

# **IDENTIFICATION OF IDEAL REGION FOR MUSCULAR MOVEMENTS USING EEG**

Submitted in partial fulfilment of the requirements for the award of  
Bachelor of Technology degree in Biomedical Engineering.

By

**SWEDHA K (37240073)**

**NIVEDHA S (37240079)**



**DEPARTMENT OF BIOMEDICAL ENGINEERING  
SCHOOL OF BIO AND CHEMICAL ENGINEERING**

## **SATHYABAMA**

**INSTITUTE OF SCIENCE AND TECHNOLOGY  
(DEEMED TO BE UNIVERSITY)**

**Accredited with Grade "A" by NAAC | 12B Status by UGC | Approved by AICTE  
JEPPIAAR NAGAR, RAJIV GANDHI SALAI, CHENNAI - 600 119**

**MARCH 2021**



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Accredited with Grade "A" by NAAC | 12B Status by UGC | Approved by AICTE  
Jeppiaar Nagar, Rajiv Gandhi Salai, Chennai - 600 119  
[www.sathyabama.ac.in](http://www.sathyabama.ac.in)

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## DEPARTMENT OF BIOMEDICAL ENGINEERING

### BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **SWEDHA K (37240073)** and **NIVEDHA S (37240079)**, who have done the project work as a team who carried out the project entitled "**IDENTIFICATION OF IDEAL REGION FOR MUSCULAR MOVEMENTS USING EEG**", under my supervision from **October 2020** to **April 2021**.

**Mr. G. UMASHANKAR, M.Tech., (Ph.D.),**  
Internal Guide

**Dr. T. SUDHAKAR, M.Sc., Ph.D.,**  
Head of the Department

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Submitted for Viva voice Examination held on – 10.04.2021

Internal Examiner

External Examiner

## DECLARATION

We, **SWEDHA K (37240073)** and **NIVEDHA S (37240079)** hereby declare that the Project Report entitled “**IDENTIFICATION OF IDEAL REGION FOR MUSCULAR MOVEMENTS USING EEG**” done by us under the guidance of **Mr. G. UMASHANKAR, M.Tech., (Ph. D),** is submitted in partial fulfilment of the requirements for the award of Bachelor of Technology degree in Biomedical engineering.

**DATE:** 10.04.2021

**PLACE:** CHENNAI

1. 
2. 

**SIGNATURE OF THE CANDIDATES**

## ACKNOWLEDGEMENT

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We convey our thanks to **Dr. J. Premkumar, M.Sc., Ph.D.**, and **Dr. T. Sudhakar, M.Sc., Ph.D.**, **Head of the Department, Dept of Biomedical Engineering** for providing us necessary support and details at the right time during the progressive reviews.

We would like to express our sincere and deep sense of gratitude to our Project Guide **Mr. G. Umashankar, M.Tech., (Ph.D.)**, **Department of Biomedical Engineering** for his valuable guidance, suggestions and constant encouragement paving the way for the successful completion of our project work.

We wish to express our thanks to our parents, all **Teaching and Non-teaching** staff members of the **Department of Biomedical Engineering** who were helpful in many ways for the completion of the project.

## **ABSTRACT**

The muscle's electrical activity can interfere with the Electroencephalograph (EEG) i.e., acquired brain signals. Besides the frontal, occipital and temporal cortex, the parietal cortex clearly plays a role in voluntary movement, by assessing the context in which they are being made. The scope of this project is to demonstrate the accurate statistical activity and to differentiate the overall acquired signal from the filtered parietal signal. The muscular movements of the wrist (flexion, supination, extension, etc.,) are acquired through placing electrodes using DAQ. The parietal signal alone is filtered from the acquired EEG signals. The filtered signal is processed using MATLAB function to compare with the overall signal and the analysis is done to obtain the ideal region of muscular movement. The classification algorithm tends to differentiate the type of action took place. In the proposed system, design of FFT (Fast Fourier Transform) based feature extraction is done. The FFT is used to convert the time domain signal to frequency domain. These components are fetched to Haar wavelet. The proposed system modulates the Deep learning pattern analysis network to evaluate the matching sequence on each action takes place. The performance of the system is measured with accuracy, precision and recall. The comparison result can be used for the implementation of neuro prosthetic applications.

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## LIST OF ABBREVIATIONS

|         |                                     |
|---------|-------------------------------------|
| AI      | Artificial Intelligence             |
| ANN     | Artificial Neural Network           |
| BCI     | Brain Computer Interface            |
| DFT     | Discrete Fourier Transform          |
| DWT     | Discrete Wavelet Transform          |
| Db      | Daubechies wavelet                  |
| DNN     | Deep Neural Network                 |
| EEG     | ELECTROENCEPHALOGRAPHY              |
| ECOG    | ELECTROCORTICOGRAPHY                |
| EWT     | Empirical Wavelet Transform         |
| EMG     | ELECTROMYOGRAM                      |
| FT      | Fourier Transform                   |
| FFT     | Fast Fourier Transform              |
| FPR     | False Positive Rate                 |
| Hz      | Hertz                               |
| ICA     | Independent Component Analysis      |
| LFP     | Local field Potential               |
| LDA     | Linear Discriminant Analysis        |
| LV-SVM  | Least Square Support Vector Machine |
| MD      | Mahal Nobis distance                |
| M-files | .m Extension files                  |
| ML      | Machine Learning                    |
| PSD     | Power spectral Density              |
| QDA     | Quadratic Discriminant Analysis     |
| ROC     | Receiver Operating Characteristic   |
| SNR     | Signal to Noise Ratio               |
| SD      | Standard Deviation                  |
| TPR     | True Positive Rate                  |
| Tanh    | Tangent                             |
| WT      | Wavelet Transform                   |

# **CHAPTER 1**

## **INTRODUCTION**

### **1.1 INTRODUCTION:**

Biomedical engineering is the utility of engineering standards and design principles to medicinal drug and biology for healthcare functions. This discipline seeks to shut the distance between engineering and remedy, combining the design and problem fixing competencies of engineering and clinical and biological sciences to increase health care remedy, including diagnosis, tracking and therapy. One such application of biomedical engineering is used for neuro imaging of brain signals which can be applied for prosthetic programs.

EEG stands for electro-encephalography or electro–encephalogram. It is the continuous recording of electrical brain activity. Human brain is made up of millions of brain cells called neurons. The neurons have axons that release neurotransmitters and dendrites receive them. When the dendrites of neurons receive the neuro transmitters from the axons of other neurons, its cause's electrical polarity change inside the neurons and it is recorded by the EEG. Post synaptic dendritic currents from the cortical pyramidal cells. The activity from one single nerve is way too small to be detected in an EEG but when thousands of neurons come together, we can measure the EEG as required i.e., from the area where a group of nerves configure which is called the Local Field Potential (LFP).

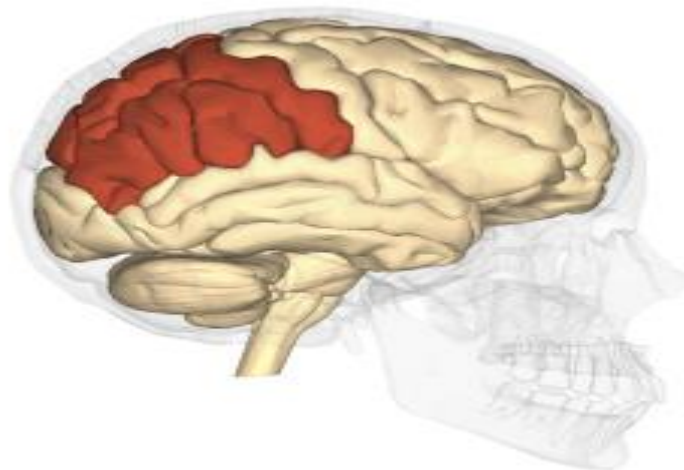
The conventional scalp EEG is used to record the EEG signals. It consists of electrode paste which helps in better conductivity when using a surface electrode. Many systems typically use electrodes, each of which is attached to an individual wire. Some systems use caps or nets into which electrodes are embedded; this is particularly common when high-density arrays of electrodes are needed. No matter whichever electrode is used the functions succeeding the signal acquisition is same. The electrodes are to conduct the electrical signals which are passed to an EEG amplifier which helps in amplifying the signal strength. The data is then sent to a data acquisition computer to store and analyse. The computer software helps to convert the signals into required forms like excel data sheets or conditioned signals (Hemant, et al., 2010).

The EEG technique was chosen among other the other technique because it is fast and captures signals in milliseconds, it is safest technique of neuroimaging. The neuroimaging helps in recognizing the part of brain and their corresponding functions, along with the frequency of the emitted brain signals. Our project is to use acquired signals analyse the various frequency ranges at which the brain signals make motor activities possible.

## 1.2. LOBES OF THE BRAIN:

### **1.2.1. Parietal:**

The parietal cortex is where the brain represents how an arm is functioning, constantly seeking information on the arm's whereabouts, its position in three-dimensional space.

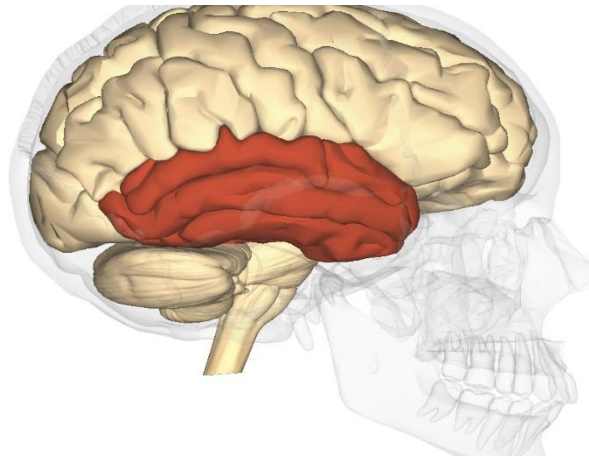


**Fig: 1.1 PARIETAL**

In the brain one of the four major lobes of the cerebral cortex is the parietal lobe. Above the temporal lobe, behind the frontal lobe and central sulcus the parietal lobe is placed.

Center of the somatic senses is the parietal lobe. Most importantly, in identifying objects around us this part of the brain plays a significant role. It helps to understand spatial relationships, and correctly analyze and compare the position of one body concerning another or the observer himself. For also pain and touch interpretation this lobe is also important.

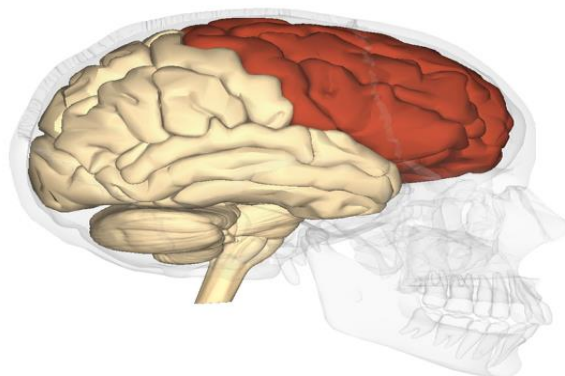
### **1.2.2. Temporal:**



***Fig: 1.2 TEMPORAL***

The temporal lobe is located below the lateral fissure at the bottom of the brain, on either side of the lateral fissure, near to the ears. The temporal lobe is where sound is processed, and it's also where the auditory language and speech comprehension systems are located. The auditory cortex is located on the temporal lobe's upper banks, inside the Sylvian fissure. Wernicke's region for speech understanding is located just posterior to the auditory cortex. The temporal lobe, however, is more than just a sound and language processing centre. The temporal lobes middle parts are thought to contain semantic knowledge's conceptual representations.

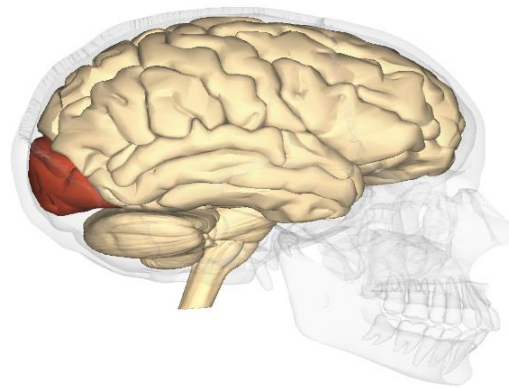
### **1.2.3. Frontal:**



***Fig: 1.3 FRONTAL***

The frontal lobes are the largest of the lobes in the brain and located at the front of the brain. It's estimated they make up about one-third of the cerebrum. The front lobe plays a major role in speech and language production in the dominant frontal lobe, reasoning, judgment, organization, planning, working memory, which involves processing recently acquired information, attention, concentration and problem-solving.

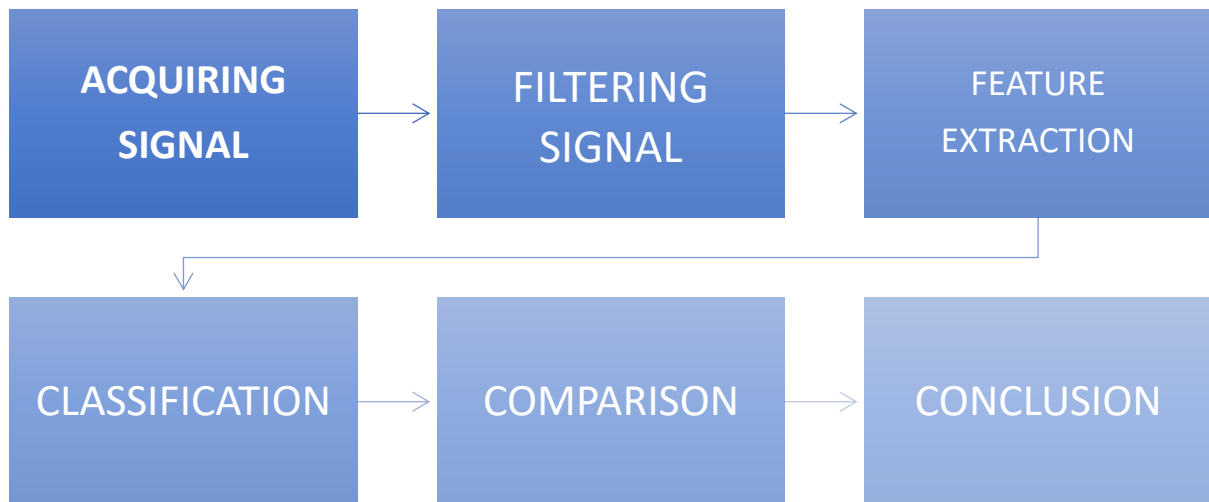
#### ***1.2.4. Occipital:***



***Fig: 1.4 OCCIPITAL***

One of the four major brain lobe pairs in the human brain is the occipital lobe. Since it rests below the occipital bone of the skull named as the occipital lobe. It is also the smallest of the lobes. The occipital lobe deals with colour determination, depth perception, object recognition, face recognition and memory information.

### 1.3. STEPS INVOLVED IN THE PROJECT:



**Fig: 1.5 WORKFLOW**

➤ **SIGNAL ACQUISITION:**

In this step the basic EEG of a normal human is taken as per required conditions using a conventional EEG setup. The data is stored in an excel sheet using an application which converts the raw EEG to numerical values.

➤ **PREPROCESSING:**

The pre-processing aims at removing noise, interferences, and artifacts before performing feature extraction.

➤ **FEATURE EXTRACTION:**

It reduces the dimensionality and helps to extract more useful information hidden in the signals by avoiding unnecessary or redundant info.

➤ **CLASSIFICATION:**

It is performed based on the selected features. The performance of the classifier depends on both how well the signals are pre-processed and the features are extracted.

## 1.4. SOFTWARE AND HARDWARE USED:

### **1.4.1. Hardware:**

The hardware used here is the Conventional scalp EEG. It has got 10-20 graphical recording technology. The signals are conducted by surface metal electrodes attached to the scalp using conduction paste. The other hardware which can be used in EEG measurement include EEG caps, epoch etc.

### **1.4.2. Software:**

MATLAB (Matrix Laboratory) is a high-performance language for technical computing. To express the solutions in familiar mathematical notation and to integrate computation, visualization, and programming in an easy way MATLAB is utilized. Typical uses include:

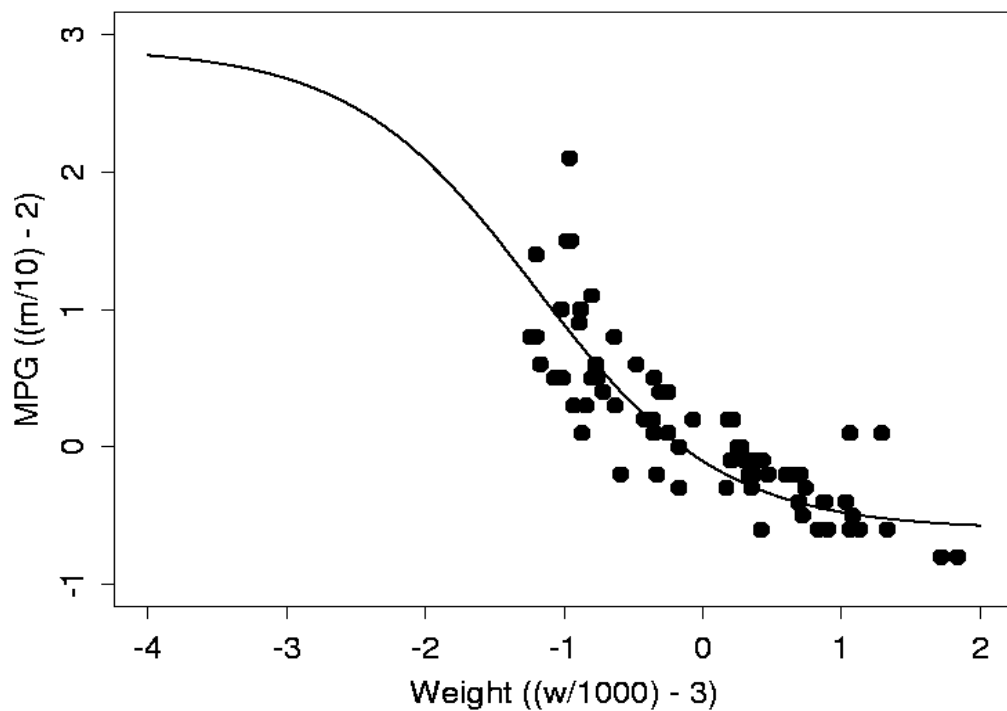
- Algorithm development
- Math and computation
- Data analysis, exploration, and visualization
- Modeling, simulation, and prototyping
- Scientific and engineering graphics
- Application development, including graphical user interface building

## 1.5. TECHNOLOGIES USED:

### **1.5.1. Deep neural network:**

Consider the best linear fit we discovered for the car data once more. The data points are not uniformly spread along the axis since we see more miles per gallon for low weights than our model expects. In truth, it appears that a simple curve will better suit these data than a straight line. Giving our neural network an additional node with a suitably curved (nonlinear) activation mechanism allows it to do curve fitting. The S-

shaped hyperbolic tangent (tanh) function is a useful function for this. Our new network is depicted in Fig: 1.7 between input and output, an extra node (unit 2) with the activation function has been added. The term "hidden device" refers to a node that is "hidden" within the network. It's worth noting that the secret unit has a weight from the bias unit as well. This bias weight is present in all non-input neural network units. The bias unit and weights are usually absent from neural network diagrams for simplicity; however, unless otherwise specified, you can still presume that they are present.

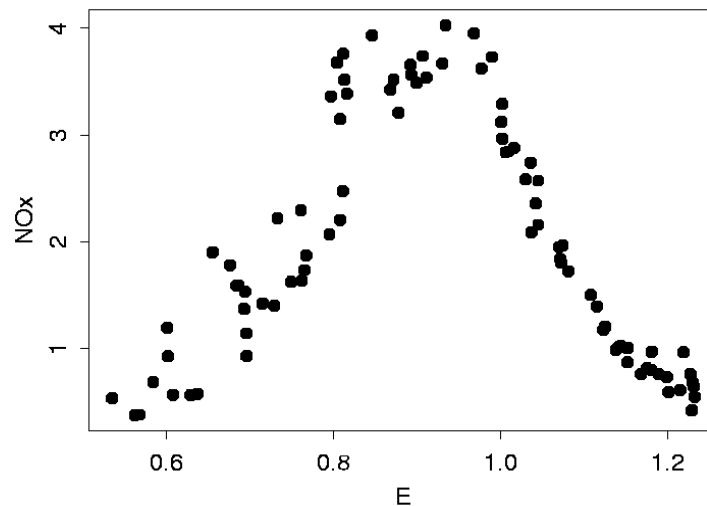


**Fig: 1.6. Weight/MPG graph**

(Fig: 1.8) when using gradient descent to train this network on car data, it learns to adapt the tanh function to the data (Fig: 1.8). Each of the network's four weights has a specific role to play in this process: the two bias weights change the tanh function in the x- and y-directions, respectively, while the other two weights scale it in all directions. The weight values that provided the solution seen in Fig. 1.8 are seen in Fig. 1.7.

### 1.5.2. Hidden Layers

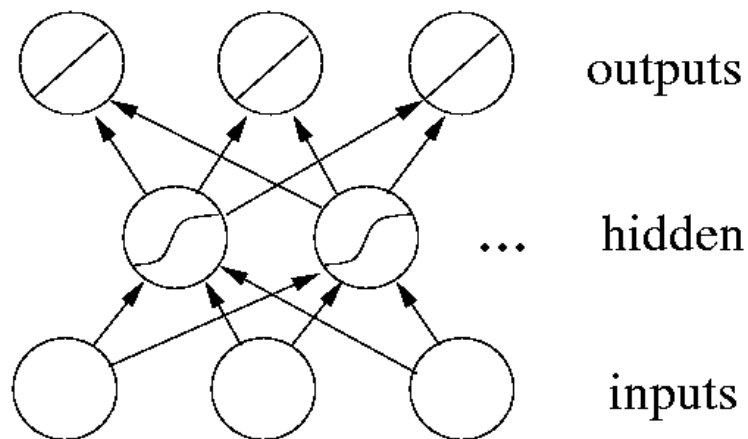
We might argue that we cheated in the example above by selecting a hidden unit activation function that matched the data well. What would we do if the data looked anything like this (Fig 1.9)?



**Fig: 1.7.E/NOx graph**

(As a result of the richness of the ethanol/air mixture burnt in a car engine, the relative concentration of NO and NO<sub>2</sub> in exhaust fumes.)

The tanh feature is unable to match this data. We might create a unique activation mechanism for each data set we experience, but that would negate the intent of learning to model the data in the first place. We'd like to provide a general, non-linear function approximation approach that allows us to suit any data set, regardless of its shape.



**Fig: 1.8. NEURAL NETWORK**

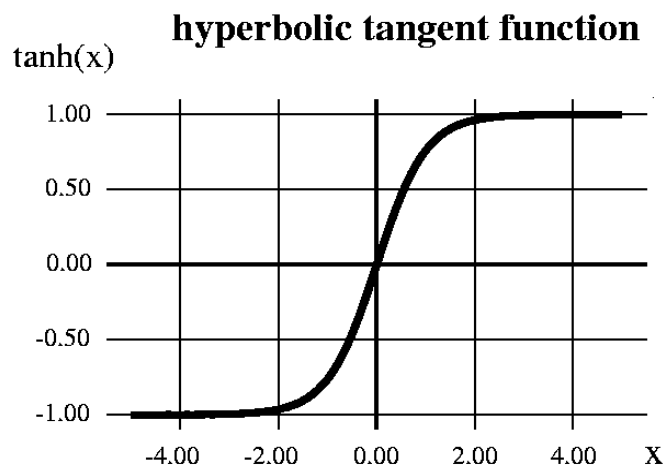
Fortunately, adding more secret units is a straightforward option! In reality, using the tanh algorithm, a network with only two hidden units (Fig. 1) will suit the data in Fig. 4 very well - can you see how? By adding more units to the secret plate, the fit can be increased even more. However, having a hidden layer that is too big - or too many hidden layers - will impair network capacity (more on this later). In general, a problem should not be solved with more secret units than are needed. (One way to make sure this happens is, to begin with, a small network.) If gradient descent fails to produce a satisfactory result, expand the network by adding a hidden unit and try again.)

Theoretical findings show that a network like the one in Fig. 5 will approximate any rational feature to the desired degree of precision if there are sufficiently hidden units. To put it another way, any function can be represented as a linear combination of tanh functions: the tanh function is a universal base function. The sigmoidal (S-shaped) basis functions (Sachin Taran & Varun Bajaj, et al., 2019) (of which tanh is one) and the radial basis functions (of which tanh is one) are two types of activation functions widely used in neural networks.

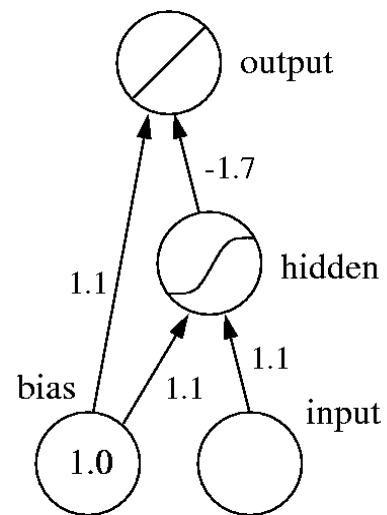
### **1.5.3. A nonlinear problem:**

Consider the best linear fit we discovered for the car data once more. The data points are not uniformly spread along the axis since we see more miles per gallon for low weights than our model expects. In truth, it appears that a simple curve will

better suit these data than a straight line. Giving our neural network an additional node with a suitably curved (nonlinear) activation mechanism allows it to do curve fitting. The S-shaped hyperbolic tangent (tanh) function is a useful function for this (Fig. 1).



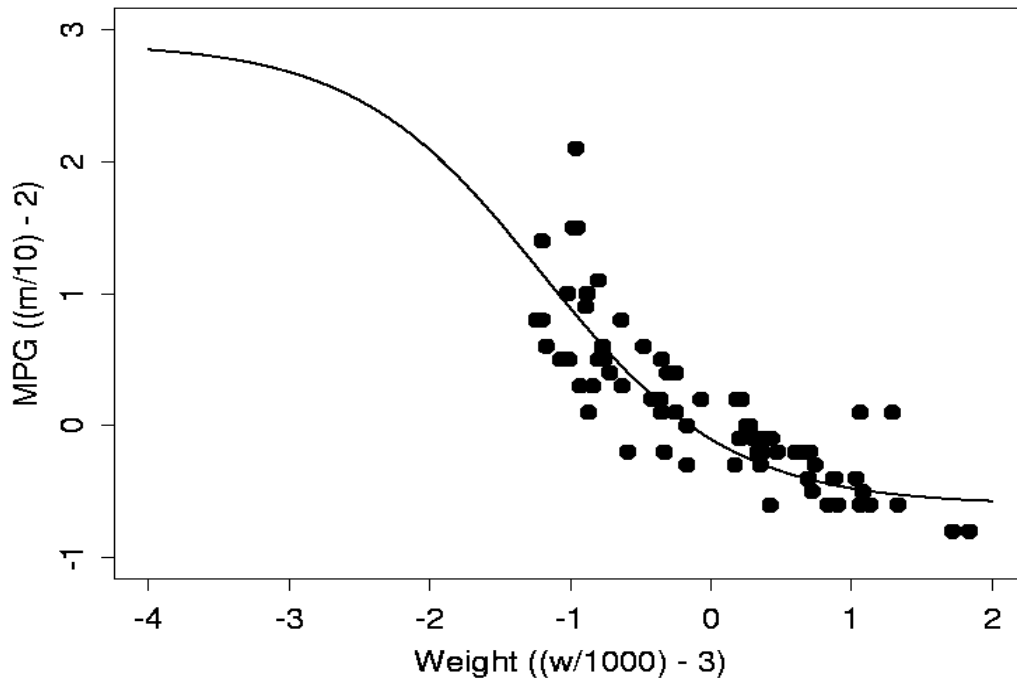
**Fig (1)**



**Fig (2)**

**Fig: 1.9 HYPERBOLIC TANGENT FUNCTION**

Our new network is seen in Figure 2: between input and output, an extra node (unit 2) with the tanh activation function has been added. The term "hidden device" refers to a node that is "hidden" within the network. It's worth noting that the secret unit has a weight from the bias unit as well. This bias weight is present in all non-input neural network units. The bias unit and weights are usually absent from neural network diagrams for simplicity. However, unless otherwise specified, you can still presume that they are present.

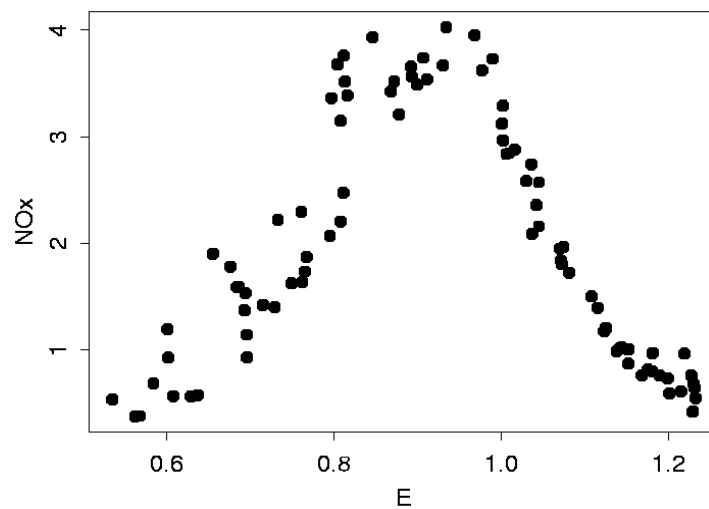


**Fig: 1.10 Weight/MPG scatter graph**

When using gradient descent to train this network on car data, it learns to adapt the tanh function to the data (Fig. 1.8). Each of the network's four weights has a specific role to play in this process: the two bias weights change the tanh function in the x- and y-directions, respectively, while the other two weights scale it in all directions. The weight values that provided the solution seen in Fig. 1.8 are seen in Fig. 1.7.

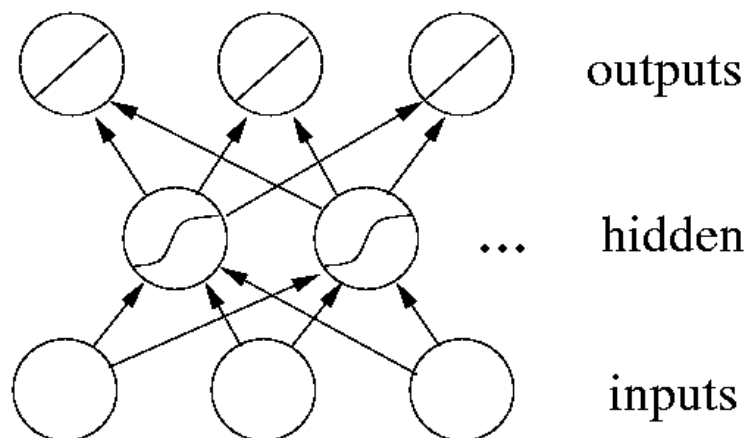
### **Hidden Layers**

We might argue that we cheated in the example above by selecting a hidden unit activation function that matched the data well. What would we do if the data looked anything like this (Figure 1.9)?



**Fig: 1.11 E/NOx scatter graph**

The tanh feature is unable to match this data. We might create a unique activation mechanism for each data set we experience, but that would negate the intent of learning to model the data in the first place. We'd like a generic, non-linear function approximation approach that would allow us to suit every data set, regardless of its shape.



**Fig: 1.12: Neural network**

#### **1.5.4. Error backpropagation:**

We've already learned how to use gradient descent to train linear networks. We run into a problem when planning to do the same with multi-layer networks: we don't have any target values for the hidden devices. How do we tell the secret units what to do? This seems to be an insurmountable challenge. This unanswered question was, in effect, the reason why neural networks faded from favour after a brief heyday in the 1950s. It took 30 years for the error back propagation (or backdrop) algorithm to become widely used as a method of training hidden units, resulting in a new era of neural network research and implementations.

Back prop, in theory, allows you to train networks of any number of secret units in any number of layers. (There are some obvious realistic limitations, which we'll go through later). In reality, the network does not have to be arranged in layers, any communication pattern that allows the nodes to be partially ordered from input to output is acceptable. To put it another way, there must be a way to arrange the units such that all relations go from "earlier" (closer to the input) to "later" (further away from the input) (closer to the output). This is the same as saying their link pattern can't have any loops in it. Feed forward networks adhere to this constraint, and their association pattern forms a directed acyclic graph, or dag.

## **CHAPTER 2**

### **LITERATURE STUDY**

#### **2.1. LITERATURE STUDY:**

The existence of electrical currents inside the brain changed into determined in 1875 by an English physician Richard Caton. He discovered the EEG from the uncovered brains of rabbits and monkeys. In 1924 Hans Verger, a German neurologist, used his normal radio device to increase the brains electric interest measured at the human scalp. He introduced that susceptible electric currents generated in the mind can be recorded without starting the cranium and depicted graphically on a strip of paper. The pastime that he located modified consistent with the practical status of the brain, including in sleep, anaesthesia, and absence of oxygen and insure neural sickness like epilepsy. Berger laid the rules for the various gift packages of electroencephalography. He extensively utilized the phrase electroencephalogram because the first for describing mind electric powered potentials in people. He was proper together with his proposal that brain interest modifications in a constant and recognizable manner when the general popularity of the difficulty modifications, as from rest to alertness. Later in 1934 Adrian and Matthews published the paper verifying idea of “human brain waves” and identified everyday oscillations (Jrad, et al., 2017) around 10 to 12 Hz which they termed “alpha rhythm”. Mind waves (Paulo Rogerio, et al., 2013) category for obtaining basic brain styles of individuals, topics are instructed to close their eyes and relax. Mind styles shape wave shapes which might be generally sinusoidal (Tephlan, et al., 2002).

In this experiment, the artefactual effects of the small muscle movements such as hand and finger movements that are necessary for the keyboard and mouse usage are investigated. Time and frequency domain features are extracted from the upper frequency bands (Rouven Kenville, et al., 2020) and sometime domain features such as variance obtain a visual difference between two states. Three-layer neural network models created for the classification of the activity and resting states and the model yields 92.2% accuracy. Secondly, for the finger artifacts the left and right finger press conditions are investigated. The effects of finger artifacts are shown by the analyzed time and frequency domain features. 64% of classification accuracy was obtained by the neural network models for the finger artifact detection. After

removing the eye blink artifacts finger artifacts classification accuracy increases to 72%. As a result, small muscle artifacts have detectable effects on the EEG signal (Gizem Yilma, et al., 2014). If the small muscle movements are intense, these effects can be observed visually. If the data has just finger movements, the effects cannot be observed visually but can be detected by machine learning methods such as neural networks. (Erhan, et al., 2016).

Another experiment relates to data adaptive empirical wavelet transform (EWT) (Abhijit Bhattacharyya & Ram Bilas Pachori, 2017) based signal decomposition method for improving the classification accuracy of MI based EEG signals. Specifically, to reduce the system complexity and execution time, the proposed method selects 18 electrodes out of 118 to analyze the non-stationary and nonlinear EEG signal behaviours. Meanwhile, the method adopts the Welch power spectral density (PSD) analysis method for single mode selection out of the total 10 for each channel, and the Hilbert transform (HT) method for both instantaneous amplitude (IA) and instantaneous frequency (IF) signal components extraction for each selected mode. EWT based algorithms using either IA or IF components are proposed to improve success rate of EEG signal classification. Specifically, to reduce the computational load, only 18 motor cortex area channels among all 118 were selected for experiments. While to further reduce the feature dimension, only one model is selected from 10 modes for each channel. The selected mode is susceptible to MI data and helps achieve the highest classification accuracy among various MI classes. Experiments with the publically available dataset IVa from BCI competition III were performed to evaluate the performance of algorithm. Results showed that the proposed EWT technique achieves higher classification accuracy. (Muhammad, et al., 2019).

Brain Computer Interface (BCI) is new area of disabled people (Ioulietta Lazarou, et al., 2018). Detection of imagination of left brain is made in a project and it can be used for external devices such as robotic arm. Scalp electroencephalogram electrodes are utilized to record the electrical activity. The signals were collected using Enobio 8 software. The collected signals are given to NE-Viewer filter to get Filtered data. The filtered data is then used to extract information from the time domain in the ALPHA and BETA bands using the wavelet transform. Some of the parameters such as power, standard deviation, and variance are extracted using

alpha and beta waves. The LDA classifier is used to classify the Imagination of left and righthand movements. In this project we had taken 40 samples for training data set and for testing phase we have taken 10 samples for testing and we have achieved 90% of accuracy (Lavanya, et al., 2016).

The aim of this thesis is to automate the procedure by developing a detector that would pick out epileptic transients containing the “Abnormal Epileptiform Paroxysmal” (AEP) type. The process was divided into two methods such as, detection of potential AEPs and the classification of the detected segments. Using sensitivity, specificity and precision as parameters, the resulting performance of the networks was studied. With respect to expert marked AEPs the overall performance of the detector was verified. To overcome the drawbacks found in using specificity an additional parameter based on detected AEP length was introduced. If the sensitivity values are high, the specificity values determined were at best an approximation of the ANN ability to pick out AEPs and hence, was not enough to reach a conclusion regarding the detector performance. For this purpose, by comparing the length of expert defined yellow boxed AEPs and detected AEPs the proposition of the overboxing score gives a much better estimation. While comparing the length, it gave an idea about how much a detected AEP is overboxed. Combining this with the number of AEPs detected (True Positives) gives a much better idea about the performance. (Sharan Rajendran, et al., 2016).

An International journal had used ANN for classification of brain signals responsible for motor imageries including wrist rotation and elbow rotation. All these papers focused on motor activities which were held responsible for EEG changes at specific location of brain. A journal on EEG classification between a normal human and an epileptic patient showed clear difference in the standard deviation values for both individuals. The statistical analysis of signals including factors such as mean, standard deviation etc., helped give a characterization of the signal. (Siuly, et al., 2015).

An International journal in which the EEG frequencies of female for various wrist movements such as flexion and extension, anticlockwise rotation and clockwise rotation, pronation and supination have been extracted in both eyes open and eyes close condition through 10 –20 electrode system. The obtained frequencies are

almost similar to that of the alpha and beta rhythms of brain signals, i.e., the frequencies lie between 22 and 28 Hz. From the observed frequency range beta waves are more prominent during these movements. Since the variations of frequency for each movement is very small, it can be analyzed through the classification techniques. These processed frequencies can be used for neuro prosthetic applications. (Umashankar, et al., 2018).

## **CHAPTER 3**

### **AIM AND SCOPE**

#### **3.1. AIM:**

The aim of the project is to identify the ideal region for muscular movement, in which the acquired overall EEG signals were compared with the filtered parietal signal which is responsible for muscle movement. The signals were processed and classified using Hybrid classification i.e., Levenberg-Marquardt algorithm. The statistical analysis of these two values is compared for accurate result and it can be implanted in neuro prosthetic application.

#### **3.2. SCOPE:**

The popularity of analysing brain rhythms and its applications in care is obvious in rehabilitation engineering (Siang Ang, et al., 2011). Motor disabilities because of stroke need rehabilitation method to regain the motor learning and retrieval. The classification of graph signals obtained by employing a low-price Brain Computer Interface (BCI) for radio-carpal joint and grip movements is employed for recovery. The BCI system, graph knowledge is extracted through recorded and processed EEG. The non-inheritable knowledge ought to have the smallest amount element of environmental noise and artifacts for effective classification. Graph signals non-inheritable from the invasive technique square measure found to exhibit least noise elements and better amplitude. However, in most applications, a non-invasive technique is most well-liked. Many folks have motor disabilities thanks to the nerve system breakdown or accidental failure of nerve system which help cure disabilities through Neuro medical specialty (neural prosthetics) and BCI. In neuro medical specialty, an answer of the matter is within the sort of connecting brain nerve system with the device and in BCI connecting brain nerve system with pc. BCI manufacture a communication between brain and pc via EEG, ECOG or one thousand signals. These signals contain data of any of our body activity (Pedron Reis, et al., 2014). Additionally, to neuro rehabilitation, helpful AI and brain management mobile robots conjointly utilize similar technologies as according recently. (Khan, et al., 2017).

### 3.3. EXISTING METHOD:

- Classification of EEG signals associated with index finger movements using Hidden Markov Models.
- Classification of EEG signals associated with left arm and right arm using SVM classifiers.
- Signal classification using ARMA [Auto Regressive Moving Average for hand movements such as finger open, finger close, wrist clockwise and wrist counter clockwise. (Ramalingam, et al., 2016)
- Signal classification using LDA, quadratic classifier (QDA) and classifier based on Mahal Nobis distance (MD) (Aqsa Shakeel, et al., 2015) for right hand and left-hand movements.
- Classification of EEG acquired EEG signals using Scaled Conjugate gradient method
- In the current method, the prediction of muscular movement through EEG signal is not accurate and the analysis presents the overall brain sensory signals.
- In the Existing Method commonly used wavelet functions are utilized to read the coefficients of the input EEG data.

### 3.4. PROPOSED METHOD:

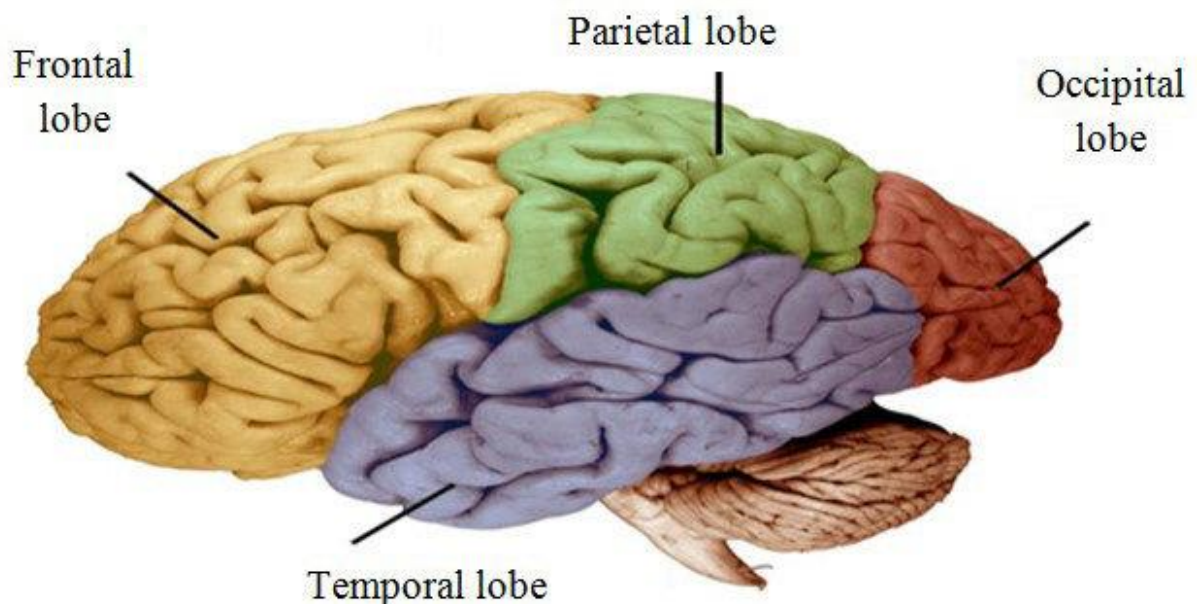
- In proposed system, the filtered parietal signal from the overall acquired brain signals and the estimation of statistical analysis of these signals produces the better implementation of neuro prosthetic application.
- The FFT is used to convert the time domain signal to frequency domain. These components are fetched to Haar wavelet.
- The proposed system modulates the Deep learning pattern analysis network to evaluate the matching sequence on each action takes place. The performance of the system is measured with accuracy, precision and recall.
- The project's goal is to obtain the power spectral density of the four channel datasets.
- To successfully create a hybrid machine learning algorithm that can be used in real time for prediction by using DWT to extract features and delete unnecessary dataset

## CHAPTER 4

### MATERIALS AND METHODS

#### 4.1. SIGNALS OF THE BRAIN:

The brain is one of the maximum complicated and remarkable organs within the human frame refer to fig: 4.1. Our brain gives us attention to ourselves and our surroundings, processing a steady stream of sensory records. It controls our muscle actions, the secretions of our glands, or even our respiration and inner temperature. Each innovative idea, feeling, and the plan is developed by using our brain. The brain's neurons document the reminiscence of each occasion in our lives.



***Fig: 4.1 BRAIN***

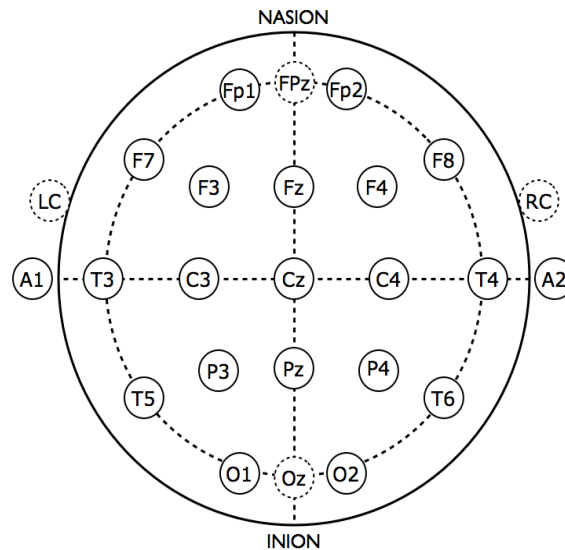
Neurons, or nerve cells, are the cells that perform all the communication and processing within the brain. Sensory neurons in the brain receive information about the state of the body and its surroundings from the peripheral nervous system. Interneurons, which are responsible for integrating and processing information transmitted to the brain by sensory neurons, make up the majority of neurons in the grey matter of the brain. Interneuron sends signals to motor neurons, which carry signals to muscles and glands. Glial cells, also known as neuroglia, are brain helper cells that assist and defend neurons. Glial cells in the

brain are divided into four types: astrocytes, oligodendrocytes, microglia, and ependymal cells.

#### 4.2. ELECTROENCHALOGRAPHY:

Electroencephalography is an electrophysiological monitoring method to record electrical activity of the brain. Electrical recordings can be divided into invasive and non-invasive techniques. Non-invasive recordings are performed by measuring the electrical activity on the patients scalp by means of electrodes. The advantage of invasive technique is that it is cheaper, risk free and is easier. (Gerrit, et al., 2016). The system by which EEG electrodes are applied to the head then displayed on EEG recordings is called the International 10-20 system.

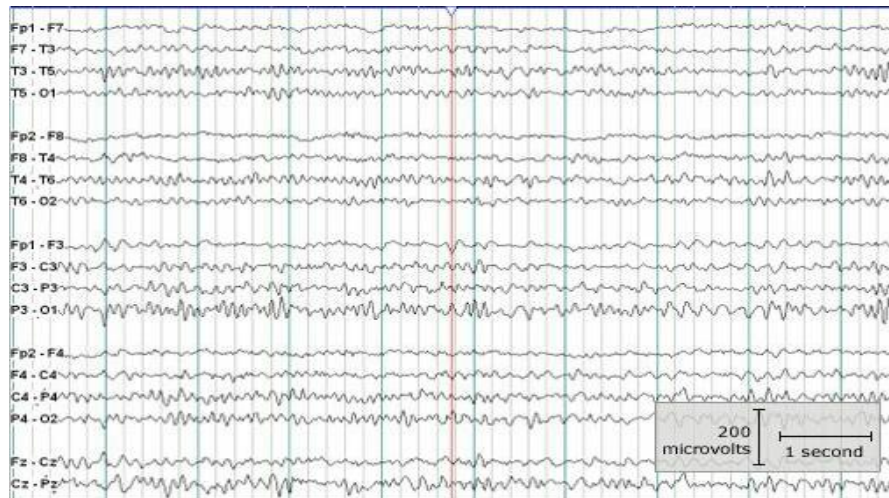
The International 10-20 system is a standard of measuring the head and placing the electrodes. It depends on four main positions on the head that are easily transferable between the patients. First is the nasion at the bridge of the nose, next is the Inion at the bony prominent at the back of the head and then two Pre-auricular points just anterior to the ear. The first measurement that is made is from nasion to the inion (front to back). This measurement is then divided into 10 and 20 percent increments and this is how the 10-20 system gets its name. Marks are placed and then the measurement is done from one pre-auricular point to the other. Again, this is divided into 10 and 20 percent increments and additional marks are made. Further marks are made in the circumference of the head and separated by 10 percent increment and the parasagittal measurements are made separated by 25 percent increments. And finally, transverse measurements are made. The intersections of the two lines are where the electrodes are finally placed.



**Fig: 4.2 10-20 ELECTRODE SYSTEM**

Each electrode is represented by a number and letter refer fig: 4.2. The numbers indicate the side of the head so that odd numbers are on the left and even numbers are on the right. In general, lower numbers mean that the electrodes are closer to the midline, the midline itself is represented by z (zero). The letters denote where on the head the individual is. F stands for frontal, C for central, P for parietal, T for temporal, O for occipital. The conventional scalp EEG is used to document the EEG signals. It consists of electrode paste which helps in higher conductivity whilst the use of a floor electrode. Many systems commonly use electrodes. That is connected to a person's scalp. Other structures use caps or nets into which electrodes are embedded. No matter which electrode has used the capabilities succeeding the sign acquisition are equal. The electrodes are to conduct the electrical indicators which are exceeded to an EEG amplifier which allows in amplifying the signal electricity. The signal is then sent to a facts acquisition computer to study and analyze. (Britton, et al., 2016)

### 4.3. ELECTROENCEPHALOGRAPH:



***Fig: 4.3 NORMAL ELECTROENCEPHALOGRAPH***

It's been used in medical diagnostics as well as neurobiological studies. The essential components of an EEG machine include electrodes, amplifiers, a computer control module, and a display device. The EEG computer, which was first developed in the early twentieth century, is still being improved. It is thought that this machine will lead to a wide range of important discoveries both in basic brain function and cures for various neurological diseases refer fig: 4.3.

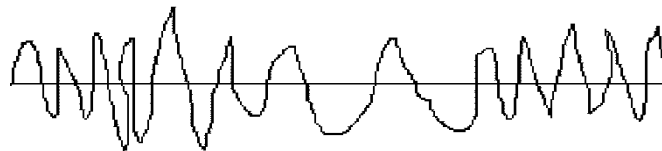
### 4.4 BRAIN ACTIVITY PATTERNS

The mind waves may be labeled with the use of their frequency, amplitude, shape, and position of electrodes on the scalp. The EEG programs recognition on a rather slim band, from 0.1 Hz to one hundred Hz, as a maximum of the EEG, sign energy lies in this frequency range (Brijesh, et al., 2016).

Time area representation of the different forms of brain waves with time in the x-axis is represented in the below diagrams for a higher understanding of different brain waves. EEG indicators are labeled primarily based on their frequency range.

#### **4.4.1. Alpha:**

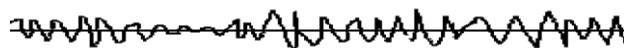
Alpha waves are in the frequency range from 7.5 Hz to 12 Hz. These types of waves originate from the occipital lobe and backside of the head refer fig: 4.4. Alpha waves dominate in relaxed and calm mental states while being awake (Yvonne Blokland, et al., 2015). They have higher amplitude compared to other waves.



***Fig: 4.4 ALPHA WAVE***

#### **4.4.2. Beta:**

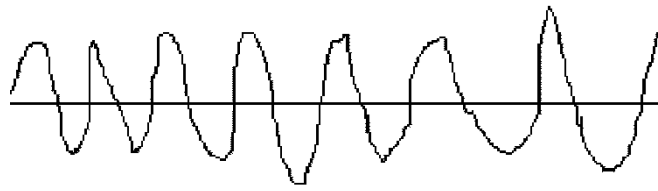
Beta waves ranging from 13 to 30 Hz, are associated to deep wondering, high awareness level and decision making refer fig: 4.5. They've huge frequency band when compared with others. Beta waves originate from cortex region of the brain and front side of head.



***Fig: 4.5 BETA WAVE***

#### **4.4.3. Theta:**

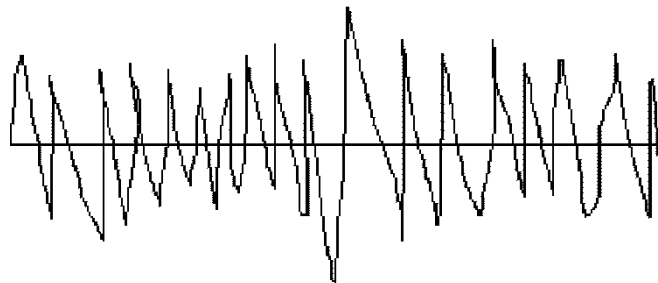
Theta waves are in the frequency range from 3.5 to 7.5 Hz. They originate from central, temporal, and parietal parts of the head refer fig: 4.6. A high level of theta waves generally occurs in abnormal adults. They arise during creative thinking, stress, and deep meditating state.



***Fig: 4.6 THETA WAVE***

#### **4.4.4. Gamma:**

Gamma waves are the waves that lie in the frequency range of 30 Hz and above refer fig: 4.7. Motor functions, simultaneous work other multi-tasking occur in this range of frequency.



***Fig: 4.7 GAMMA WAVE***

#### **4.4.5. Delta:**

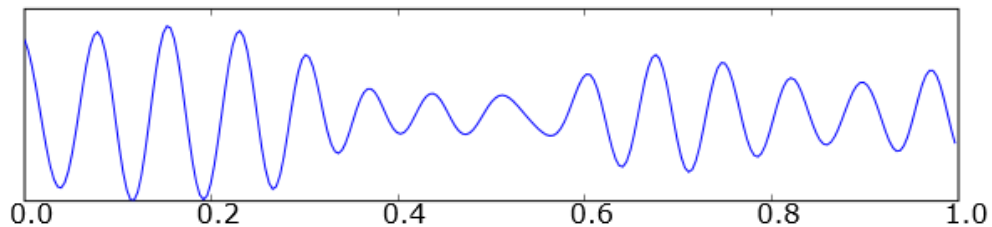
Delta waves are inside the frequency varies from zero.5 to a few.5 Hz. They may be the slowest waves compared to others refer fig: 4.8. Delta waves normally occur in deep sleep and typically once wide awake.



***Fig: 4.8 DELTA WAVE***

#### 4.4.6. MU

MU is associated with motorsports and is additionally located within the brain wave frequency variety, but anywhere the maximum amplitude is recorded over the motor place therefore it mainly triggers as soon as there may be an actual movement or there may be a motive to move (Ran Xiao, et al., 2013).



**Fig: 4.9 MU WAVE**

#### 4.5. MATLAB:

MATLAB (Matrix Laboratory) is a high-performance language for technical computing. To express the solutions in familiar mathematical notation and to integrate computation, visualization, and programming in an easy way MATLAB is utilized. Typical uses include:

- Algorithm development
- Math and computation
- Data analysis, exploration, and visualization
- Modeling, simulation, and prototyping
- Scientific and engineering graphics
- Application development, including graphical user interface building

Dimensioning is not required by the basic data elements of an array by the MATLAB interactive system. Many technical computing problems, especially matrix and vector formulation can be solved in a fraction of time, such as the time taken by interactive languages as C or FORTRAN.

The name MATLAB stands for matrix laboratory. In university environments, it is the basic instructional method for introductory and advanced mathematics, engineering, and science courses at universities. In the industry, MATLAB is the tool of choice for high-productivity research, development, and analysis toolboxes are important

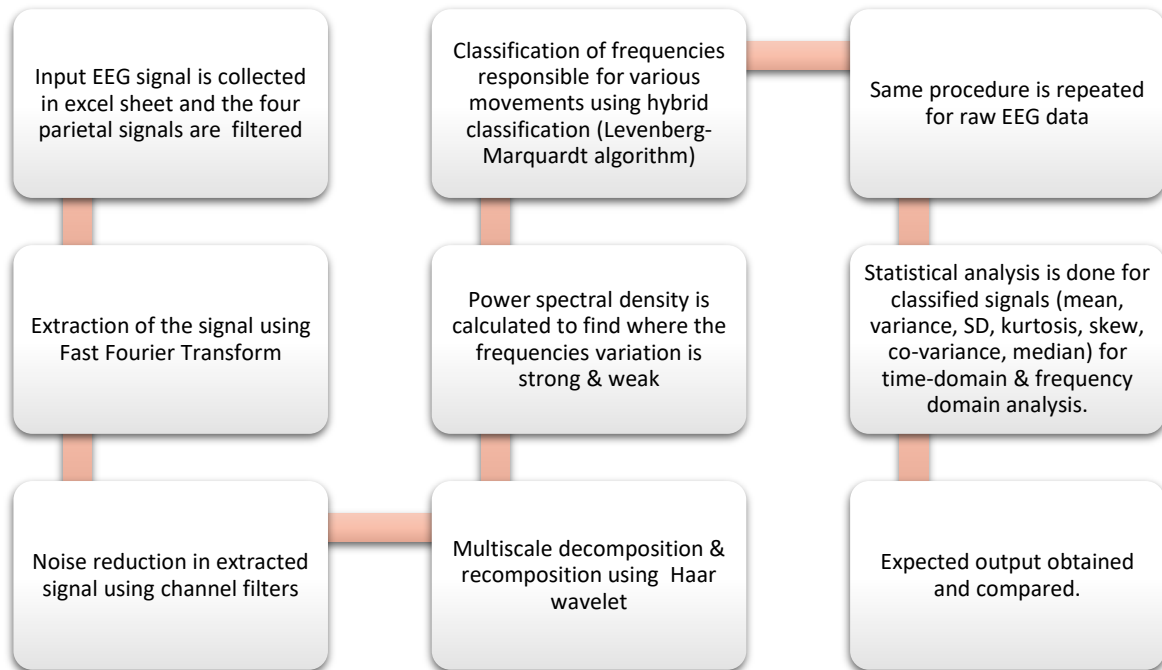
for most MATLAB users because they enable you to learn and apply advanced technology. Toolboxes are comprehensive collections of MATLAB functions (M-files) that extend the MATLAB environment to solve classes of problems. Signal processing, control systems, neural networks, fuzzy logic, wavelets, simulation, and many other areas have toolboxes available. Signals are conditioned, classified, and analyzed using a simple MATLAB program. The whole process is well discussed further.

#### **4.5.1. MATLAB Programming Language:**

The MATLAB programming language is easier to learn than most other programming languages. It is known as a high-level language because it is closer to the human language than the computer or machine language.

- The semi-colon in MATLAB indicates the end of the statement. It may also be used to halt the execution of a sentence. For example, if you type in `x=5+3` without the semicolon and click the Execute button, MATLAB will display the result as `x=8`. If you type in `x=5+3;` with the semicolon, and click Execute, MATLAB will not display the result of the computation.
- The % sign is used to indicate that the text following is a comment and not to be interpreted by MATLAB. Comments are used by programmers to provide examples for the code they are writing. For example, in MATLAB you can write `a=b+5` and use the % sign to explain that 'a' is the length of a room and 'b' is the width.
- Variable names in MATLAB are case-sensitive. For example, if you create a variable 'TempEveryHour' to represent the temperatures every hour, and need it to use this variable in a mathematical formula, you would need to call the variable by its exact same name: `TempEveryHour` and not `TemperatureEveryHour` or `temp every hour`.

## 4.6. METHOD:



**Fig: 4.10 PROCEDURE OF THE PROJECT**

### 4.6.1. Signal acquisition:

- The electrodes are placed according to the 10-20 International Montage system.
- Electrode paste helped the electrode to get secured to the scalp.
- The individual is asked to execute certain wrist movements and the EEG is recorded simultaneously.
- Movements include Clockwise rotation, Anti-clockwise rotation, flexion and extension, Pronation, and Supination.
- Each movement was attempted 5 times, with a duration of 12s each, in both eyes open and eyes closed condition.
- The data was later sent and saved in an excel sheet.



***Fig: 4.11 EEG test of a healthy male***

The following picture (fig: 4.11) depicts a healthy male (32 yrs.) during an EEG test. The electrodes used are scalp electrodes. The laptop software program enables to conversion of the signals into required paperwork like excel data sheets or conditioned signals. The same procedure (fig: 4.12) was carried for a female (21 yrs.). This was done to ensure a more accurate EEG comparison. This in turn helped us give relative conclusions.



***Fig: 4.12 EEG test of a healthy female***

|    | A      | B     | C     | D     | E      | F     | G     | H     | I      | J     | K     | L     | M      | N     | O     | P     | Q |
|----|--------|-------|-------|-------|--------|-------|-------|-------|--------|-------|-------|-------|--------|-------|-------|-------|---|
|    | FP2-F4 | F4-C4 | C4-P4 | P4-O2 | FP1-F3 | F3-C3 | C3-P3 | P3-O1 | FP2-F8 | F8-T4 | T4-T6 | T6-O2 | FP1-F7 | F7-T3 | T3-T5 | T5-O1 |   |
| 3  | 15     | -1    | 8     | -90   | -6     | 25    | -64   | 26    | 31     | -23   | -8    | -69   | -37    | 23    | 2     | -8    |   |
| 4  | -1     | 15    | 1     | -103  | 0      | 10    | -44   | 20    | 25     | -19   | -14   | -79   | -30    | 20    | -6    | 3     |   |
| 5  | -23    | 34    | -10   | -115  | 4      | -19   | -1    | 7     | 20     | -23   | -24   | -88   | -21    | 10    | -10   | 12    |   |
| 6  | -41    | 56    | -31   | -121  | 2      | -48   | 43    | -5    | 20     | -30   | -36   | -92   | -20    | -1    | -9    | 21    |   |
| 7  | -45    | 89    | -71   | -121  | -7     | -61   | 66    | 2     | 25     | -40   | -41   | -93   | -28    | -7    | -2    | 37    |   |
| 8  | -39    | 126   | -119  | -119  | -18    | -60   | 68    | 24    | 30     | -48   | -40   | -94   | -41    | -10   | 9     | 56    |   |
| 9  | -27    | 150   | -156  | -118  | -28    | -55   | 57    | 49    | 32     | -50   | -36   | -97   | -56    | -12   | 23    | 68    |   |
| 10 | -13    | 156   | -173  | -120  | -32    | -50   | 42    | 68    | 29     | -46   | -30   | -103  | -64    | -15   | 37    | 70    |   |
| 11 | -3     | 148   | -172  | -122  | -30    | -52   | 29    | 78    | 25     | -43   | -22   | -109  | -62    | -24   | 48    | 63    |   |
| 12 | 0      | 135   | -159  | -121  | -26    | -63   | 23    | 78    | 22     | -42   | -12   | -112  | -56    | -35   | 50    | 52    |   |
| 13 | -3     | 119   | -141  | -113  | -24    | -80   | 28    | 69    | 14     | -38   | -5    | -108  | -46    | -45   | 41    | 42    |   |
| 14 | -9     | 109   | -130  | -101  | -22    | -93   | 37    | 52    | 2      | -31   | -2    | -100  | -36    | -51   | 25    | 36    |   |
| 15 | -13    | 113   | -131  | -92   | -21    | -92   | 42    | 35    | -7     | -24   | 0     | -91   | -27    | -53   | 9     | 34    |   |
| 16 | -15    | 127   | -140  | -89   | -22    | -81   | 45    | 20    | -8     | -21   | -2    | -85   | -20    | -49   | 0     | 31    |   |
| 17 | -16    | 141   | -147  | -93   | -22    | -68   | 54    | 2     | -4     | -18   | -8    | -85   | -18    | -41   | 1     | 23    |   |
| 18 | -18    | 148   | -142  | -102  | -21    | -57   | 68    | -23   | 3      | -16   | -15   | -87   | -22    | -27   | 11    | 6     |   |
| 19 | -22    | 151   | -130  | -108  | -18    | -45   | 74    | -42   | 13     | -16   | -17   | -90   | -33    | -8    | 22    | -12   |   |
| 20 | -25    | 154   | -118  | -105  | -17    | -25   | 60    | -37   | 22     | -15   | -12   | -88   | -46    | 12    | 30    | -14   |   |
| 21 | -27    | 158   | -110  | -92   | -19    | -1    | 31    | -5    | 27     | -14   | -2    | -82   | -57    | 28    | 30    | 5     |   |
| 22 | -33    | 161   | -104  | -77   | -19    | 15    | 3     | 38    | 25     | -15   | 11    | -74   | -58    | 36    | 25    | 34    |   |
| 23 | -47    | 159   | -99   | -63   | -17    | 23    | -14   | 72    | 22     | -20   | 23    | -70   | -48    | 35    | 18    | 59    |   |

**Fig: 4.13 Raw data collected in an excel sheet (includes all electrodes)**

|    | A     | B     | C     | D     | E | F | G | H |
|----|-------|-------|-------|-------|---|---|---|---|
|    | C4-P4 | P4-O2 | C3-P3 | P3-O1 |   |   |   |   |
| 3  | 8     | -90   | -64   | 26    |   |   |   |   |
| 4  | 1     | -103  | -44   | 20    |   |   |   |   |
| 5  | -10   | -115  | -1    | 7     |   |   |   |   |
| 6  | -31   | -121  | 43    | -5    |   |   |   |   |
| 7  | -71   | -121  | 66    | 2     |   |   |   |   |
| 8  | -119  | -119  | 68    | 24    |   |   |   |   |
| 9  | -156  | -118  | 57    | 49    |   |   |   |   |
| 10 | -173  | -120  | 42    | 68    |   |   |   |   |
| 11 | -172  | -122  | 29    | 78    |   |   |   |   |
| 12 | -159  | -121  | 23    | 78    |   |   |   |   |
| 13 | -141  | -113  | 28    | 69    |   |   |   |   |
| 14 | -130  | -101  | 37    | 52    |   |   |   |   |
| 15 | -131  | -92   | 42    | 35    |   |   |   |   |
| 16 | -140  | -89   | 45    | 20    |   |   |   |   |
| 17 | -147  | -93   | 54    | 2     |   |   |   |   |
| 18 | -142  | -102  | 68    | -23   |   |   |   |   |
| 19 | -130  | -108  | 74    | -42   |   |   |   |   |
| 20 | -118  | -105  | 60    | -37   |   |   |   |   |
| 21 | -110  | -92   | 31    | -5    |   |   |   |   |
| 22 | -104  | -77   | 3     | 38    |   |   |   |   |
| 23 | -99   | -63   | -14   | 72    |   |   |   |   |
| 24 | -96   | -54   | -17   | 93    |   |   |   |   |
| 25 | -95   | -51   | -8    | 99    |   |   |   |   |
| 26 | -94   | -49   | 7     | 91    |   |   |   |   |
| 27 | -92   | -50   | 22    | 75    |   |   |   |   |
| 28 | -90   | -55   | 32    | 59    |   |   |   |   |
| 29 | -91   | -62   | 36    | 54    |   |   |   |   |
| 30 | -92   | -66   | 34    | 63    |   |   |   |   |

**Fig: 4.14 Raw data collected in an excel sheet (specific electrodes).**

#### **4.6.2. Signal Extraction using FFT:**

A fast Fourier transform (FFT) is an algorithm that divides a signal into its frequency components by sampling it over time (or space). The discrete Fourier transform (DFT) of a sequence, or its inverse, is computed by an FFT algorithm (IFFT). Simple waves may be used to decompose a complex signal. The Fourier Transform is used to determine how much of each wave is needed. Fourier transforms (FT) take a signal and decompose it into the frequencies that make it up. The Fourier transform (FT) decomposes a function of time (a signal) into the frequencies that make it up.

##### **SYNTAX:**

$Y = \text{fft}(X)$

$Y = \text{fft}(X, n)$

$Y = \text{fft}(X, n, \text{dim})$

#### **4.6.3. Noise reduction using filters**

Preprocessing in the spatial, time, or frequency domains have been found to be beneficial. Contributed to enhancing the signal caused especially by external factors.

Improving the signal-to-noise ratio (SNR) of EEG signals is done by increasing the signal level and/or decreasing the noise level. Independent Component Analysis is a common spatial filtering technique (ICA).

ICA performs unsupervised spatial filtering by decomposing the observed EEG into statistically independent components (ICs). It aims to improve EEG signal SNR by separating task-related EEG components from task-irrelevant EEG components.

Components and the artifactual components. Temporal-based preprocessing can contribute to removing artifacts from the signal using a linear combination of the EOG-contaminated EEG signal and the EOG

Signal recorded using eye movement recording electrodes. Linear regression models are used to assess the mixture variables.

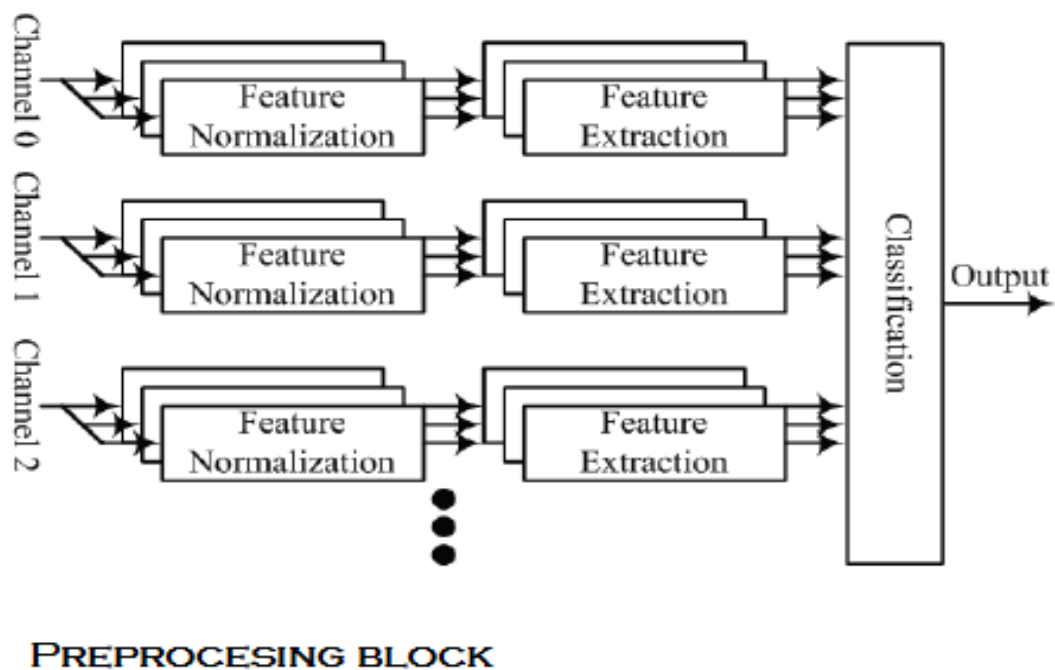
While it is the most common approach for extracting ocular artifacts from EEG signals, due to the difficulty of placing muscular detection electrodes (Xiangxin Li, et., 2017), it does not achieve the same degree of success when removing EMG

signals (Byeongnam Kim, et al., 2017). Frequency-band filtering assists in removing noise and artifacts. It can also provide significant help with handling the internal nonstationarity factors. The task-related frequencies can be chosen for use in BCI systems for further study. This filtering type does not require extra electrodes to detect eye or muscle movement.

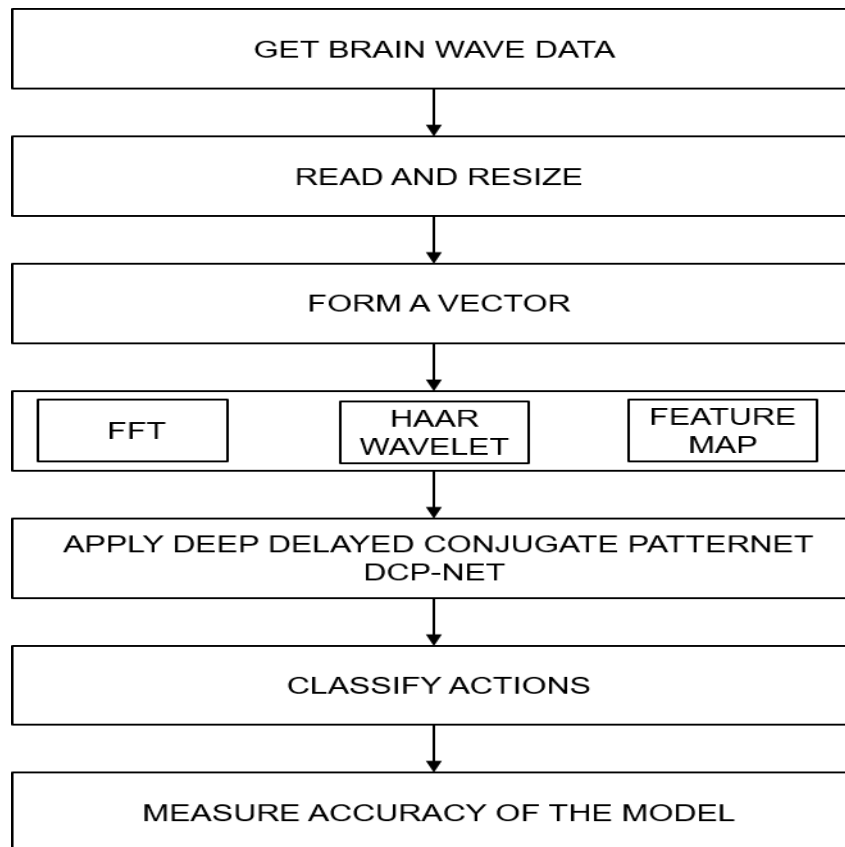
The advantage of using filtering is its simplicity. However, the effect for this method degrades if the unrelated signal overlaps or lies in the same frequency band as the signal of interest.

If the unrelated signal overlaps or is in the same frequency band as the signal of interest, this approach degrades.

PREPROCESSING:



**Fig: 4.15 PREPROCESSING**



**Fig: 4.16 Classification block diagram**

#### **4.6.4. FEATURE EXTRACTION:**

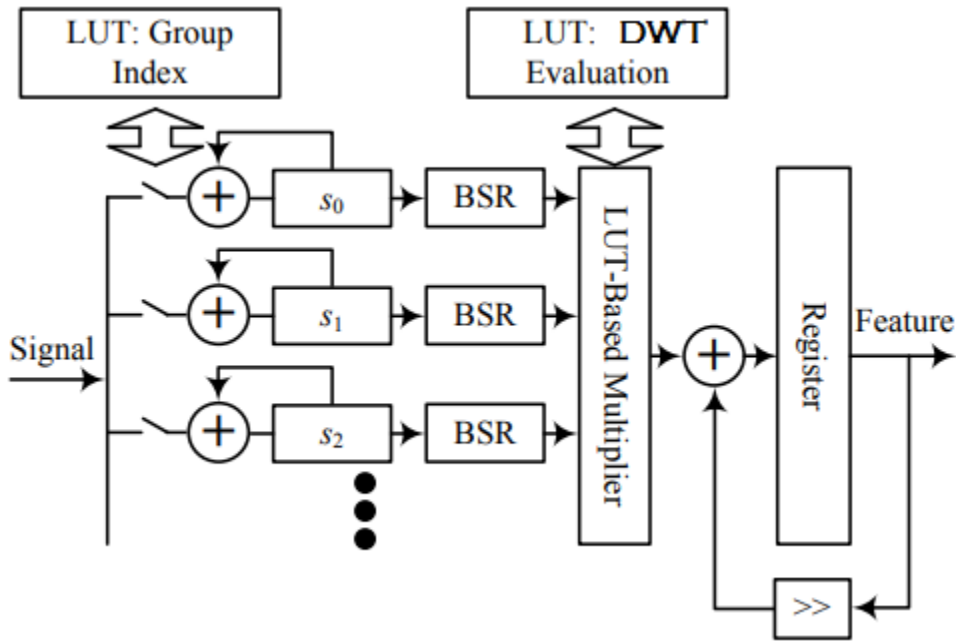
Once the ultrasonic test signals acquired in a form of digitized data are pre-processed, we need to determine features from the raw signal by the use of digital processing techniques. This process is named ‘feature extraction’. A special form of dimensionality reduction is feature extraction. Feature extraction reduces the number of resources needed to accurately define a wide collection of data. Since not all features extracted from ultrasonic signals for a given classification problem must be used due to redundancy, a second process is needed to reduce redundancy by maintaining only an informative subset of them. Feature selection is the term for this stage of processing.

#### Forward Discrete Fourier Transform (DFT):

$$X_k = \sum_{n=0}^{N-1} x_n \cdot e^{-i 2\pi k n / N}$$

#### Inverse Discrete Fourier Transform (IDFT):

$$x_n = \frac{1}{N} \sum_{k=0}^{N-1} X_k e^{i 2\pi k n / N}$$



**Fig: 4.17 PREPROCESSING BLOCK DIAGRAM**

##### 4.6.4.1. Feature extraction using DWT:

The discrete wavelet transform is used to remove properties from a signal on different scales, followed by high pass and low pass filtering. The wavelet coefficients are the successful continuation of the approximation and detail coefficients. The basic feature extraction procedure consists of

1. Decomposing the signal using DWT into N levels using filtering and decimation to obtain the approximation and detailed coefficients.
2. The DWT coefficients are used to extract features.

The discrete wavelet transform is used to remove properties from a signal on different scales, followed by high pass and low pass filtering.

#### *4.6.4.2. Feature extraction algorithm DWT:*

Initially, it is verified that the digitized flaw data are available in the powers of 2 for making the effective decomposition. The various steps involved in the feature extraction algorithm are as follows:

Step 1: The ultrasonic flaw data are decomposed into four detail subbands using Discrete Wavelet Transform (DWT). The subbands are high-frequency detail band coefficients and low-frequency approximation band coefficients.

Step 2: The approximation co-efficient is further decomposed using DWT to extract localized information from the subband of detail coefficients. In this work, four levels of decomposition have been done using biorthogonal wavelet. Four level approximation and detail coefficients of six classes of defect are graphically represented in Appendix 1.

Step 3: The frequency vector (in radians/sample) is extracted for four detail subbands using the periodogram function in Matlab.

Step 4: The features are computed either by using syntax or by implementing the formulae. They are mean, variance, mean of energy, maximum amplitude, minimum amplitude, maximum energy, minimum energy, average frequency, mid-frequency, maximum frequency, minimum frequency, half point of the function.

The M-file program for four level signal decomposition and features extraction using DWT are provided in Appendix 2.

Step 5: The features are computed either by using syntax or by implementing the formulae. They are mean, variance, mean of energy, maximum amplitude, minimum amplitude, maximum energy, minimum energy, average frequency, mid frequency, maximum frequency, minimum frequency, half point of the function. The M-file program for four level signal decomposition and features extraction using DWT are provided in Appendix 2.

Step 6: Finally, the extracted features for the six classes of defects are tabulated and analyzed for classification.

#### 4.6.4.3. Extraction feature:

The Discrete wavelet transform (DWT) coefficients of ultrasonic test signals obtained from the six defect groups are used to extract twelve features in this study. The extracted features from the signal are as below:

Mean: It is nothing but an average value

$$m = \left( \frac{1}{n} \right) \sum_{i=1}^n x_i$$

Variance: The variance is defined as the sum of square distances of each the term in the distribution from the mean, divided by the number of terms in the distribution.

$$m_e = \left( \frac{1}{n} \right) \sum_{i=1}^n x_i^2$$

Mean of the energy: It is the average value of the energy.

$$m_e = \left( \frac{1}{n} \right) \sum_{i=1}^n x_i^2$$

Maximum Amplitude: This is the signal's amplitude's peak value.

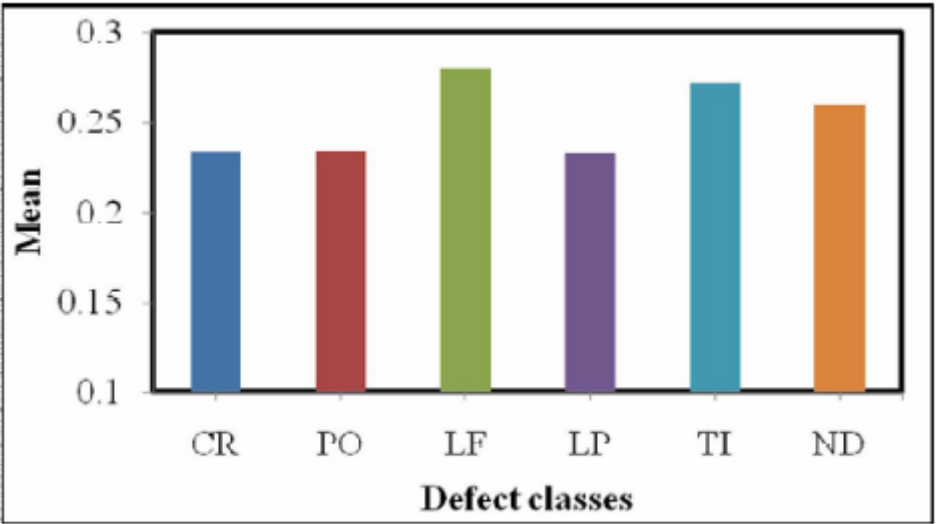
Minimum Amplitude: It is the lowest value of the amplitude of the signal.

Maximum Energy: It is the highest energy value obtained from the signal. The lowest energy value derived from the signal is known as the minimum energy.

#### 4.6.4.4. Selection of feature:

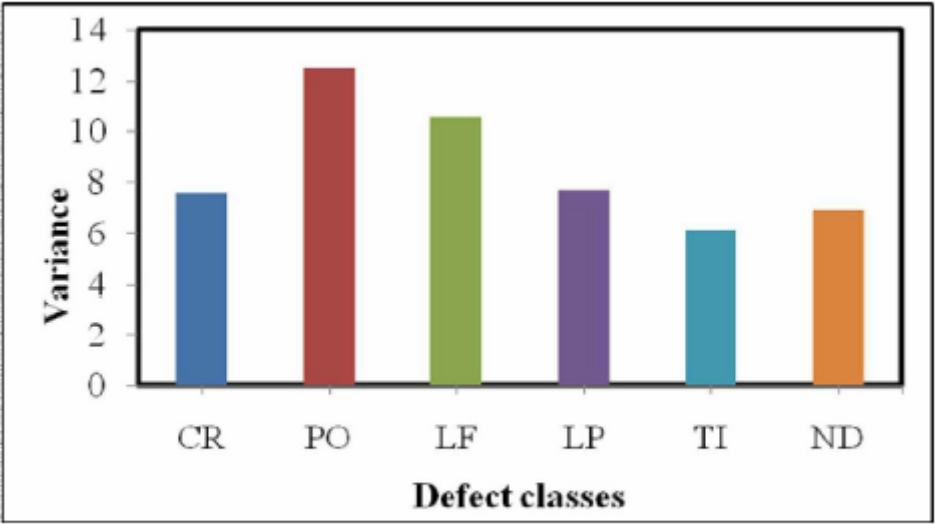
Since the relationship between ultrasonic signal characteristics and fault classes is not straightforward, feature extraction is crucial to classification accuracy and serves as the foundation for classification decision-making. The variation of the twelve features for each class of defect is analyzed and for each defect, the average values for all the features are determined and are plotted in graphs. The average feature values for the six classes of a defect in the first level sub-band are marked in the

graph representing defects in the x-axis and average values in the y axis. The variation in the feature values for the six classes of the defect are shown in the following graphs.



**Variation of mean for six classes of defect**

***Fig: 4.18 Defect classes and mean chart for six classes***



**Variation of variance for six classes of defect**

***Fig: 4.19 Defect classes and mean chart for six classes***

#### 4.7. WAVELET TRANSFORM:

As signal frequency varies over time, wavelet transforms are a statistical method for performing signal analysis. For certain classes of signals and images, wavelet analysis provides more precise information about signal data than other signal analysis techniques. The basic function consists of wavelets, everyone being a scaled and transformed version of an identical wave. The wave transform makes it potential to study a characteristic in numerous scales at the same time. This is the most advantageous feature of wavelet transformation. Adding thereto, the amount of resolution depends on the size (Lung Chuin Cheong, et al., 2015).

- Support for the wavelet in terms of time, frequency, and decay rate.
- The wavelet's symmetry or anti-symmetry. The perfect reconstruction filters that go with it have a linear process.
- The total number of vanishing moments for a broad class of signals and pictures, wavelets with increasing numbers of vanishing moments result in sparse representations.
- The wavelet's regularity. Sharper frequency resolution is achieved with smoother wavelets. Additionally, iterative wavelet construction algorithms converge faster.
- Formula for wavelet transform  $F(a,b)=\int_{-\infty}^{\infty} f(x)\psi * (a,b)(x)dx$
- Existence of a scaling function.

##### **4.7.1. Haar wavelet:**

In mathematics, the Haar wavelet is a sequence of rescaled "square-shaped" functions which together form a wavelet family or basis. In the same way that Fourier analysis allows a target function over an interval to be interpreted in terms of an orthonormal basis, Wavelet analysis does the same. The Haar sequence is now widely regarded as the first wavelet base, and it is often used as a teaching tool.

Alfréd Haar proposed the Haar series in 1909. (Yang Li, et al., 2020) These functions were used by Haar to illustrate an orthonormal scheme in the space

of square-integrable functions on the unit interval  $[0, 1]$ . Wavelets were not studied until much later, and the word "wavelet" was not coined until much later. The Haar wavelet is also known as Db1 because it is a special case of the Daubechies wavelet.

The Haar wavelet is also the most basic wavelet possible. The Haar wavelet has the technical drawback of not being continuous and therefore not being differentiable. This property can, however, be an advantage for the analysis of signals with sudden transitions, such as monitoring tool failure in machines.[2] The Haar wavelet's mother wavelet function  $\psi(t)$  can be described as

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

Its scaling function  $\varphi(t)$  can be described as

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

#### 4.8 POWER SPECTRAL DENSITY:

For continuous spectra, the power spectral density (PSD) is used. The average power in the signal over a given frequency band is computed using the integral of the PSD over that frequency band. The range of the frequency vector depends on the Spectrum Type value. The frequency response of a random or periodic signal is known as PSD. It shows the distribution of average power as a function of frequency. The PSD is deterministic and time-independent for some forms of random signals<sup>1</sup>. The power spectrum plots the portion of a signal's power (energy per unit time) that falls within specified frequency bins for a given signal. The most common way of generating a power spectrum is by using a discrete Fourier transform, but other techniques such as the maximum entropy method can have been used. Any waveform can be characterized by a summation of a (possibly infinite) number of sinusoids, each with its amplitude and phase, according to Fourier theory. Such a representation is referred to as the signal's spectrum (or its frequency-domain representation).

#### 4.9 PATTERNET IN NEURAL NETWORK:

One of the major challenges in deep learning is retrieving sufficiently large labelled training datasets, which can become expensive and time-consuming to collect. Using Deep Neural Network (DNN) models with a small number of initially named training samples is a novel approach to segmentation training. The method entails generating synthetic data and calculating affine transformations to apply to it using image registration. The method takes a small dataset and generates a high-quality augmented reality synthetic dataset with a strong variance while maintaining consistency with real cases. The results show improved segmentation in different target features as well as an increase in average target trust. The motivation for synthetic data is due to the lack of available labelled data, which is recommended in large volumes for supervised deep learning. Data collection is difficult, particularly for resource-constrained research groups, due to monetary and time costs. Furthermore, deep learning is susceptible to poor training efficiency, and full training in a deep neural network requires a significant amount of time especially if computing resources are limited. By improving data accessibility and training optimization, the pace of development in this area can be accelerated.

Data augmentation is a technique for increasing the size of a dataset, and it has shown to improve deep learning (Sunil Jacob, et al., 2019) efficiency even with synthetic data. Data augmentation has been shown to help image segmentation models, which is particularly useful when working with small training datasets. A dataset can be augmented using a variety of processing tools, mainly by adding noise to an image, performing geometric transformations, or adjusting the original colors and contrast. As a result, the augmented dataset artificially introduces new information that can improve the generalization of the network and prevent over fitting. In situations where training data is expensive to obtain and manually label, synthetic data can provide valuable additional training sets. Synthetic targets are generated

from a blueprint and multiplied by the use of transformations for segmentation tasks. To build their corresponding labelled masks, the synthetic training targets can be conveniently binarized using a global threshold. This process is both efficient and inexpensive in generating training samples and their labels. The quality and size of the dataset are arguably just as important as the optimization of network parameters. External videos of an object showing the desired motion (Bu Il Jeon, et al., 2019) were used to obtain the transformation matrices to apply to the synthetic data. These videos do not necessarily have to be of the same style representing the model; only the dynamic properties of the object need to be representative. The sequence of frames can then be superimposed onto a sequence of background images after the synthetic data has been transformed.

#### 4.10 LEVENBERG-MARQUARDT ALGORITHM:

The Levenberg-Marquardt algorithm, also known as the damped least-squares method, was created with loss functions in the form of a sum of squared errors in mind. It works even though the exact Hessian matrix isn't computed. Instead, it employs the Jacobian matrix and the gradient vector.

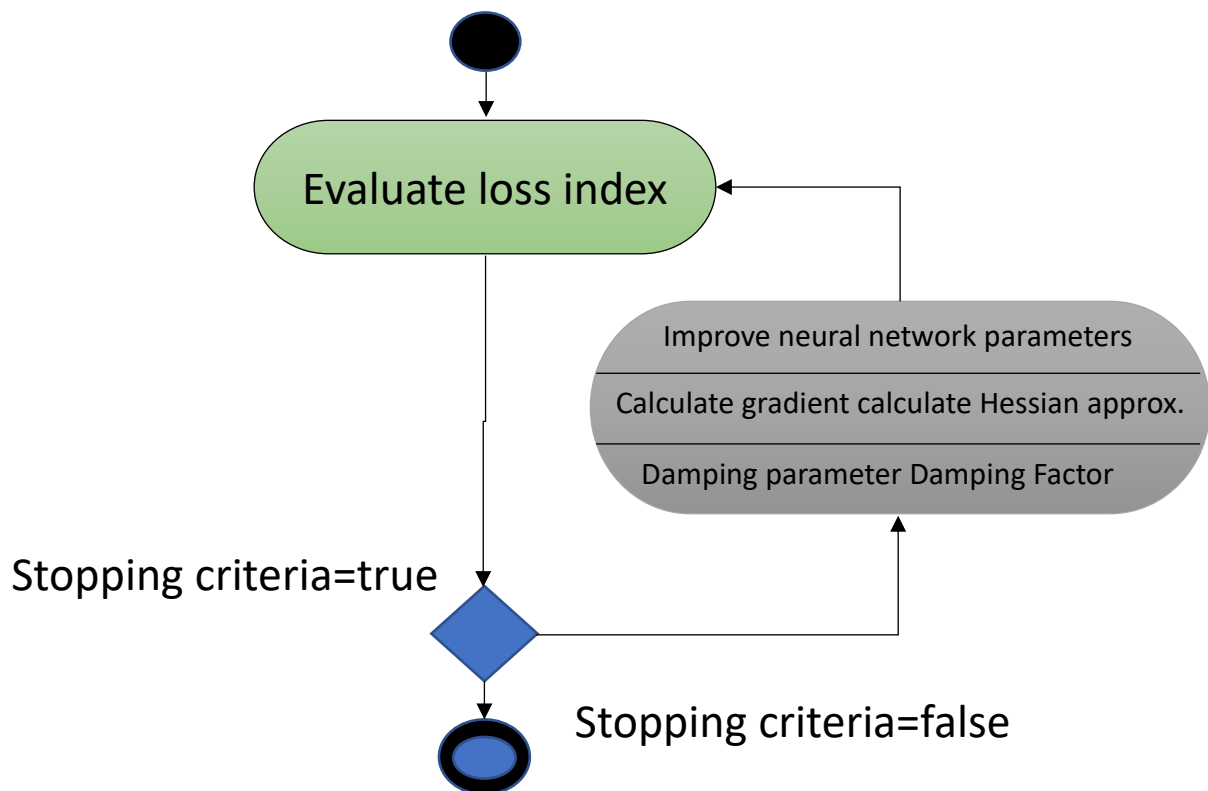
$$f = \sum_{i=1}^m e_i^2$$

Consider a loss function that is a sum of squared errors of the form the number of instances in the data set is denoted by  $m$

$$\mathbf{J}_{i,j} = \frac{\partial e_i}{\partial \mathbf{w}_j},$$

We can define the Jacobian matrix of the loss function as that containing the derivatives of the errors concerning the parameters, When the damping parameter is zero, Newton's approach is used, which uses an approximate Hessian matrix. When  $\lambda$  is high, however, this becomes gradient descent with a slow training rate. The parameter  $\lambda$  is set to a large value to ensure that the first changes are small steps in the direction of gradient descent. If a mistake happens during some iteration,

then some truth  $\lambda$  is increased. Otherwise, as the loss grows smaller,  $\lambda$  is smaller, and the Levenberg-Marquardt algorithm approaches the Newton method. The convergence to the minimum is usually accelerated by this method. The state diagram below depicts the training phase of a neural network using the Levenberg-Marquardt algorithm. The loss, gradient, and Hessian approximation must all be calculated first. The damping parameter is then modified for each iteration to reduce the loss.



**Fig: 4.20 LEVENBERG-MARQUARDT ALGORITHM BLOCK DIAGRAM**

The Levenberg-Marquardt algorithm, as shown, is a method designed for sum-of-squared-error functions. That makes it to be very fast when training neural networks measured on that kind of errors. However, this algorithm has some drawbacks. The first is that it can't be used to calculate functions like the root mean squared error or cross-entropy error. Furthermore, for large data sets and neural networks, the Jacobian matrix grows enormously large, necessitating a lot of memory. As a result, when dealing with large data sets or neural networks, the Levenberg-Marquardt algorithm is not recommended.

## 4.11. STATISTICAL ANALYSIS:

### **4.11.1. Standard deviation:**

It is the measure of how spread out the data is. A low SD denotes that the data points tend to be close to the mean thus are not widespread, while the high SD values indicate less closeness to mean, and thus the data is wide spread.

### **4.11.2. Mean:**

It is the foremost common and best general-purpose measure of the mid-point (around which all other values cluster) of a set of values, however, is prone to distortion by the presence of extreme values and may need the use of a measure of distortion (such as deviation or standard deviation). Additionally, known as the arithmetic mean.

### **4.11.3. Median:**

The median is the value that separates the upper and lower halves of a data set, population, or probability distribution. For a data set, it may be thought of as the "middle" value. In statistics and probability theory, the median is a widely used estimate of a data set's properties.

### **4.11.4. Kurtosis**

The flatness or peakness of a distribution curve is known as kurtosis. Kurtosis is an important point for interpreting data variability. Kurtosis is an indication factor that reveals some characteristics of normality of data distribution. People can easily determine the normality of data distribution by interpreting the shape of the kurtosis curve.

### **4.11.5. Skew:**

The time difference between the real and predicted arrival time of a clock signal is known as skew. Skew may be extrinsic or intrinsic in nature. The latter is

defined as the difference in propagation delays between the system outputs and is internal to the driver (generator circuitry).

#### **4.11.6. Co-variance:**

When two input signals are shifted by one another, correlation computes a measure of similarity between them. When the two signals are the most similar, the correlation result hits a limit. When a certain input signal is added to a linear device, convolution is used to compute the output.

#### **4.12. CODE TESTING:**

Testing is the method of running a program and looking for flaws. Our program must be error-free in order to perform well. If the testing is completed successfully, the program will be free of all errors. Principles of Testing: - (i) All tests must satisfy the customer's requirements. (ii) To make our software testing should be performed by the third party (iii) It's not possible to try to thoroughgoing analysis. Supported the application's risk analysis, we'd like the smallest {amount} amount of testing doable. (iv) All tests that will be performed should be prepared before they are carried out. (v) It follows the Pareto rule (80/20 rule) which states that 80% of errors come from 20% of program components. (vi) Begin with small parts and work your way up to larger ones.

##### **1. UNIT TESTING:**

It concentrates on the tiniest aspect of software development. This is where we measure a single unit or a group of interconnected units. Using sample input and observing the corresponding outputs is a popular method used by programmers.

##### **EXAMPLE:**

- a) In a programme, we check to see whether a loop, function, or variable exists. The role is working properly.
- b) Arithmetic precedent is misunderstood or inaccurate.
- c) Incomplete or incorrect initialization

## 2. INTEGRATING TESTING:

The goal is to take unit-tested components and use them to create a software framework that is determined by design. Integration testing is when a set of components is combined to obtain a result.

There are four forms of integration testing: (i) top down (ii) bottom up (iii) sandwich (iv) big bang

As an example

(a) Black Box Testing: This is a form of validation testing.

External operating mechanisms are ignored in this.

What is the output? Is the emphasis.

(b) White Box Testing: This is a form of verification testing.

We will concentrate on internal mechanisms, i.e.

What method is used to obtain the desired result?

## 3. REGRESSION TESTING:

Any time a new module is introduced, the software is altered. This method of checking ensures that the whole component functions correctly even after it has been added to the whole software. Example: In a school record, let's say we have modules for teachers, pupils, and finance. Integrating these modules and verifying whether they perform well after integration is regression testing.

## 4. ALPHA-TESTING:

Validation checking is what this is.

It's a form of approval testing that takes place before a product is made available to the public. QA personnel are usually in charge of this.

EXAMPLE:

When software testing is done inside a company, the corporation.

## 5. BETA TESTING:

Beta testing is the process of putting a product the trial test is carried out at one or more consumer locations by the software's end-user. This version is only available to a small number of users for testing in a real-time environment.

EXAMPLES:

When software testing is done for a certain purpose, the number of individuals

## 6. SYSTEM TESTING

This app has been thoroughly reviewed to ensure that it runs well on a variety of operating systems.

It's shielded by the black box research approach. We just concentrate on the necessary input and output while ignoring internal operations.

Protection monitoring, recovery testing, stress testing, and performance assessment are also included.

Consider the following scenario:

This encompasses both functional and non-functional research.

## 7. STRESS TESTING:

In this experiment, we put the device under adverse conditions to see how it responds. Example: (a) Test cases that need the most memory or other resources are run; (b) Test cases that may trigger thrashing in a virtual operating system are run; (c) Test cases that may necessitate a large amount of disc space are run.

## 8. PERFORMANCE TESTING:

Its aim is to evaluate software's run-time output in the sense of an embedded framework.

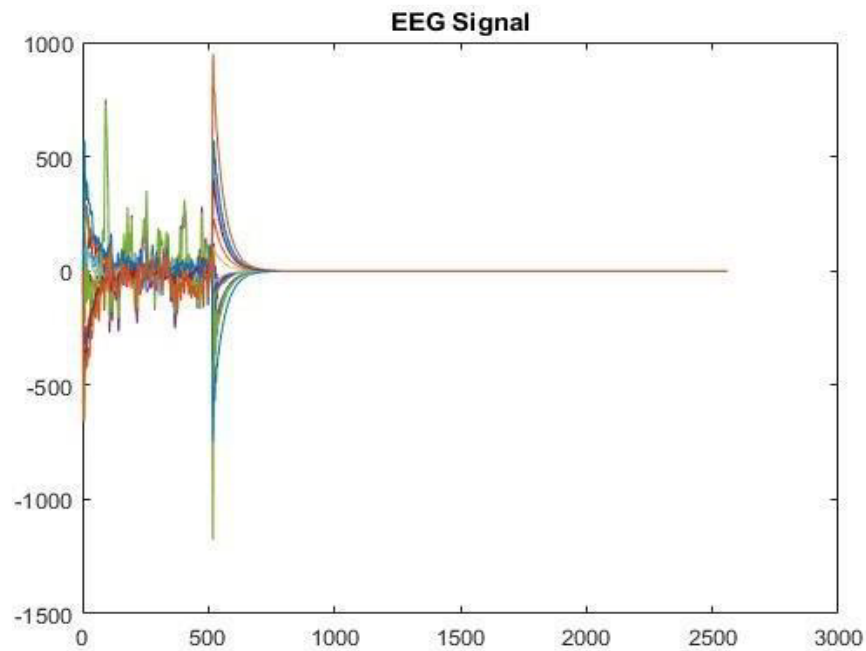
It's used to see how quick and powerful a programme is.

## CHAPTER 5

### RESULTS & DISCUSSION

#### 5.1 RESULTS FROM FREQUENCY DOMAIN ANALYSIS

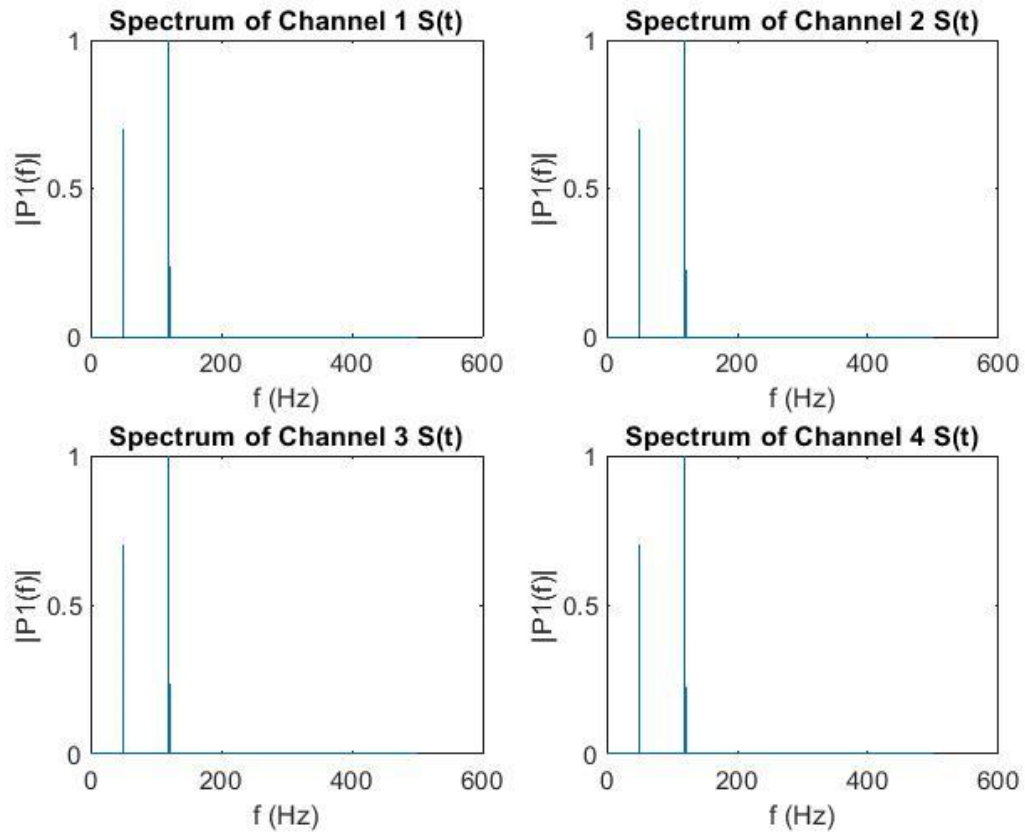
##### *5.1.1 Input EEG Signal*



***Fig: 5.1 Input EEG Signal***

In the above figure, it can be seen that the EEG signals that were captured are given as an input signal. These signals are in the excel form which are loaded to form a graph plot which is shown in form of time domain signal as shown above.

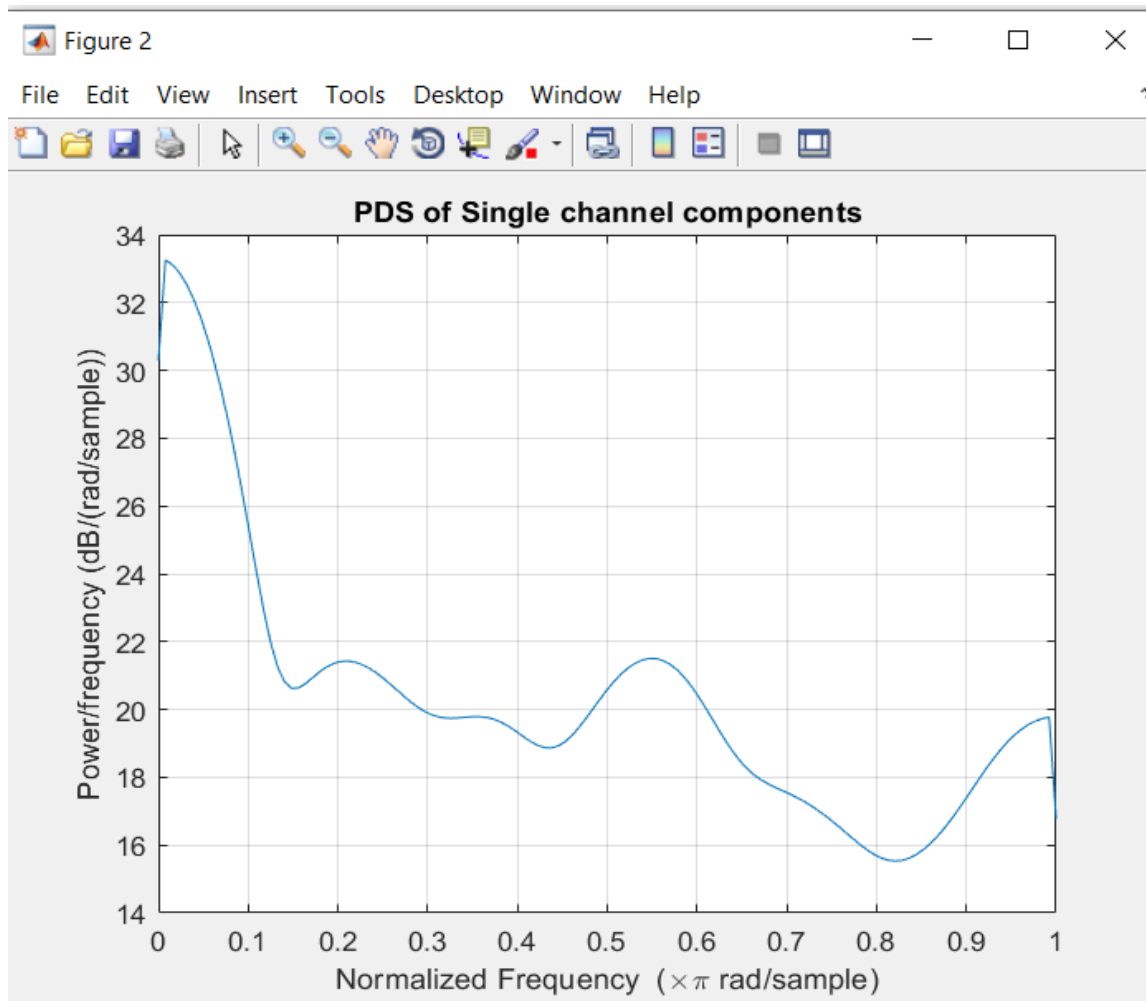
### 5.1.2 Spectrum of 4 channels



**Fig: 5.2 Spectrum of 4 channels**

The above figure shows the spectrum of four channels, which were individually obtained for the four channels. Spectrum is referred to a plot of signals as a function of frequency, also known as spectral density. A graphical representation of the signal as a function of the dependent variable is also referred to as a spectrum. This figure depicts the classified spectrum of four channels individually, the peak values were obtained above 100Hz and below 120Hz.

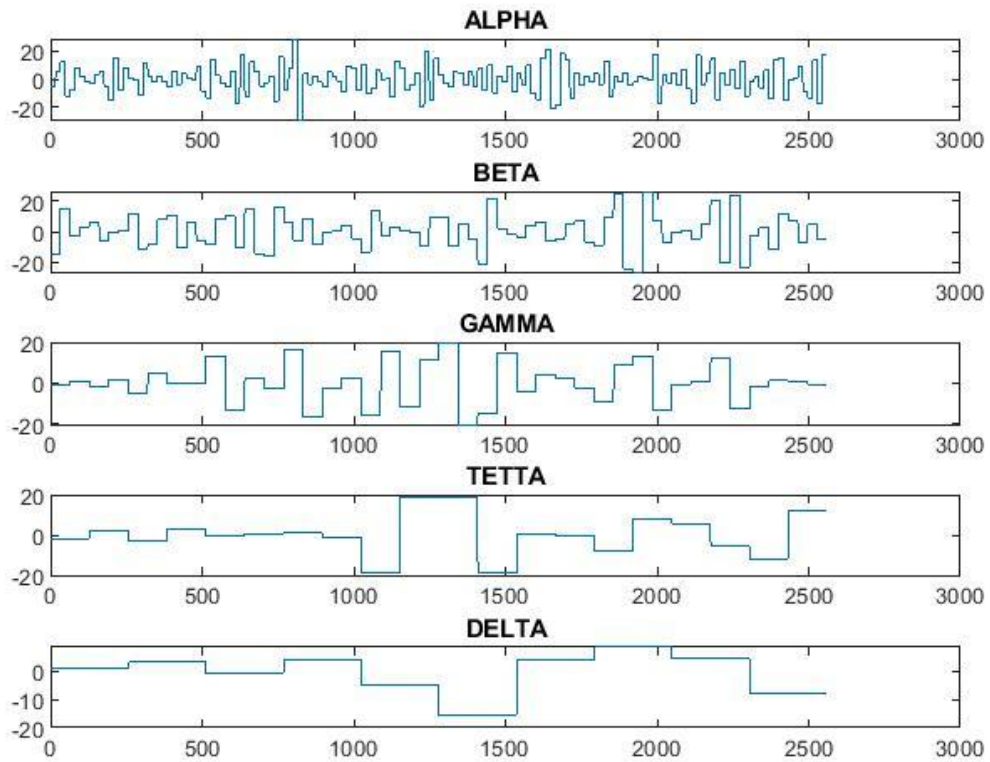
### 5.1.3. PSD of Single Channel



**Fig: 5.3 PSD of single channel**

The above image shows the Power Spectral Density of single channel after classifying the signals. The signal's power spectral density determines how much power is present in the signal as a function of frequency. The figure plotted is the measure of signal's power versus frequency, which depicts the point where the maximum frequency of 33Hz is obtained. From the above PDS value, it is clear that the obtained frequency provides the correct range of beta waves. Peak value in the output image denotes the corresponding frequency for the particular wrist movement.

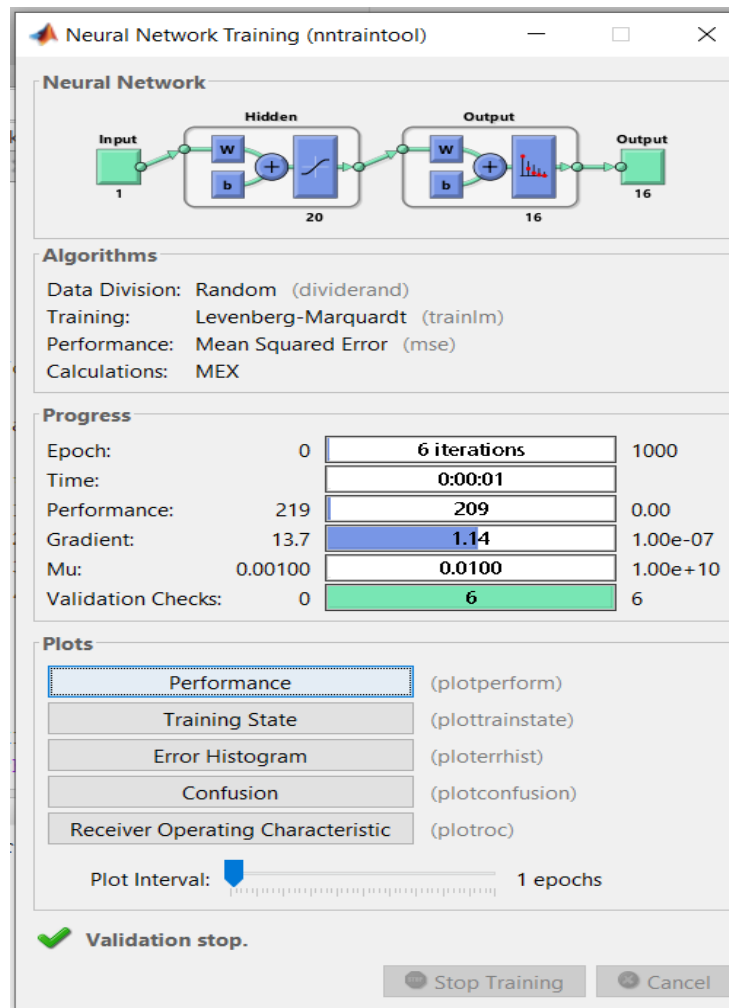
#### 5.1.4. Extracted Frequencies



**Fig: 5.4 Extracted frequencies**

The different types of wave signals such as alpha, beta, gamma, theta and delta waves are extracted from the input signal and plotted as separate signals that can be seen in the above given figure from which each and every differentiation in the wave can be noted. The waves provided above in the image is obtained as a result of Haar wavelet, thus the frequencies of these waves were represented as the square waves instead of sine waves.

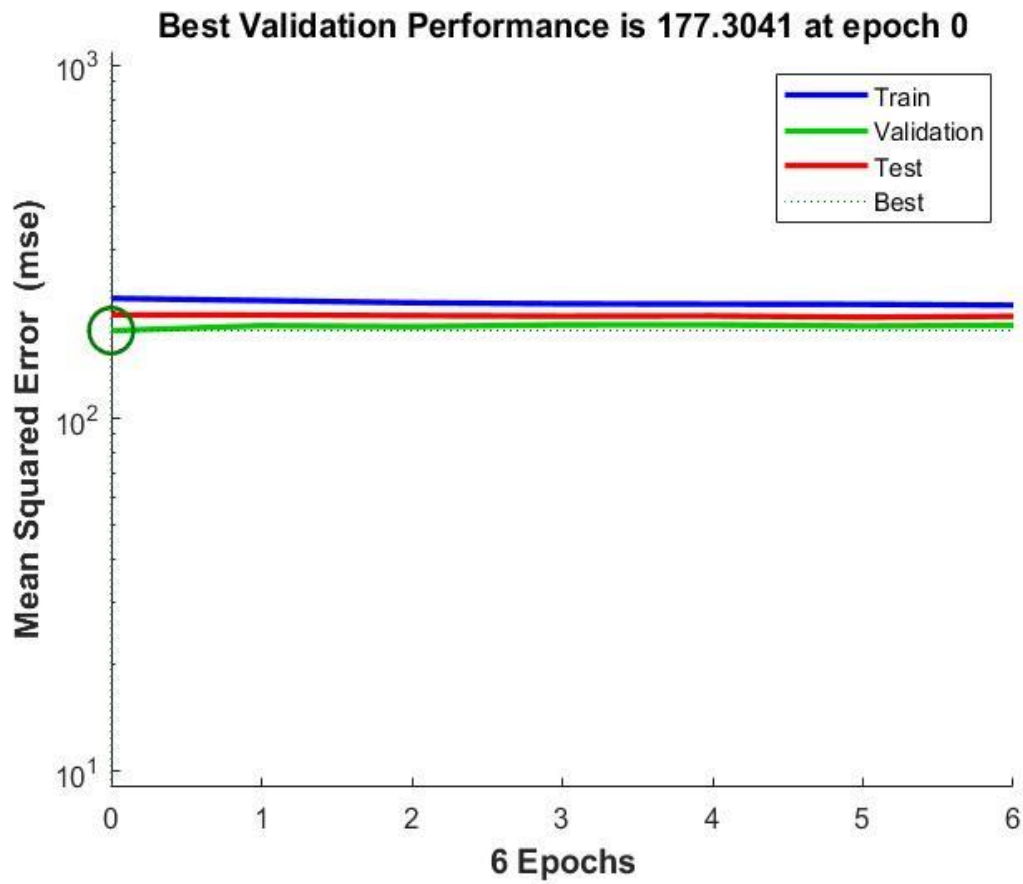
### 5.1.5. Hybrid Neural Network



**Fig: 5.5 Hybrid Neural Network**

The above image shows the automatic block generation which contains all the details regarding how the signals are trained and the number of hidden layers used inside. Thus, we can analyse the output by clicking on whatever requirements we need such as performance, training state, error histogram, confusion, receiver operating characteristics.

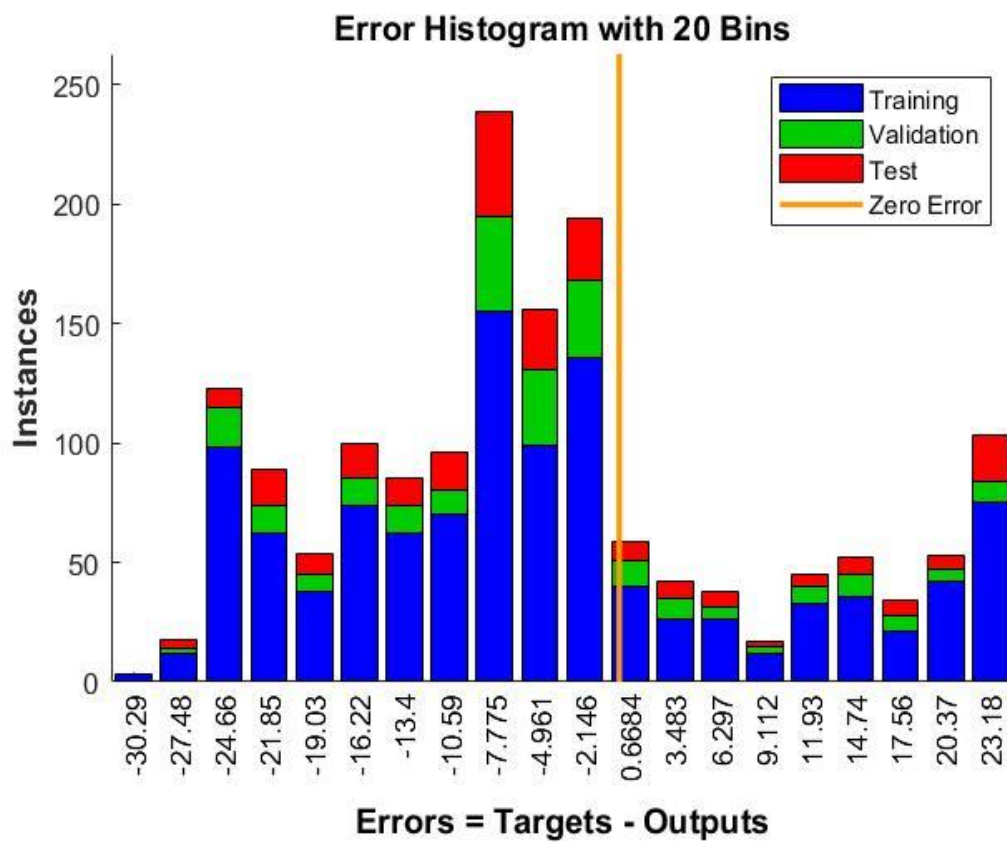
#### 5.1.6. Performance measure:



**Fig: 5.6 Performance measure**

The above figure presents the Mean Squared Error (MSE) for training, validation (check), and test steps. According to this figure, the least MSE in the validation step is happened at epoch 0, which has the best validation performance equal to 177.3041.

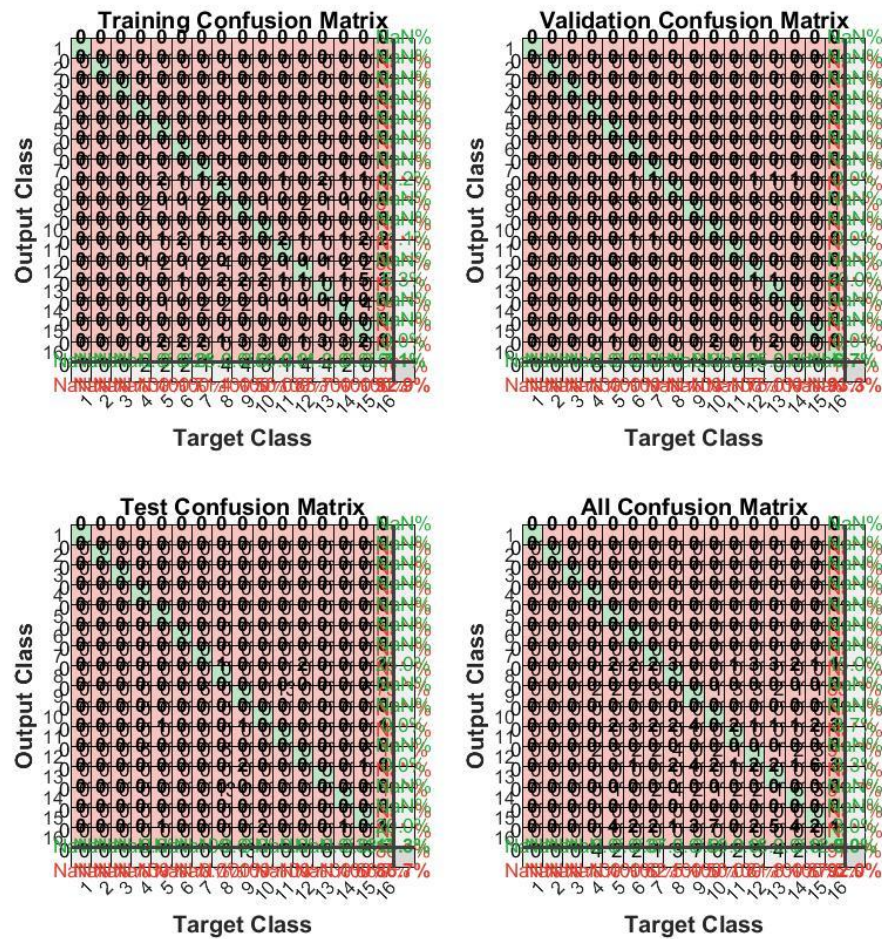
### 5.1.7. Error Histogram:



**Fig: 5.7 Error Histogram**

The above figure shows the error histogram graph obtained after training. The histogram of errors between target values and predicted values after training is known as the error histogram. The error is obtained from the difference of targets and the outputs. The errors from training, validation and testing were represented in different colours for their variations. This histogram shows the average rate of the decrease of errors which can be seen through validation process being carried out in the system and also shows the point where very minimal error is being obtained (0.6684).

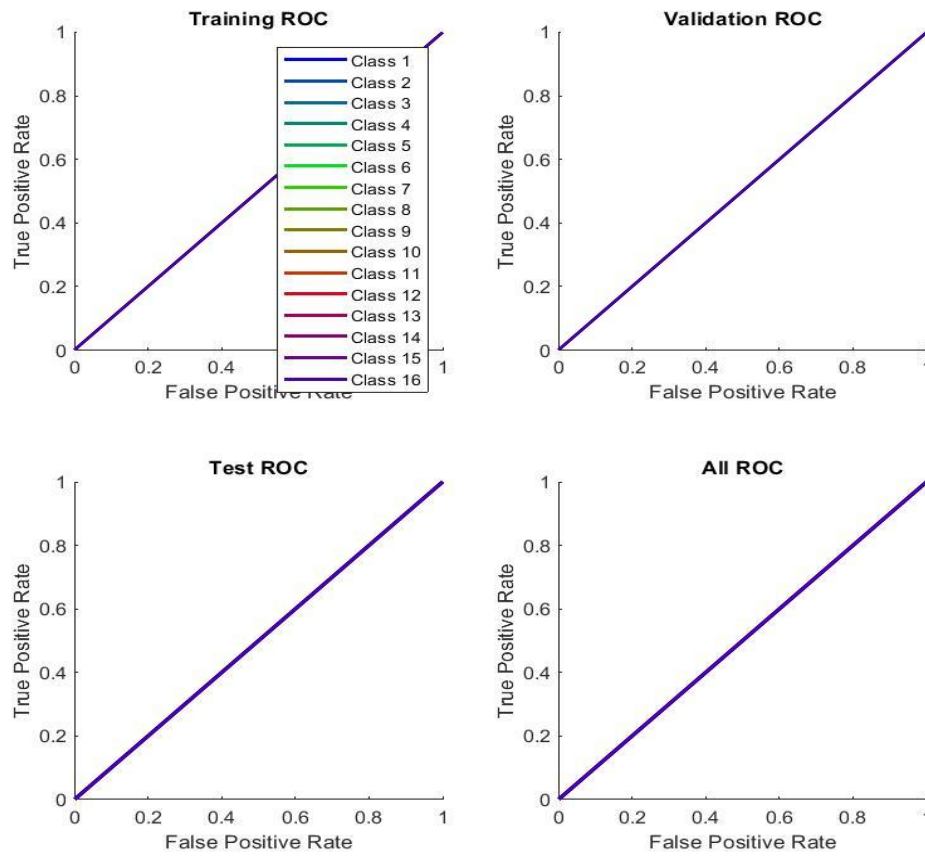
### 5.1.8. Confusion Plot:



**Fig: 5.8 Confusion matrix**

In the above image we can see the confusion matrix plotted that is been obtained. Confusion matrix basically gives us an idea about how well our classifier has performed, with respect to performance on individual classes. As a result, a confusion matrix is usually filled out using the known test set's true labels. Confusion Matrix consists of 4 parameters such as true positives, true negatives, false positives and false negatives. This allows more detailed analysis when the numbers of observations in different classes vary greatly.

### 5.1.9. ROC Plot

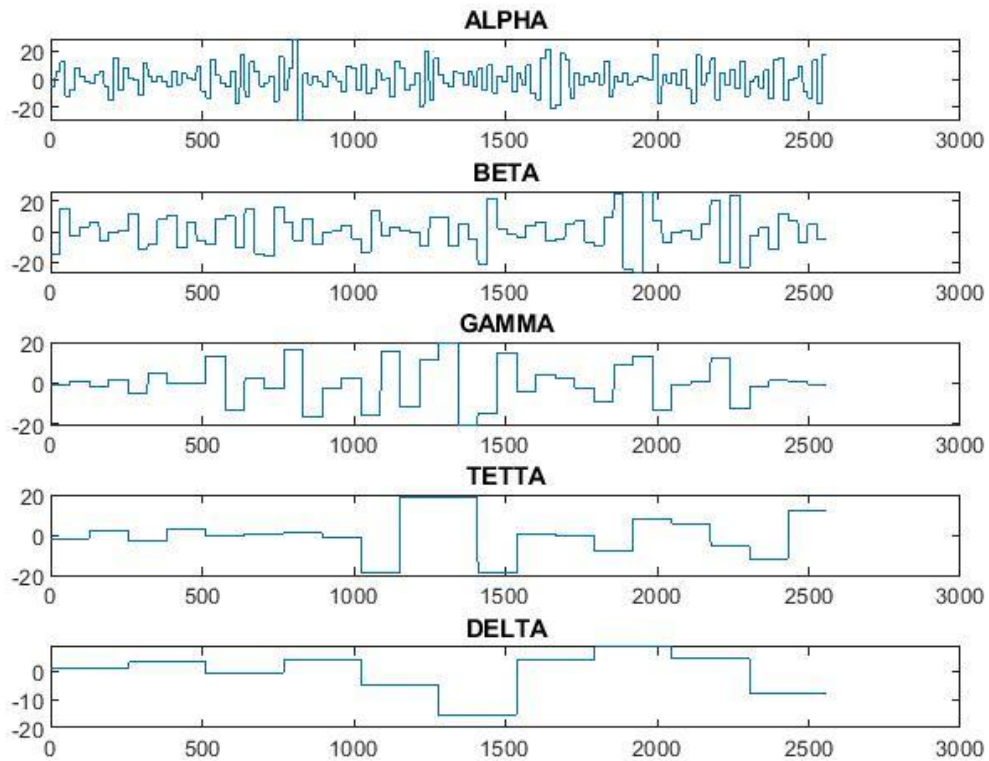


**Fig: 5.9 ROC**

The above figure shows the ROC plot of the model. A receiver operating characteristic curve (ROC curve) is a graph that shows how well a classification model performs over all classification thresholds. Plotting the true positive rate (TPR) against the false positive rate (FPR) at different threshold points yields the ROC curve. The measure becomes less reliable as the curve approaches the ROC space's 45-degree diagonal. It can thus be used to test classifiers that predict rare events.

## 5.2 RESULTS FROM TIME DOMAIN ANALYSIS

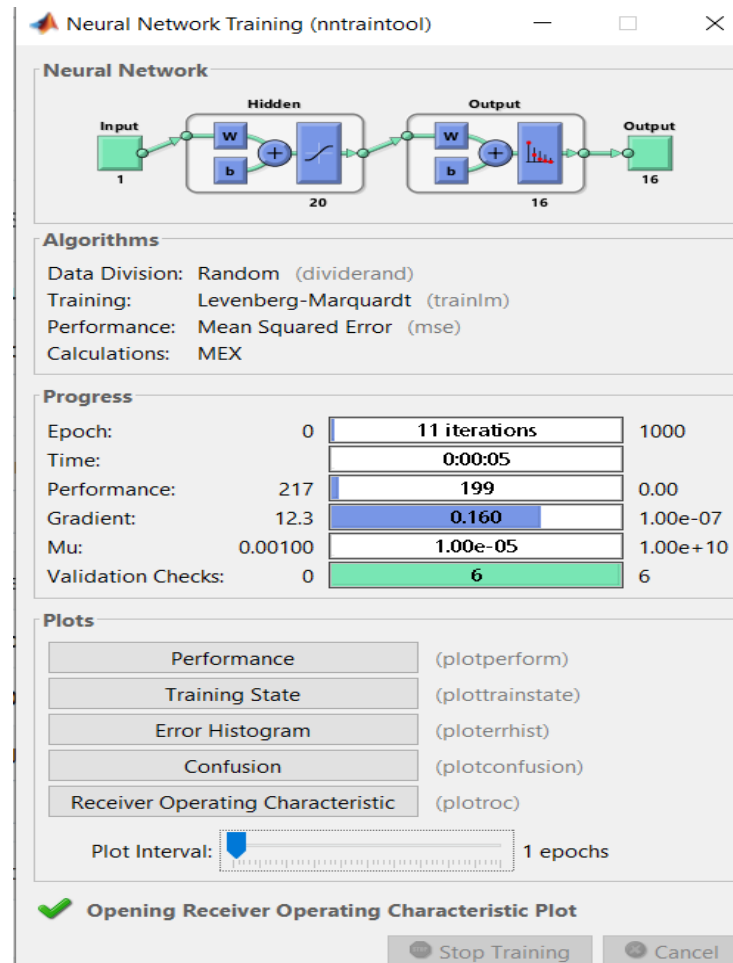
### 5.2.1 *Extracted frequencies:*



**Fig: 5.10** *Extracted frequencies*

The different types of wave signals such as alpha, beta, gamma, theta and delta waves are extracted from the input time signals and plotted as separate signals that can be seen in the above given figure from which each and every differentiation in the wave can be noted. The waves provided above in the image is obtained as a result of time domain values with Harr wavelet, thus the frequencies of these waves were represented as the square waves instead of sine waves.

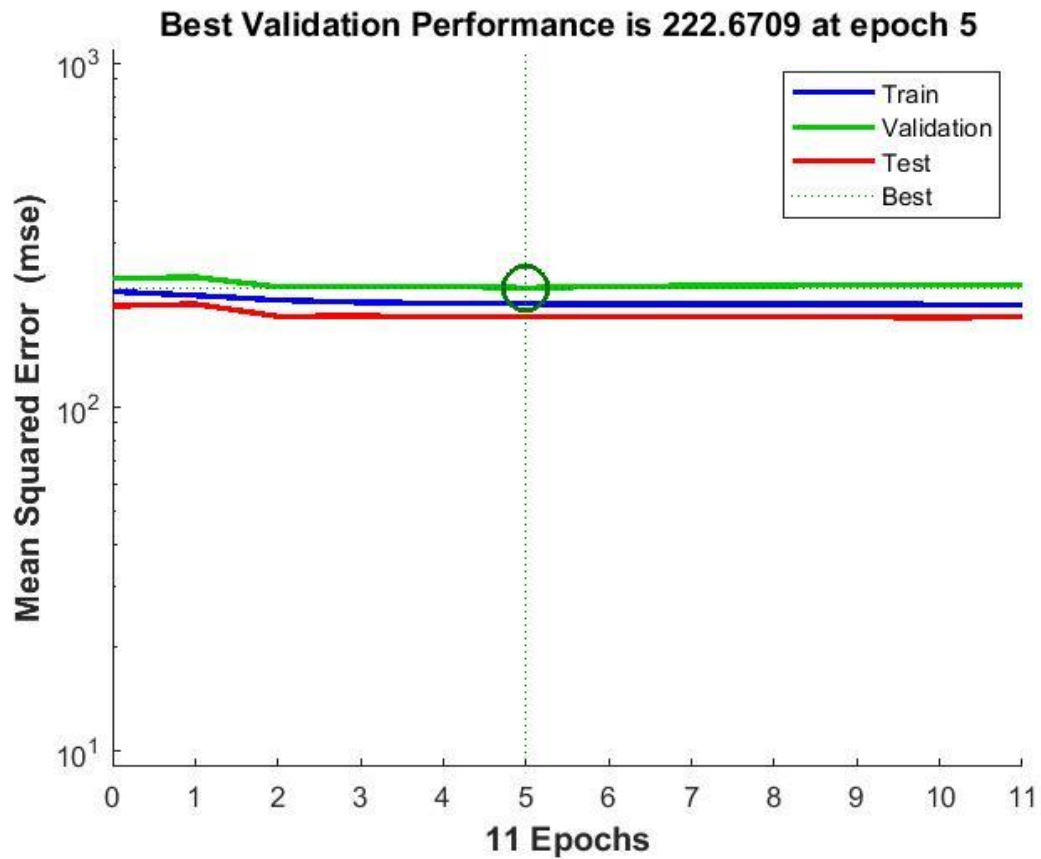
### 5.2.2 Hybrid Neural Network:



**Fig: 5.11 Hybrid Neural Network**

The above image shows the automatic block generation which contains all the details regarding how the signals are trained in the time domain values and the number of hidden layers used inside. Thus, we can analyse the output by clicking on whatever requirements we need such as performance, training state, error histogram, confusion, receiver operating characteristics.

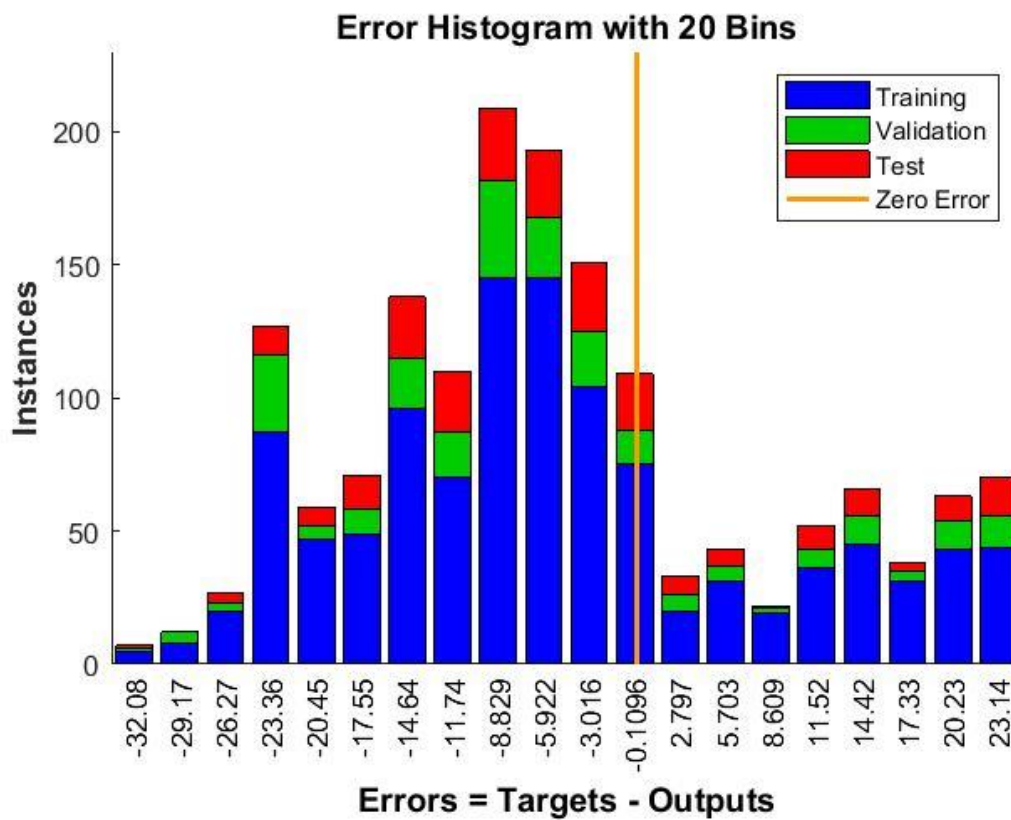
### 5.2.3 Performance Measure:



**Fig: 5.12 performance measure**

The above figure presents the Mean Squared Error (MSE) for training, validation (check), and test steps. According to this figure, the least MSE in the validation step is happened at epoch 5, which has the best validation performance equal to 222.6709.

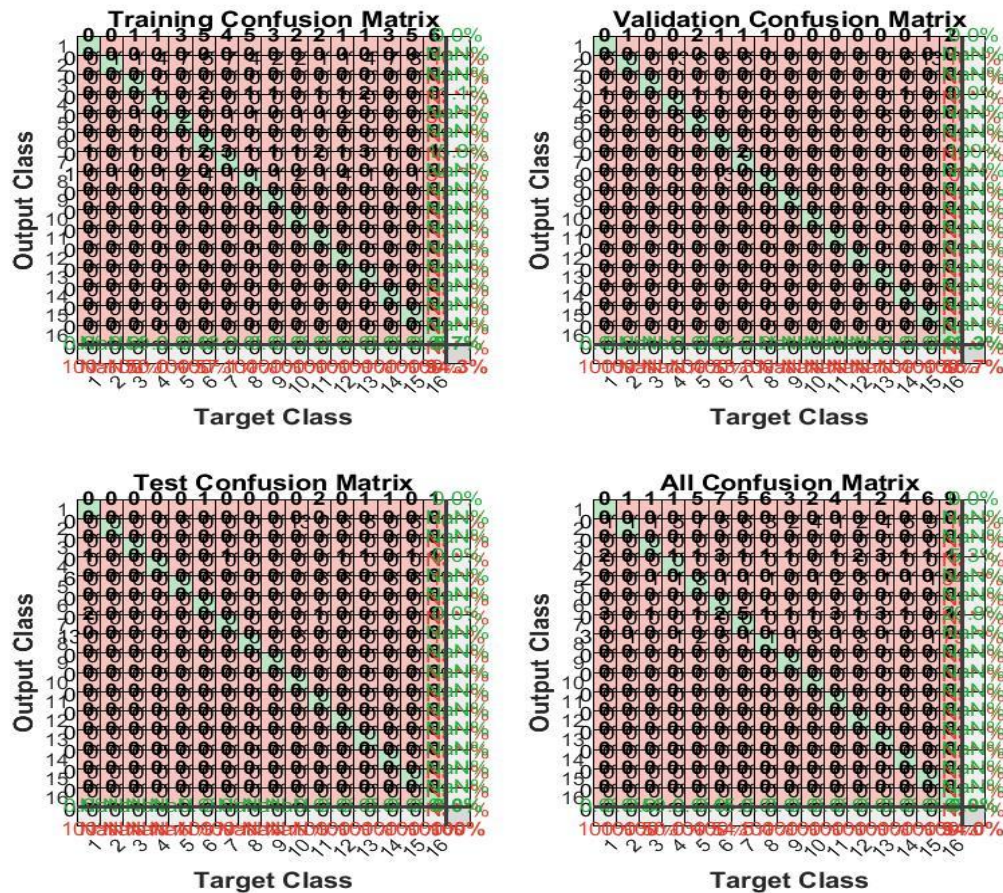
#### 5.2.4 Error Histogram:



**Fig: 5.13 Error Histogram**

The above figure shows the error histogram graph obtained after training the time domain values. The histogram of errors between target values and predicted values after training is known as the error histogram. The error is obtained from the difference of targets and the outputs. The errors from training, validation and testing were represented in different colours for their variations. This histogram shows the average rate of the decrease of errors which can be seen through validation process being carried out in the system and also shows the point where very minimal error is being obtained (-0.1096).

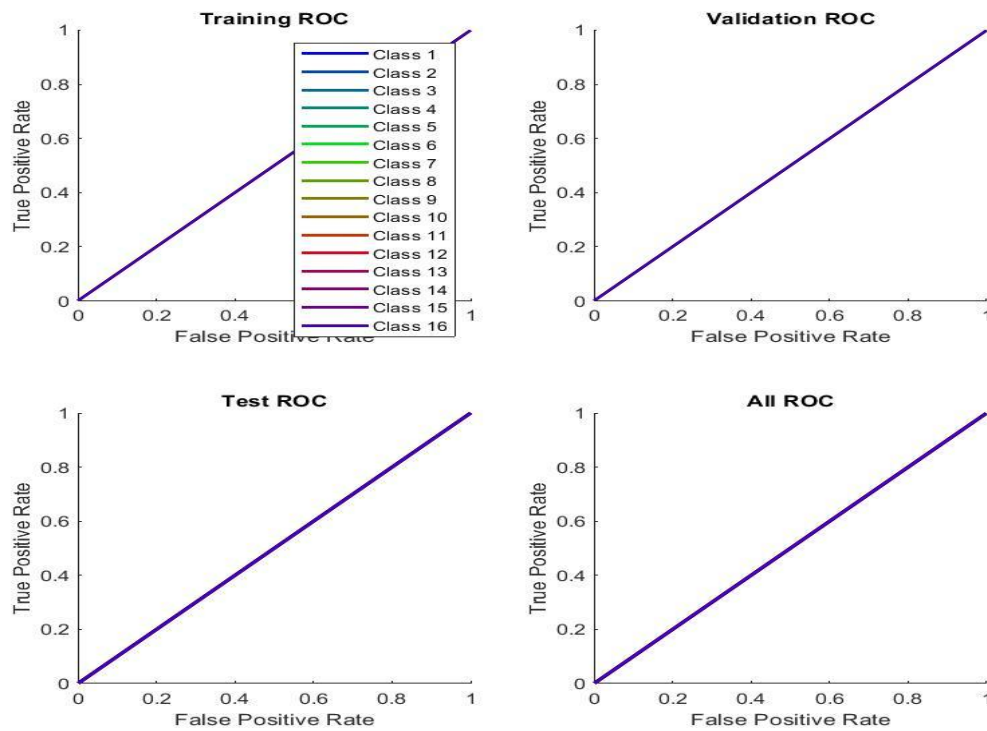
### 5.2.5 Confusion Plot:



**Fig: 5.14 Confusion plot**

In the above image we can see the confusion matrix plotted that is been obtained with time series. Confusion matrix basically gives us an idea about how well our classifier has performed, with respect to performance on individual classes. As a result, a confusion matrix is usually filled out using the known test set's true labels. Confusion Matrix consists of 4 parameters such as true positives, true negatives, false positives and false negatives. This allows more detailed analysis when the numbers of observations in different classes vary greatly.

### 5.2.6 ROC Plot:



**Fig: 5.15 ROC plot**

The above figure shows the ROC plot of the time domain values. A receiver operating characteristic curve (ROC curve) is a graph that shows how well a classification model performs over all classification thresholds. Plotting the true positive rate (TPR) against the false positive rate (FPR) at different threshold points yields the ROC curve. The measure becomes less reliable as the curve approaches the ROC space's 45-degree diagonal. It can thus be used to test classifiers that predict rare events.

### 5.3 STATISTICAL ANALYSIS:

Levenberg-Marquardt Algorithm:

Frequency domain analysis:

(With filtration):

TABLE: 5.1

| PARAMETER          | VALUES   |
|--------------------|----------|
| Accuracy           | 100      |
| Kurtosis           | 4.3656   |
| Skew               | 2.0373   |
| Standard Deviation | 61.587   |
| Mean               | 30.5421  |
| Co-variance        | 379.2953 |
| Median             | 6.5185   |

Frequency domain analysis:

(Without filtration)

TABLE: 5.2

| PARAMETER          | VALUES  |
|--------------------|---------|
| Mean               | 25.763  |
| Median             | 2.71314 |
| Standard Deviation | 596.176 |

Discussion:

The table given (5.1 & 5.2) above frequency domain analysis for the datas with filtration and without filtration.

Frequency data analysis is done for PSD after processing of signal takes place in frequency domain.

The mean value i.e., the frequency value for this wrist movement is observed to be 30.5421. Whereas in frequency domain analysis of without filtration the mean value is observed to be 24.763.

The average spread out of data i.e., SD of the Frequency analysis with filtration is 61.587 and for without filtration is 596.176

Time domain analysis:

(With filtration):

TABLE: 5.3

| PARAMETER          | VALUES   |
|--------------------|----------|
| Accuracy           | 100      |
| Kurtosis           | 1.9507   |
| Skew               | 0.71628  |
| Standard Deviation | 15.0275  |
| Mean               | 16.45    |
| Co-variance        | 225.8258 |
| Median             | 11       |

Time domain analysis:

(Without filtration):

TABLE: 5.4

| PARAMETER          | VALUES   |
|--------------------|----------|
| Average            | -0.49949 |
| Standard Deviation | 93.08799 |
| Kurtosis           | 4.651081 |

Discussion:

The table given (5.3 & 5.4) above is the time domain analysis for the datas with filtration and without filtration.

Time data analysis is done for raw EEG signal without processing takes place in time domain.

The mean value for this time domain analysis with filtration for the wrist movement is observed to be 16.45. Whereas in time domain analysis of without filtration the mean value is observed to be -0.49949.

The average spread out of data i.e., SD of the time analysis with filtration is 15.0275 and for without filtration is 93.08799.

## 5.4. DISCUSSION

The results obtained from, Identification of ideal region for muscular movement using EEG in which the obtained EEG input signals of wrist movements are been recorded by using 10-20 electrode system and is being processed by Levenberg Marquardt Algorithm gives the performance measures such as power spectral density as 33Hz, Accuracy as 100%, Mean value as 30.5421 and Error as 0.6684% as compared with the existing literature. Analysis of small muscle movement effects on EEG signals (Erhan Yanteri, 2016) in which the EEG signals are classified by Neural network pattern recognition of tool of MATLAB which gives the output as power spectral density as 25Hz and accuracy as 72%. From the above results it is clear that the result obtained by Levenberg-Marquardt algorithm provides the more accuracy on comparing with the method which is used in the existing literature system.

Motor Imagery EEG signals classification based on mode application and frequency components using Empirical wavelet transform (Muhammad Tariq Sadiq, et al., 2019) in which the EEG signals are recorded in fully relaxed seated state, feature extraction process is done by using Empirical wavelet transform then the trained data are classified using Least square support vector machine (LV-SVM) classifier which gives the performance measures such as Power spectral density as 26Hz, Mean as 94.60 and Accuracy as 97.22%, On comparing both the results the values obtained by using Hybrid algorithm yields more accuracy than the accuracy vale obtained by using LV-SVM, this shows Levenberg-Marquardt algorithm provides better result.

Spectral information of EEG signals with respect to epilepsy classification (Markos Tsipouras, 2019) in which EEG signals are processed by DWT (Discrete wavelet Transform) and WPD (Wavelet packet decomposition) and the classification is based on the Random forest classifier, which is an ensemble learning method based on the construction of a multitude of decision trees. It gives the performance measures such as power spectral density in the range of 32Hz, accuracy as 90.08%. From the above results, it is clear that the result obtained by Levenberg-Marquardt algorithm gives more accuracy values on comparing with the method which is used in the existing literature system.

As compared to the current literature, the EEG signals are pre-processed using Haar wavelet, and the feature extraction stage is carried out using Patternet DCP-NET. Finally, the EEG signals are classified using the Levenberg Marquardt Algorithm, which gives performance measurements such as power spectral density of 33Hz, accuracy of 100 percent, mean value of 30.5421, and error of 0.6684 percent. Identification and Use of PSD-Derived features for the contextual detection and classification of EEG epileptiform transients (Sharan Rajendran, 2016) in which the EEG signals are recorded for five confidence levels are processed by and classified by Artificial Neural Network i.e., Feed forward Neural Network. It gives the performance measures such as Power spectral density in the range of 37Hz. On comparing both the results the values obtained by using Hybrid algorithm yields more accuracy than the accuracy value obtained by using Feed forward Neural Network, this shows Levenberg-Marquardt algorithm provides better result.

A Hybrid approach for extracting EMG signals by filtering EEG data for IoT applications for immobile persons (Aman Kurapa, et al., 2020) in which EEG signals are recorded and filtered using hybrid digital filters which yields the Power spectral density as 31Hz. From the above results, it is clear that the result obtained by Levenberg-Marquardt algorithm gives more accuracy values on comparing with the method which is used in the existing literature system.

Awareness and the EEG power spectrum: analysis of frequencies (Dressler Schneider, et al., 2017) in which the power spectral density was measured as 36Hz with accuracy of 95%, thus from this statement it is clear that the values obtained from Levenberg- Marquardt algorithm provides more accurate values than the existing literature system.

Another experiment, Recognition of finger movement of EEG signals for control of upper limb prosthesis using logistic regression (Amna Javed, et al., 2017) in which the signals that are acquired are classified into movements on the basis of feature vector after being extracted from raw signals. This paper presents a novel method of classification of four finger movements (thumb movement, index finger movement, middle and index finger combined movement and fist movement) of the right hand on the basis of EEG (Electroencephalogram) data of the movements. The data-set was obtained from a right-handed neurologically intact volunteer using a

non-invasive BCI (Brain-Computer Interface) system. Classification of the features is done using various classifiers. Various classifiers have been tested and compared on basis of the mean class accuracy achieved. The classifier chosen for the study is logistic regression, which gives an accuracy of 65% and power spectral density of 30Hz, thus from this it is clear that the values obtained from Levenberg- Marquardt algorithm provides more accurate values than the existing literature system.

In this method the EEG signals are pre-processed using Haar wavelet and the feature extraction step is being carried out by using Patternet DCP-NET and is being classified by Levenberg Marquardt Algorithm gives the performance measures such as power spectral density as 33Hz, Accuracy as 100%, Mean value as 30.5421, Standard Deviation as 61.587 and Error as 0.6684% as compared with the existing literature. Detection of Epileptic seizure in EEG recordings by spectral method and statistical analysis (Ravish, et al., 2013) in which EEG database of epileptic patients were recorded and obtained the values such as Mean as 39.45, Standard deviation as 55.73, Accuracy as 95%, thus from this it is clear that the values obtained from Levenberg- Marquardt algorithm provides more accurate values than the existing literature system.

Acquiring and processing of female EEG signals of various wrist movements for neuro prosthetic applications (Umashankar, et al., 2018) in which EEG database of various wrist movements of female placing 10-20 electrodes were recorded and the database is pre-processed by DB wavelet (Daubechies wavelet transform) and the classification is done using wavelet transformation. It provides the performance measure values such as Power spectral density as 28Hz, Mean as 29.712, Standard deviation as 112.976. Thus, from this it is clear that the values obtained from Levenberg- Marquardt algorithm provides more accurate values than the existing literature system.

## **CHAPTER 6**

### **SUMMARY AND CONCLUSION**

#### **6.1 SUMMARY:**

In this study we obtained the input EEG signals data acquisition by using 10 – 20 electrode system by placing the electrodes in our scalp and recording the different types of wrist movements such as clockwise, anti- clockwise, flexion, extension, pronation and supination for a time period of 8 seconds for each dataset. Here we totally recoded 50 datasets of signal. The signals after data acquisition are now pre-processed by using DWT filter which is done to remove the excess noise and other disturbances from the signals and the pre-processed signal is now feature extracted by using Haar wavelet which gives us 5 different types of waveforms which is present only in the EEG signal they are alpha waves, beta waves, gamma waves, theta waves and delta waves which are all obtained in time domain format which is then converted into frequency domain signals.

Now these signals are given as for the testing, training and the cross validation process which is being carried out. The final result is obtained by giving a test input signal along with the trained model which is now processed in MATLAB by using Levenberg-Marquardt algorithm this gives us the desired output of the wrist movement by identifying their frequency range for all the waveforms and it also displays the accuracy and specificity of the input signal which helps us in determining the accuracy of the signals. Power spectral density is calculated to find where the frequencies variation is strong & where the frequencies variation is weak and classification of frequencies responsible for various movements is obtained in peak value of PSD graph. Finally, it is observed that the average frequency is approximately 30-33 Hz. So, it is finalized in these comparisons “beta waves” (21-30 Hz) are more dominant during the wrist movements. The obtained classified frequencies can be used in prosthetic applications.

Thus, the design of EEG based wrist movement prediction is successfully implemented using MATLAB software. Simulation RESULTS are verified by applying various test procedures. The newly created Deep learning hybrid patternet creates better accuracy.

## 6.2 CONCLUSION:

The use of FFT for feature extraction has helped us find a certain EEG range of 30-33 Hz for the wrist movements (clockwise rotation, anticlockwise rotation, flexion extension, pronation, supination). The obtained frequency ranges were seen to hinder depending on physiological changes of the individual who were put into the EEG test. These frequency ranges were cross checked with the already existing theory about the alpha and beta waves responsible for motor activities merging from central and frontal regions. The standard deviation obtained in the frequency domain was compared with the statistics mentioned in a pre-existing journal. The values were approximately similar, thus the filtered parietal signal is alone better for the movement detection rather than the overall signals. The outputs from this project gives us certain performance measures such as accuracy, specificity and errors which indeed shows us the quality of the input signal we have taken. The main scope of this work is to use these trained and tested input signals in rehabilitation patients for their wrist movement detection. Though the frequency detected is not enough to make up a prosthetic device but coloration with engineering idea can make it happen.

## 6.3 FUTURE DEVELOPMENT:

The proposed development can be extended further by providing Live EEG data with the help of 32 Sensors and streaming the analysis and prediction through Deep Learning Fast networks. Also, the method can be worked also by using real time signals that can be measured by using EEG recorder which can be fed into the system for further data analysis. The values were approximately similar, thus opening a word in support with the real time application of this idea. Though the frequency detected is not enough to make up a prosthetic device but coloration with engineering idea can make it happen.

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## APPENDICES

Code for frequency domain analysis:

```
clc;
clear all;
close all;
warning off;

[feaVec,frespecVec,fcont,spcont]=train_samples();

[ndata, text, alldata] =
xlsread('C:\Users\nived\OneDrive\Desktop\muscular\Action_detection_updated\B_New\11.xlsx');

%
*****

****

signal_ch_1=ndata(:,1);
signal_ch_2=ndata(:,2);
signal_ch_3=ndata(:,3);
signal_ch_4=ndata(:,4);

% CHANNEL 1
subplot(2,2,1)
X1=signal_ch_1;
[req1,Ph1]=fft_al(X1);
title('Spectrum of Channel 1 S(t)')
% pause(1);
% CHANNEL 2
subplot(2,2,2)
X2=signal_ch_1;
[req2,Ph2]=fft_al(X2);
title('Spectrum of Channel 2 S(t)')
% pause(1);
% CHANNEL 3
subplot(2,2,3)
X3=signal_ch_1;
[req3,Ph3]=fft_al(X3);
title('Spectrum of Channel 3 S(t)')
% pause(1);
% CHANNEL 4
subplot(2,2,4)
X4=signal_ch_1;
[req4,Ph4]=fft_al(X4);
title('Spectrum of Channel 4 S(t)')

sdata=[X1,X2,X3,X4];
[fc4,sp4]=Channel_Filter(sdata);
```

```

freq_coeff_ch4=cell2mat(sp4)
%
*****
*****

fc=freq_coeff_ch4;
fcontt=sum(sum(fc));

fc;
feaVec=imresize(feaVec,[39 16]);
for i=1:100
for j=1:16
train_vectors(j,i)=feaVec(randi(39),j);
end
end

for i=1:100
for j=1
test_vectors(j,i)=fc(randi(numel(fc(:)))));
end
end
[percentErrors,fpL,fnL,tpL,tnL]=train_data(abs(test_vectors),abs(train_vectors));
[ACC1,PREC1,REC1,F1SCO1,SPEC1]=performance_measure_routine(tpL,tnL,fpL,fnL);
par1=num2str((abs(ACC1*100)));
par2=num2str(abs(PREC1));
par3=num2str(abs(REC1));
par4=num2str(abs(F1SCO1));
par5=num2str(abs(SPEC1));
par6=num2str(abs(kurtosis(test_vectors)));
par7=num2str(abs(skewness(test_vectors)));
par8=num2str(abs(std(test_vectors)));
par9=num2str(abs(mean(test_vectors)));
par10=num2str(abs(cov(test_vectors)));
par11=num2str(abs(median(test_vectors)));

fprintf('***** Levenberg-Marquardt Algorithm (Wfft)
*****\n\n');
fprintf('Levenberg-Marquardt Algorithm NN \n ACCURACY=%s \n',(par1));
fprintf('Kurthosis=%s\n',(par6));
fprintf('Skew=%s\n',(par7));
fprintf('Standard Dev=%s\n',(par8));
fprintf('Mean=%s\n',(par9));
fprintf('Co-Variance=%s \n',(par10));
fprintf('Median=%s\n',(par11));
fprintf('*****\n');

```

Code for time domain analysis

```
clc;
clear all;
close all;
warning off;

[feaVec,frespecVec,fcont,spcont]=train_samples_Wo_FFT();
%
*****
****
[ndata, text, alldata] =
xlsread('C:\Users\nived\OneDrive\Desktop\muscular\Action_detection_updated\D
B_NEW\11.xlsx');
%
*****
****
signal_ch_1=ndata(:,1);
signal_ch_2=ndata(:,2);
signal_ch_3=ndata(:,3);
signal_ch_4=ndata(:,4);
%
*****
****
% CHANNEL 1
%
*****
****
subplot(2,2,1)
X1=signal_ch_1;
X2=signal_ch_1;
X3=signal_ch_1;
X4=signal_ch_1;
sdata=[X1,X2,X3,X4];
[fc4,sp4]=Channel_Filterts(sdata); %check
freq_coeff_ch4=cell2mat(sp4)
%
*****
****
fc=freq_coeff_ch4;
fcontt=sum(sum(fc));

fc;
feaVec=imresize(feaVec,[39 16]);
for i=1:100
for j=1:16
train_vectors(j,i)=feaVec(randi(39),j);
end
end
```

```

for i=1:100
for j=1
test_vectors(j,i)=fc(randi(numel(fc(:)))));
end
end
[percentErrors,fpL,fnL,tpL,tnL]=train_data(test_vectors,train_vectors);
[ACC1,PREC1,REC1,F1SCO1,SPEC1]=performance_measure_routine(tpL,tnL,fpL,fnL);
par1=num2str((ACC1*100));
par2=num2str(PREC1);
par3=num2str(REC1);
par4=num2str(F1SCO1);
par5=num2str(SPEC1);
par6=num2str(kurtosis(test_vectors));
par7=num2str(skewness(test_vectors));
par8=num2str(std(test_vectors));
par9=num2str(mean(test_vectors));
par10=num2str(cov(test_vectors));
par11=num2str(median(test_vectors));

fprintf('***** Levenberg-Marquardt Algorithm WO-FFT
*****\n\n');
fprintf('Levenberg-Marquardt Algorithm NN \n ACCURACY=%s \n',(par1));
fprintf('Kurthosis=%s\n',(par6));
fprintf('Skew=%s\n',(par7));
fprintf('Standard Dev=%s\n',(par8));
fprintf('Mean=%s\n',(par9));
fprintf('Co-Variance=%s\n',(par10));
fprintf('Median=%s\n',(par11));
fprintf('*****\n');

```