | 4.78 | 6.79 | -31.74 |
| 1.85 | 3.45 | 8.31 | 9.89 | -41.91 |
| 1.43 | 2.81 | 5.73 | 5.49 | -41.94 |
| 2.61 | 4.42 | 12.49 | 11.37 | -34.08 |
| 1.13 | 2.53 | 5.01 | 4.78 | -44.79 |
| 1.67 | 3.25 | 7.60 | 7.75 | -47.45 |
| 2.47 | 4.06 | 10.28 | 10.49 | -12.89 |
| Alpha Sub-band | | | | |
| 3.33 | 5.42 | 18.51 | 12.44 | -11.63 |
| 4.02 | 6.58 | 27.29 | 13.68 | -16.21 |
| 4.17 | 6.77 | 28.56 | 19.36 | -15.11 |
| 3.81 | 6.32 | 25.54 | 16.03 | -18.16 |
| 4.82 | 7.70 | 36.41 | 15.65 | -15.36 |
| 3.07 | 4.99 | 15.66 | 11.23 | -12.01 |
| 4.08 | 6.55 | 26.45 | 17.10 | -14.51 |
| 5.24 | 8.63 | 47.12 | 25.47 | -18.94 |
| 3.97 | 6.19 | 22.79 | 11.80 | -10.66 |
| 3.60 | 5.80 | 20.93 | 14.92 | -11.23 |
| 3.37 | 5.40 | 18.25 | 13.78 | -14.73 |
| 3.27 | 5.23 | 16.91 | 10.76 | -9.58 |
| 5.57 | 8.83 | 47.09 | 16.98 | -17.39 |
| 1.94 | 3.11 | 6.08 | 5.14 | -8.15 |
| 3.56 | 5.68 | 19.91 | 10.82 | -11.79 |
| 4.23 | 6.73 | 27.39 | 12.93 | -12.54 |
| Theta Sub-band | | | | |
| 8.30 | 13.57 | 118.23 | 35.26 | -27.82 |
| 10.40 | 17.14 | 179.45 | 35.78 | -42.57 |
| 10.80 | 17.96 | 208.85 | 74.95 | -44.27 |
| 9.87 | 16.17 | 175.61 | 35.84 | -53.71 |
| 11.70 | 18.64 | 210.74 | 45.43 | -33.40 |
| 8.86 | 13.89 | 125.71 | 26.63 | -31.74 |
| 10.98 | 17.75 | 206.74 | 58.44 | -49.58 |
| 15.05 | 25.46 | 366.12 | 56.16 | -63.88 |
| 8.9014 | 14.01 | 115.31 | 27.38 | -26.70 |
| 8.8689 | 14.63 | 128.62 | 39.23 | -26.91 |
| 9.3072 | 15.20 | 140.35 | 29.60 | -38.68 |
| 8.4238 | 13.94 | 114.09 | 31.18 | -27.54 |
| 13.8206 | 22.20 | 304.12 | 45.14 | -48.33 |
| 5.7632 | 8.94 | 52.80 | 17.50 | -21.58 |
| 9.2524 | 14.27 | 127.57 | 25.69 | -29.22 |
| 11.7382 | 18.91 | 226.68 | 48.92 | -35.23 |

*Table 3: Features from Abnormal Data for One Person*

| MAV | STD | BP | Max | Min |
|---|---|---|---|---|
| Beta Sub-band | | | | |
| 3.21 | 5.59 | 20.95 | 19.10 | -26.93 |
| 4.94 | 8.02 | 39.88 | 19.81 | -24.71 |
| 3.53 | 5.78 | 21.11 | 25.41 | -22.17 |
| 5.02 | 7.91 | 37.52 | 18.57 | -19.37 |
| 2.17 | 3.67 | 8.81 | 13.23 | -11.48 |
| 3.71 | 6.03 | 22.36 | 15.20 | -27.32 |
| 3.74 | 6.10 | 23.31 | 15.90 | -21.55 |
| 4.45 | 7.09 | 30.55 | 15.62 | -15.90 |
| 2.93 | 4.86 | 15.01 | 19.75 | -12.06 |
| 5.32 | 8.56 | 45.31 | 31.08 | -22.39 |
| 3.44 | 5.81 | 22.36 | 52.88 | -13.04 |
| 6.97 | 10.97 | 71.23 | 19.04 | -24.44 |
| 2.47 | 4.08 | 10.43 | 11.07 | -18.69 |
| 5.39 | 8.76 | 48.16 | 45.90 | -19.76 |
| 3.82 | 6.27 | 25.01 | 40.99 | -13.51 |
| 5.85 | 9.44 | 54.48 | 25.86 | -21.22 |
| Alpha Sub-band | | | | |
| 8.07 | 13.20 | 108.71 | 29.80 | -35.09 |
| 13.60 | 21.89 | 290.22 | 39.03 | -48.74 |
| 9.48 | 15.32 | 142.92 | 26.26 | -40.82 |
| 15.11 | 23.67 | 328.45 | 45.63 | -42.35 |
| 6.14 | 10.32 | 68.43 | 32.22 | -32.61 |
| 10.50 | 16.82 | 171.47 | 37.03 | -38.20 |
| 10.31 | 17.12 | 184.20 | 35.32 | -44.99 |
| 13.12 | 20.74 | 254.75 | 40.04 | -41.18 |
| 8.49 | 14.02 | 123.77 | 33.64 | -34.79 |
| 14.54 | 23.45 | 334.71 | 40.37 | -43.61 |
| 8.96 | 14.75 | 134.83 | 35.42 | -33.86 |
| 19.92 | 30.77 | 545.93 | 49.98 | -45.15 |
| 6.47 | 10.64 | 71.04 | 25.40 | -24.22 |
| 15.69 | 25.06 | 376.05 | 50.27 | -50.37 |
| 10.77 | 17.39 | 183.35 | 39.62 | -38.27 |
| 16.34 | 26.04 | 407.30 | 50.73 | -45.36 |
| Theta Sub-band | | | | |
| 19.53 | 32.78 | 680.56 | 100.13 | -116.90 |
| 30.97 | 49.67 | 1490 | 83.52 | -107.53 |
| 21.99 | 35.56 | 794 | 59.67 | -95.73 |
| 34.81 | 54.37 | 1764 | 122.93 | -93.88 |
| 14.21 | 23.77 | 377.6 | 79.59 | -70.01 |
| 24.06 | 38.14 | 900.8 | 93.84 | -66.15 |
| 23.76 | 38.97 | 974.6 | 85.73 | -84.77 |
| 30.29 | 47.12 | 1332 | 91.54 | -94.09 |
| 19.20 | 31.58 | 632.2 | 78.31 | -79.47 |
| 32.50 | 52.21 | 1730.1 | 92.32 | -107.82 |
| 20.28 | 33.40 | 706.2 | 91.91 | -69.93 |
| 44.57 | 68.14 | 2760.4 | 117.07 | -109.54 |
| 15.24 | 25.23 | 402.5 | 66.13 | -65.13 |
| 35.61 | 57.44 | 2013.5 | 123.10 | -113.74 |
| 25.11 | 39.99 | 980.3 | 88.58 | -87.00 |
| 37.21 | 59.46 | 2245.8 | 130.85 | -112.78 |

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### 4.5 Support Vector Machine SVM

SVM is one of the new learning systems that introduce a good performance in pattern recognition in actual world and applications of data mining like hand written recognition, text classification, bioinformatics, classification of image, voice recognition and signal classification. Although they give solutions that are accurate, they are not good in online implementations where they should be classified very quickly. This is reverting to the truth the great set of basic functions that is often needed to SVM classifier, making it expensive and complex [32,33].

Some people considered support vector machines the best stock classifier. SVMs introduce good solution for data sets that lies outside the training set. Advantages of SVM are: generalization error is low, easy to interpret results, inexpensive computationally. SVM disadvantages are: sensitive to kernel select and tuning parameters and only dealing with binary classification. SVMs attempt to maximize margin by solving a quadratic optimization problem. SVM is robust statistical classification mechanism foremost used in case of data scarcity [34,35,36].

The SVM, originally proposed by Vapnik et al. [37]. The concept of SVM is based on dimensions of Vapnik Chervonenkis (VC). The VC is known as the maximum number of patterns that are separated into two sets by the set of functions. Simple instance example of using SVMs for classification is separating samples that are classified in one of two classes by a linear function and draws the boundaries between these samples. In other words, all training data are either in class 1 or 2 [38,39,40]. The data is separated by a decision function that takes the form:

$$D(X) = W^T X + b \qquad (10)$$

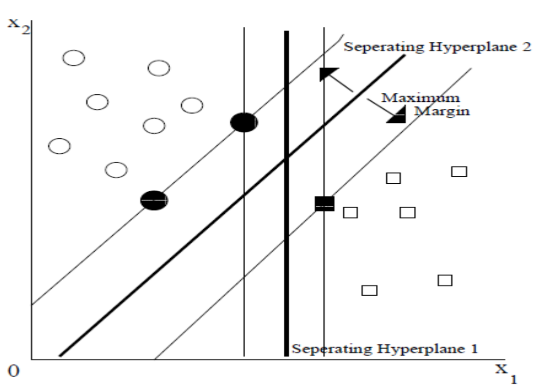


*Figure 15: Two Classes SVM Separation*

In the cases where the data is not linearly separable, the input is mapped into a multi-dimensional dot-product space called a feature space [38].
for nonlinear separable the data is separated by the equation:

$$D(X) = W^T g(X) + b \qquad (11)$$

The function x needs to meet a positive semidefinite kernel conditions also called a Mercer kernel.

### 4.6 Classification

The classification purpose is to sit a borders between two or more groups and to classify them based on their measured characteristics. The target of classification is to minimize the distance between target values and actual outputs. Brain signals are classified into two categories, the first is the normal and second is abnormal signal based on their features and to identify the abnormal signals from others. At this stage the signals are classified as normal and abnormal by the SVM classifier. SVM was used for classification, training and distinguishing between the different patterns. SVM is one of the best methods used for classification. The SVM classification has two phases, training phase and testing phase. The total signals which are collected from ten patients are 320 signals. They are divided into two halves, 160 signals are used for training and other 160 signals are used for testing. Features extracted from the Beta, Alpha and Theta sub-bands are used as input to the SVM to be classified as Normal and Abnormal and to identify cases of brain abnormalities. So, the number of inputs to the SVM network is fifteen, five from each of the three sub-bands.

## 5. RESULT AND DISSCUTION

The proposed method was trained and tested on data collecting from ten people. Five are normal and other are abnormal. These data consisting of 160 normal signals and 160 abnormal signals to be the total data 320 signals. These data were divided into two groups 160 signals were used for training and 160 others were used for testing. In this work the threshold technique was used to separate the background from the signals and gave a good result, where all the signals from the images were well separated. And then all signals were extracted from images as digital signals. All signals are filtered by FIR filter, by this filter we obtained noise-free signal with good result as shown in figure (8,9). The DWT method used for signals analysis has proved effective in decomposition of the signal into multi sub-bands.

The features used in this work are able to distinguish the differences between signals that leads to a good classification of signals. As shown in tables 2,3 show features from two state: normal and abnormal. Where, the columns represent the extracted features, and the rows represent the sixteen signals for each sub-band. The values of these features are small in the normal case and increased in the abnormal case. Where, the power of the signal in abnormal case is greater than the power of the signal in normal case. The Support Vector Machine (SVM) was used in the proposed method. SVM used these features to train the network and store it in a database. The proposed method is able to recognize abnormalities in the brain with accuracy of 96.8 %. The proposed method DWT has been a practical and useful method for analyzing brain signals and extract the brain rhythms and then extract the features. Five features were extracted from each rhythm. These features were trained and categorized SVM. The network receives fifteen features used as input to SVM. The network consists of the two output: Normal and Abnormal.

## 6. CONTRIBUTION

This work based on the medical EEG report that is recorded on paper and then used it for analysis and classification of the signals extracted from this report, see fig 3.

Designing appropriate network structure and extract the main brain rhythms and used them to extract good features that are able to distinguish between normal and abnormal signals, despite slight gaps between normal and abnormal signals due to the nature of the EEG system report, unlike a global database of signals taken direct as signals there is a clear gap between them, which is used by most former researchers.

## 7. CONCLUSION

EEG signal is one of the good techniques for brain activity measure that has been widely used in clinical diagnoses. In this work, we have proposed a method for the classification of brain abnormalities based on Discrete Wavelet Transform DWT and Support Vector Machine SVM. DWT is effective and powerful tool for decomposition of the signals into multi sub-bands. The use of the SVM with (Beta, Alpha and Theta) sub-bands extracted by DWT method gives a very good result in the classification and it is able to distinguish and classify brain signals with high accuracy. Classification accuracy obtained in this work is 96.8 %.

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