Classification of Motor Imagery Based EEG Signals

Leena R, Ashok Kumar R

Abstract*: Brain Computer Interface (BCI) enable the user to interact with system only through brain activity, usually measured by Electroencephalography (EEG). BCI systems additionally offers analysis of Motor Imagery EEG, which may be appeared, is a novel way of communication for the patients who are physically disabled. Motor Imagery based EEG data (left hand, right hand, or foot) movements supplied by BCI Competition IV dataset1. The data signals were band-pass filtered between 0.05 and 200Hz and sampled at 100Hz. The features extracted from the raw data with respect to time and frequency domain of required channels. Motor Imagery based EEG (left hand, right hand or foot) data classified using machine learning algorithm namely Support Vector Machine (SVM) and Back Propagation Neural Network (BPNN) for four normal human subjects (a, b, f, g). Analysis of motor imagery-based EEG data was studied using EEGLAB toolbox. Selected data are presented from raw data in channel data (scroll), representation of channel location in 2D and 3D form, channel spectra and maps and channel properties.

***Index Terms*: Brain computer Interface, Back Propagation Neural Network, EEGLAB, Motor Imagery, Support Vector Machine.**

I. INTRODUCTION

Brain Computer Interface (BCI) is an evolving technology for giving another output channel for brain signals to interact or manage external equipment's without utilizing the natural neuromuscular pathways that connects human brain with man-made devices. BCI acknowledges the target of the user with electrophysiological and alternative signals from the brain, decrypts in progress neural activity and changes over it into yield directions to satisfy the user objective. It additionally enables communication between the brain and the different machines [1], [13]. The most convoluted organ in the human body is Human Brain. The outermost portion of the brain is cerebral cortex which is classified into four lobes as represented in Fig 1 (Image source www.farmagain.com/braininjury.html) along with its function.

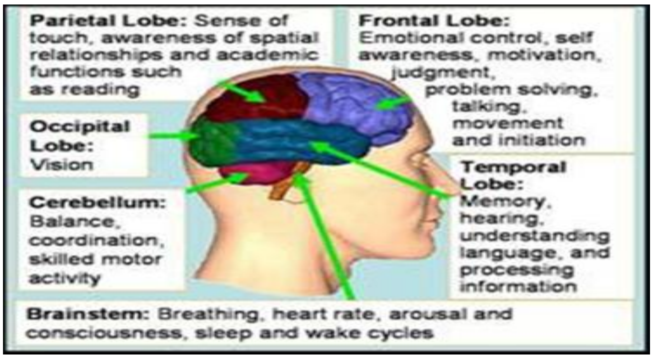

Fig 1: Depicting Brain Lobes and Its Function

Electroencephalogram (EEG) is a non-invasive test which examines the electrical activity in the brain. Certain brain disorder which includes head injury, brain tumor, memory problems, sleep disorders, stroke, dementia, seizure disorders, encephalitis etc... can be recognized with the assistance of EEG test. Based on International 10-20 system electrodes are placed on the brain scalp in order to obtain the signals from the various regions of brain as shown in Fig 2 (Image source https://cdn-blog. adafruit.com/uploads/2017/06/tdcs-2-1.gif) [15].

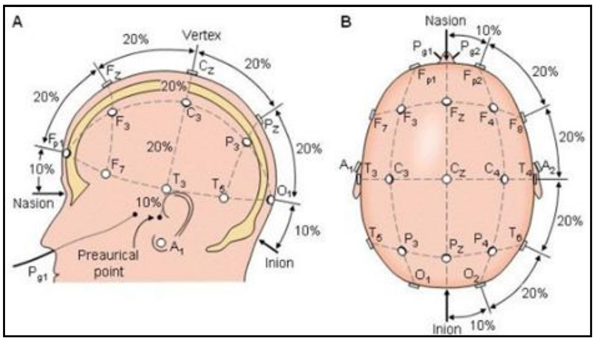

Fig 2: International 10-20 system electrode placement seen from (A) left and (B) above the head

The EEG signal is classified into five types: alpha, beta, gamma, delta and theta and each type has its own significance in brain [16]. They are classified according to the EEG frequency and its corresponding activity is given in Table 1.

Table 1: Depicting various Brain Rhythms with Frequencies and Activity

Rhythms	Frequencies (Hz)	Activity
Delta	0.5-4	Deep Sleep
Theta	4-8	Falling
Alpha	8-13	Relaxing
Beta	13-30	Physical Activity, Thinking, Solving Mathematical problems
Gamma	30-40	Higher mental movement together with Problem solving, Perception, awareness, Fear

People that are affected by paralysis or those who are not in a position to move always need some kind of communication through which they can express themselves to the world. BCI also used in classification of mental tasks such as hand and foot movements (Motor Imagery) which provides a new way of communication for physically disabled. When a subject imagines that he/she doing an action, such mental task is referred to a Motor Imagery. For certain patients like differently abled, classification of Motor Imagery tasks become important. Unlike the existing research [2], [11] which focused on classification accuracy, this research focus on Classification of mental tasks such a left hand, right hand or foot movement. The data are classified using Support Vector Machine algorithm, Back Propagation Neural Network. EEGLAB is used for visualization of channel location, channel properties, channel spectra and maps. This research is organized into five sections in the following way: Section II presents related work carried out; Section III presents Methodology followed in order to carry out this work. Section IV provides information on EEGLAB Analysis. Section V describes the results and lastly Conclusion and Future Work is delineated in Section VI

II. RELATED WORK

Bin He, Bryan Baxter, Bradley, J. Edelman, Christopher C. Cline worked on Noninvasive Brain -Computer Interfaces Based on Sensorimotor Rhythms [1]. This paper provides information on research that has been carried out on however the brain will use BCI systems to regulate external devices, in the area of Neuroengineering. The principles and methods used in their study to develop BCI in accordance with sensorimotor rhythm EEG have been reviewed. It likewise incorporates portraying of scalp EEG signals to the outer layer of cerebrum and management of physical gadgets for users' engagement development. Jessy Parokaran Varghese worked on Analysis of EEG Signals for EEG-based Brain-Computer Interface [3]. This paper provides information on analysis of EEG signals. EEG is all the more broadly utilized in the diagnosis of brain diseases, which is a powerful minimal cost technique. The research focuses on growing new intensifying intelligence and control innovation for the certain with extreme neuromuscular disorders in the area of BCI. Examination of EEG data to perceive how people can control machines utilizing their thoughts. Which is examined by differentiating event related synchronization and desynchronization of Mu and beta rhythms. It happens in sensory motor cortex of person during inventiveness of left hand and right hand activity. S. Dhivya et.al worked on review of machine learning algorithms for EEG signals [10]. Electrical Activity of the brain are recorded and represented by the EEG. Analysis and Diagnosis of various brain diseases, brain condition with the help of information obtained from the signals. Different Machine Learning algorithms for the analysis of various brain activities have been reviewed in this paper. Rinkal G. Shah and Prof. Rutu Nayak worked on Hand Movement Classification Using Motor Imagery EEG [4]. The aim of this paper is to collect data that are accessible on the Physionet ATM or BCI competition datasetIII, for the Classification of Hand Movement (left hand, right hand). Two sorts of methods namely Independent Component Analysis and Wavelet Transform used for features extraction. Classification is done using Support vector Machine and K-Means clustering to identify the sort of movements (left hand or right hand). Rajdeep Chatterjee and Tathagata Bandyopadhyay worked on EEG based Motor Imagery Classification using SVM and MLP [5]. This paper focus on Motor Imagery grouping of left hand and foot, left hand and right hand movements experiment was done on healthy subjects. Filtering to remove unwanted signals using band pass filters. Particularly C3 and C4 electrodes were examined for the left-right limb movements. Statistical-based, Root Mean Square and wavelet-based energy-entropy etc.; were the features extracted in their study. SVM algorithm is utilized for the classification and the outcomes were contrasted with MLP.

III. METHODOLOGY

To collect BCI datasets and analyze the brain patterns. The datasets would be used to extract information on Motor Imagery. Frequency domain and Time domain features should be extracted. Type of movements (left hand, right hand or foot) should be classified using two classifiers in particular SVM, BPNN. The Analysis of the results should be visualized based on channel locations, channel properties, channel spectra and maps, using EEGLAB. The below block diagram depicted in Fig 3 represents proposed work carried out which is illustrated as follows. The EEG signals of Motor Imagery obtained from the BCI Competition IV dataset1. It includes recorded EEG data for the task of Motor Imagery such as left hand, right hand, or foot movements. Required channels are chosen for performance improvement. Features like Discrete Wavelet Transform, Mean, Standard Deviation, Skewness, Zero Crossing, Hjorth (mobility, complexity), Auto regression, Variance, Kurtosis, Slope Sign Change, Waveform length were extracted. Classification is achieved using two classifiers namely SVM and BPNN for the type of movements (left hand, right hand or foot).

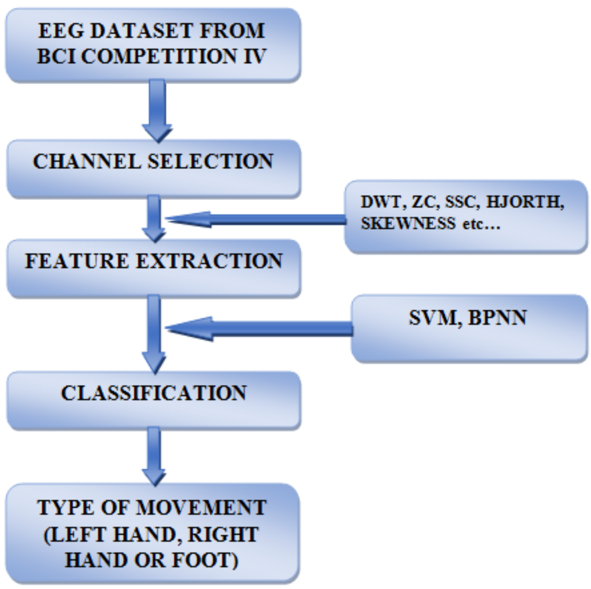

Fig 3: Block diagram of the Proposed Work

A. *Eeg Data*

EEG data for Motor Imaginary task accomplished by seven normal human subjects are acquired from BCI Competition IV Dataset 1[5]. Within the experiment, every subject was approached to choose two mental assignments to execute out of three errands like (left hand, right hand or foot movements). For representing left hand, right hand and foot movements the visual sign on the computer screen were presented in which arrows inform left, right or down respectively. The sign showed up in the center of the screen for the 4s time frame, that interspersed with 2s of clear screen and 2s with an obsession cross.

B. *Channel* Selection

The main purpose behind channel selection procedure is:

- To lower computational intricacy of any processing task carried on EEG signals by extracting the features of the appropriate channels of significant importance.
- To reduce the number of over fitting which will emerge owing to the utilization of unnecessary channels, for the aim of rising the execution.
- To decrease the setup time in certain applications. Ten channels labeled as FC5, FCz, FC6, C5, C3, Cz, C4, CP3, CPz and CP6 [21] were use

C. *Feature Extraction*

The goal of feature extraction procedure is to excerpt desired signals from the raw EEG data and eradicate unwanted signals. The EEG signals are grouped based on frequency bands such as gamma, beta, alpha, theta, and delta band. The frequency of motor imagery typically lies in alpha or beta band. Therefore, the EEG signal processing should be measure in term of frequency. The EEG signals that are in time domain need to change over frequency domain for better feature extraction. Extracting appropriate features is a prerequisite of Feature Extraction strategy so as to classify the EEG data [8]. Signal analysis plays an essential role in extracting information from signal by applying appropriate technique. Different methods used for feature extraction are Frequency Domain and Time Domain. The details of the same are discussed below

a. DISCRETE WAVELET TRANSFORM (DWT)

The DWT is the discretization of continuous wavelet and therefore the wavelet coefficients reflect restricted data of the signal in time space and recurrence space. For handling non stationary signal, particularly EEG it is very suitable. DWT was used in this work to analyze the signal and feature extraction, $f(t)$ denotes obtained discrete EEG signal S. DWT of the signal $f(t)$ is represented as follows

$$C_{j,k}\left(f,\varphi_{j,k}\right)=2^{\frac{-j}{2}}\sum_{n=-\infty}^{\infty} f(t)\overline{\varphi}\left(2^{-j}t-k\right)\; j,k\in Z$$

DWT hold sufficient information and thus enables the reconstruction of an excellent signal from the coefficients of the wavelet. Haar wavelet is a method that replaces adjacent pairs by taking the mean and differences elements in the signal. An input signal is grouped into two sub signals with Haar wavelet transform. Low pass and high pass filter are applied in Haar wavelet. From Haar wavelet transform two signal are produced one has low coefficient (low band) and another have high coefficient (high band) [4], [14], [20]. Daubechies4 wavelet is used to discover appropriate EEG decomposition. Coefficients and length for the signal are obtained which fed as input for calculating statistical parameters as follows

i. MEAN

It is also called average, is the central value of a distinct set of numbers: Precisely, the sum of the values partitioned by the number of values is given as

$$\overline{X} = \frac{\sum_{i=1}^{n} x_i}{n} \qquad (1)$$

Here n indicates the signal length and x_i represents the EEG data.

ii. STANDARD DEVIATION

It is the dispersed value in a set of data values from the average. If the standard deviation obtained is low implies the values are near the mean. If the obtained standard deviation is high implies the values are spread out from our mean. The SD is given as

$$S_x = \sqrt{\frac{\sum_{i=1}^{n}\left(x_i-\overline{x}\right)^2}{n-1}} \qquad (2)$$

Here x indicates observed values of EEG data, and $\overline{x}$ represents mean value of these observation and N represents absolute number of observation in EEG data.

iii. WAVEFORM LENGTH (WL)

WL is represented as the waveform's cumulative length over the time segment. WL is associated with the amplitude, frequency and time of the waveform.

$$WL = \sum_{i=1}^{N}\left|\Delta x_j\right| \qquad (3)$$

Where, Δx_j is the difference of consecutive samples.

iv. ENERGY

It shows the strength of the signal, as it provides the area under the curve at each interval of time given as

$$E = \sum_{n=-N}^{N}\left|\left(x(n)\right)\right|^2 \qquad (4)$$

Other Time Domain Features extracted are

v. ZERO CROSSING

The zero y-axis is intersected by a technique comprised of counting the number of times the EEG signal amplitude value. This method produces poor outcomes when dealing with highly noisy signals. As a result, the zero crossing count is increased when equation (5) and (6) are satisfied

$$\{x_j < 0 \ and \ x_{j+1} > 0\} or \ \{x_j > 0 \ and \ x_{j+1} < 0\} \quad (5)$$

$$|x_j - x_{j+1}| \geq \varepsilon \quad (6)$$

Where x_j, x_{j+1} represents consecutive samples

vi. SLOPE SIGN CHANGE (SSC)

SSC represents EEG signal frequency information. To avoid the interference in EEG signal, the number of positive to negative slope transitions is estimated among three portions with reference to a threshold function. The slope sign change is incremented for the given samples x_j, x_{j+1} and x_{j-1} if equation (7) and (8) are satisfied

$$\{x_j < x_{j+1} \ and \ x_j < x_{j+1}\} or \ \{x_j > x_{j+1} \ and \ x_j > x_{j+1}\} \quad (7)$$

$$|x_j - x_{j+1}| \geq \varepsilon \ and \ |x_j - x_{j+1}| \geq \varepsilon \quad (8)$$

vii. HJORTH (MOBILITY, COMPLEXITY)

The Hjorth parameter is one among the methods for demonstrating measurable property of a signal in time space and the parameters used in this study are Mobility and Complexity. The proportion of standard deviation of the power spectrum is represented by Mobility parameter. Complexity parameter shows however the form of a signal is same as to a pure sine wave. The form of signal gets more same as to a pure sine wave then the estimation of Complexity converges to 1. These parameters facilitate in analyzing signals in time domain and additionally contain data regarding frequency spectrum of the signal. Hjorth parameters are often given as

$$Mobility = \sqrt{\frac{\operatorname{var}\frac{dy(t)}{dt}}{\operatorname{var}(y(t))}} \quad (9)$$

$$Complexity = \frac{mobility\left(\frac{dy(t)}{dt}\right)}{mobility(y(t))} \quad (10)$$

viii. VARIANCE

It computes how far each number in the set is from the average. Variance is given as,

$$\begin{aligned}\operatorname{var}(X) &= \operatorname{cov}(X, X) \\ &= E\left[(X-\mu)^2\right]\end{aligned} \quad (11)$$

ix. AUTOREGRESSIVE (AR)

For EEG signal analysis, the AR model has been generally utilized. An AR model is basically a linear regression of the present observation of the series against at least one earlier observations of the series. Usually it is given as,

X(t) = a1 X(t1)+ a2 X(t2)+ a3 X(t3)+… ap X(tp)+Et (12)

x. SKEWNESS

The inequality of the probability distribution of a real-valued random variable over its mean is measured by skewness, where the curve seems to be distorted either to the left or to the right side of the distribution. The moment's estimator of the population skewness for a sample of n values given as

$$skew = \frac{\sum_{i=1}^{N}(x_i - \mu_x)^3}{(n-1)\sigma_x^3} \quad (13)$$

xi. KURTOSIS

It is the peak measurement of the probability distribution of EEG signals. The data sets which has high kurtosis will in general have a specific peak close to the mean, and data sets which has low kurtosis tend to own a flat top close the mean, instead of sharp peak. The moment coefficient often given as

$$kurt = \frac{\sum_{i=1}^{N}(x_i - \mu_x)^4}{(n-1)\sigma_x^4} \quad (14)$$

D. CLASSIFICATION

The type of movements (left hand, right hand or foot) are classified using two classifiers namely SVM, BPNN which are discussed below

a. SUPPORT VECTOR MACHINE (SVM)

A hyper plane or set of hyper planes in a high dimensional space which may be utilized for grouping, regression or different assignments can be developed with the assistance of this technique. An excellent separation is accomplished by the hyper plane with the largest range to the closest training-data purpose of every category (so-called functional margin), since typically the larger the margin the lower the classifier generalization error [6], [7].In this study used multisvm () function for the classification of data, which takes three input parameters that are Training Set, Group Train, Test Set. Given training set modeled by SVM classifier with a corresponding group vector and given test set is classified

b. BACK PROPAGATION NEURAL NETWORK (BPNN)

BPNN is taken into account to be ideal Neural Network. Back Propagation is that the learning or training algorithm instead of network itself. We want to present the output referred to as the Target for a selected input for the aim of training network. Training Pair represents the input and its equivalent target. When the network is trained for any of the input patterns, BPNN will yield the desired output [13], [19]. Feed Forward Back Propagation Neural Network created by the newff () function and also initializes the Network automatically. Input vector, target vector, size of hidden layers are fed as input to the newff () function. With the use of train () function Network is trained whenever train () function is called, which takes three input arguments that are initial Network generated by newff (), input vector, and output vector

E. EEGLAB ANALYSIS

For processing EEG and other electrophysiological data the signal processing toolbox called EEGLAB is used. The

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first step involves loading dataset by selecting import data option available from File Menu and output is shown in Fig 4(a) which displays the information on number of channels, frames per epoch, sampling rate etc... Next the data is represented with channel data (scroll) in the form of waves where x label represents time and y label represents No of channels are represented in Fig 4(b). The visualization of channel location in 2-D and 3-D form is represented in Fig 4(c) and (d) with help of edit channel location menu. The individual data channel spectrum of activity is represented in each shaded trace. The scalp allocation of power at 6 Hz is appeared in the furthest left scalp map where the data is focused on frontal midline and the scalp allocation of power at 10 Hz and 22 Hz appeared in other scalp map which is shown in Fig 4(e). With the help of channel properties option the selected channel activity spectrum and the location of scalp can be represented which is shown in Fig 4(f) for channel 1 and same can be done for any number of channels [19].

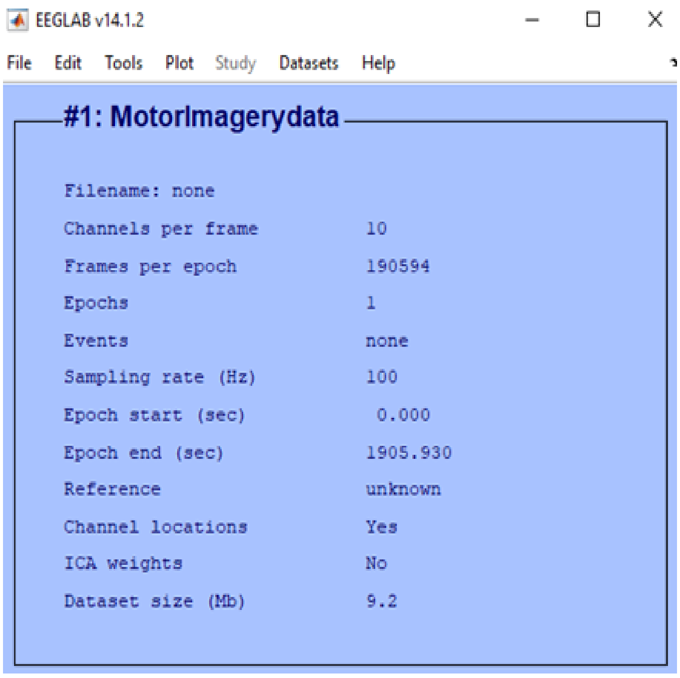


Fig 4 (a): EEGLAB window after loading dataset

Fig 4.2(b): Channel Data (scroll)

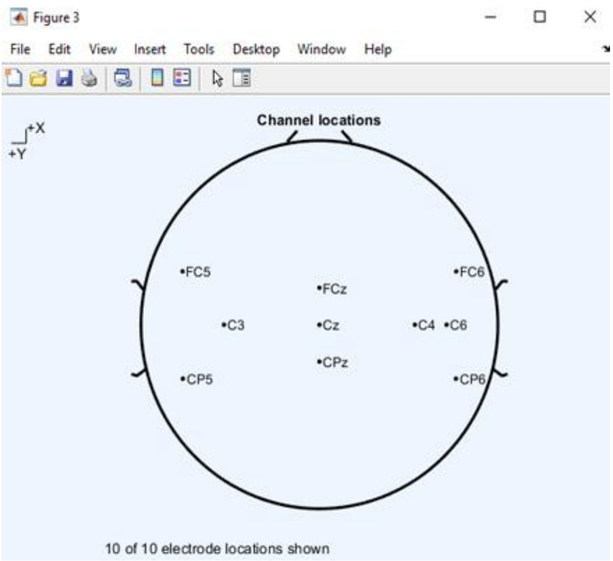


Fig 4 (c): Channel Location in 2-D form

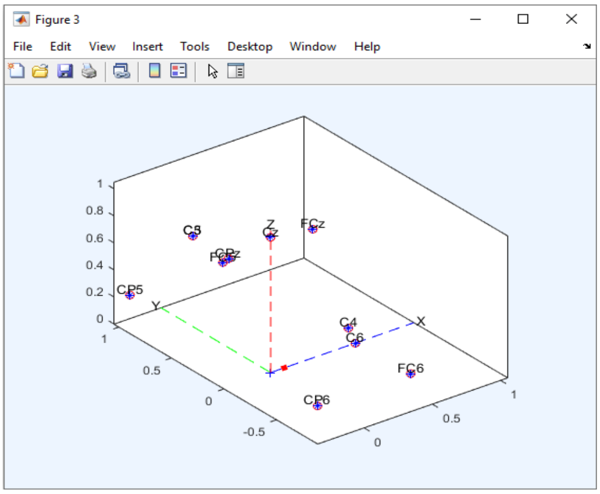
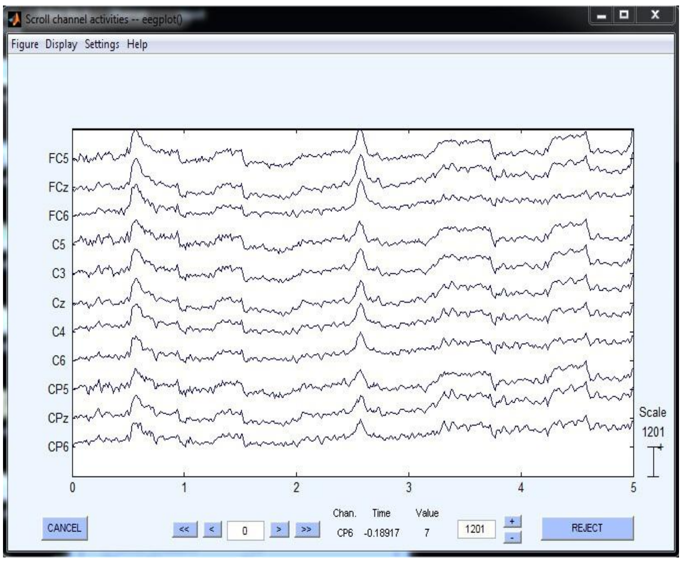


Fig 4 (d): Channel Location in 3-D form



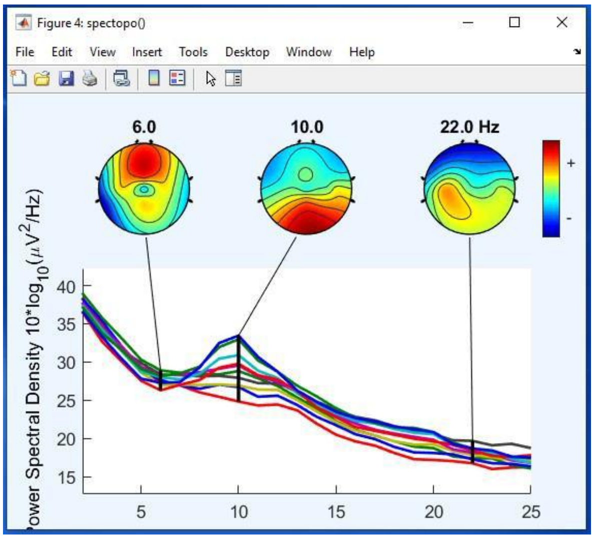


Fig 4(e): Channel spectra and Maps

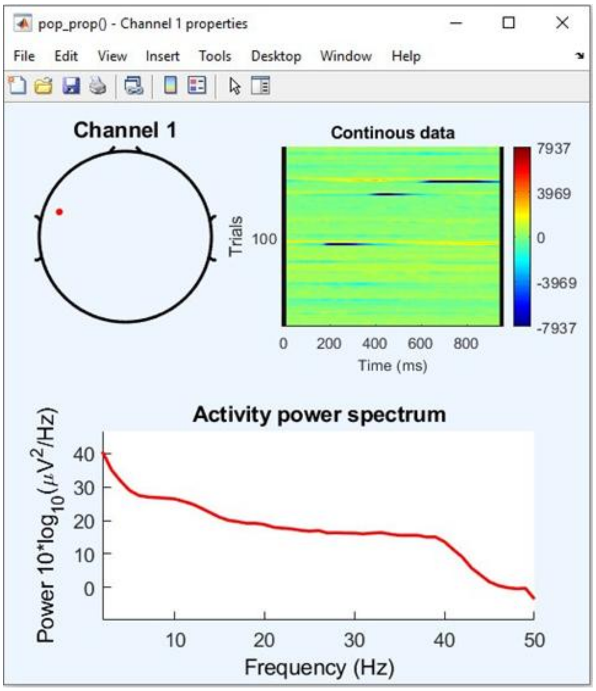


Fig 4 (f): Channel Properties of Channel 1

IV. RESULTS

The results of different methodologies of various algorithms applied to the raw EEG data are presented in this section for four subjects (a, b, f, g). The input signal graph for the subject a is represented in Fig 5. The message box generated after performing SVM classification for the type of movements of subject a is represented in Fig 6. The Fig 7 represents message box generated for the type of movements after performing BPNN classification for subject a. The input signal graph for the subject b is represented in Fig 8. The message box generated for the type of movements after performing SVM classification for subject b is represented in Fig 9. The Fig 10 represents message box generated for the type of movements after performing BPNN classification for subject b. The subject f input signal graph is represented in Fig 11. After performing SVM classification for subject f, it generates a message box for the type of movements which is represented in Fig 12. The Fig 13 represents message box generated for the type of movements after performing BPNN classification for subject f. The input signal graph of subject g is represented in Fig 14. After performing SVM classification for subject g, it generates a message box for the type of movements which is represented in Fig 15. After performing BPNN classification for subject g, it generates a message box for the type of movements which is represented in fig 16.

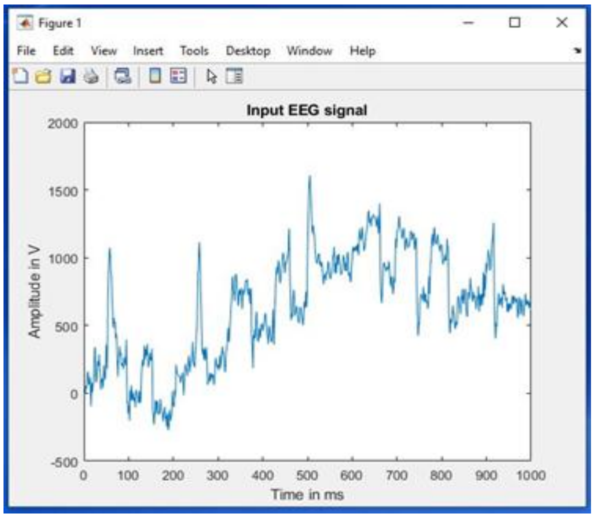


Fig 5: Input EEG Signal of subject a

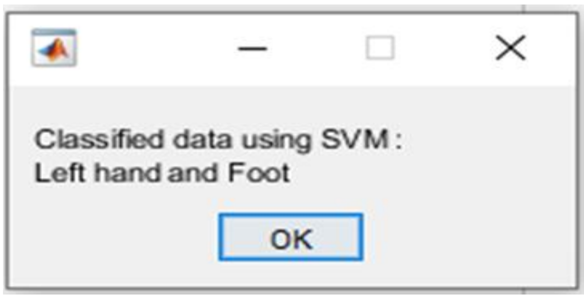


Fig 6: Message box generated for subject a after applying SVM Classifier

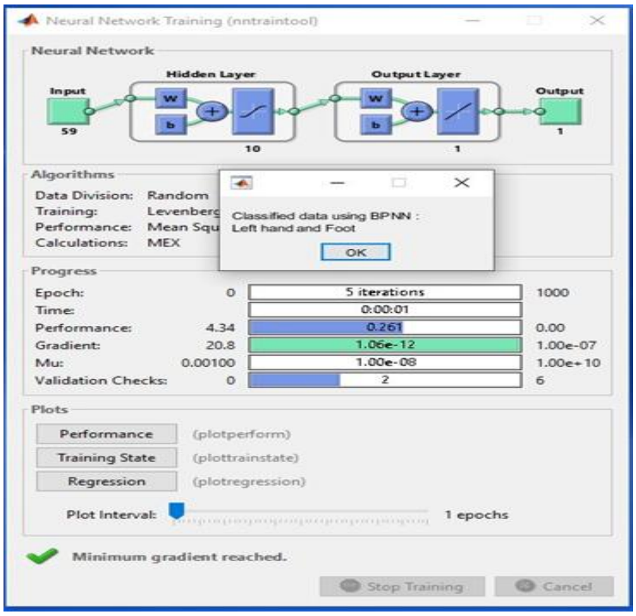


Fig 7: Message box generated for subject a along with neural network toolbox after applying BPNN Classifier

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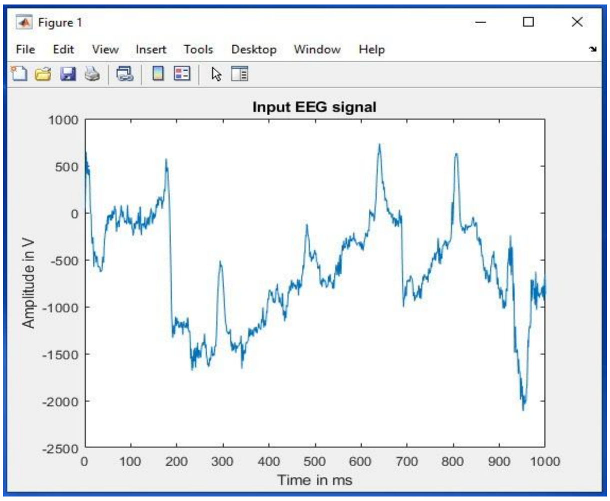

Fig 8: Input EEG Signal of subject b

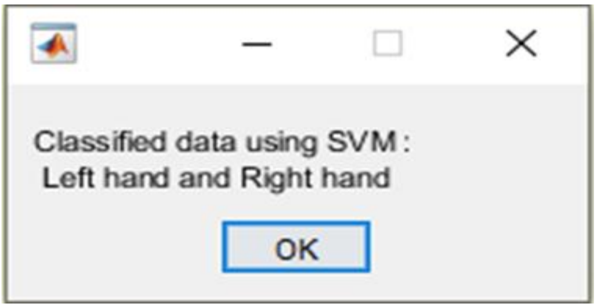

Fig 9: Message box generated for subject b after applying SVM Classifier

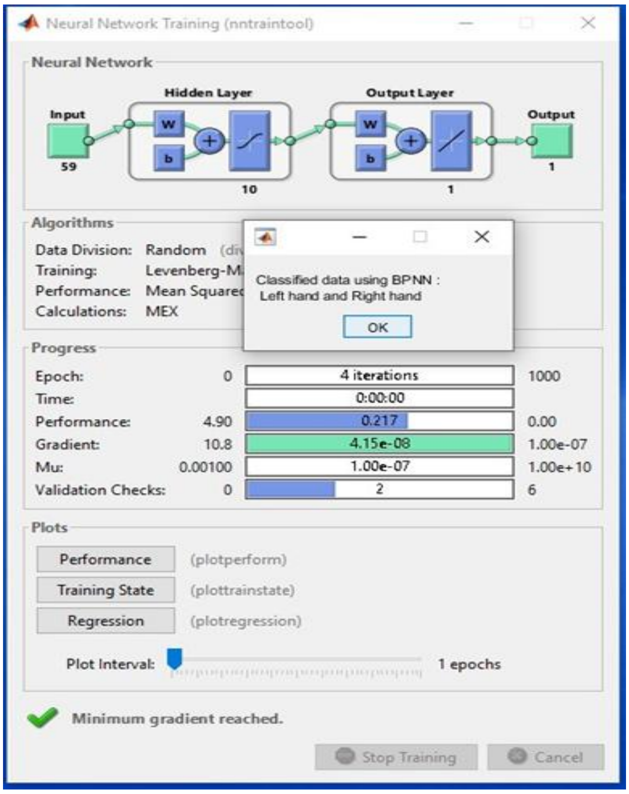

Fig 10: Message box generated for subject b along with neural network toolbox after applying BPNN Classifier

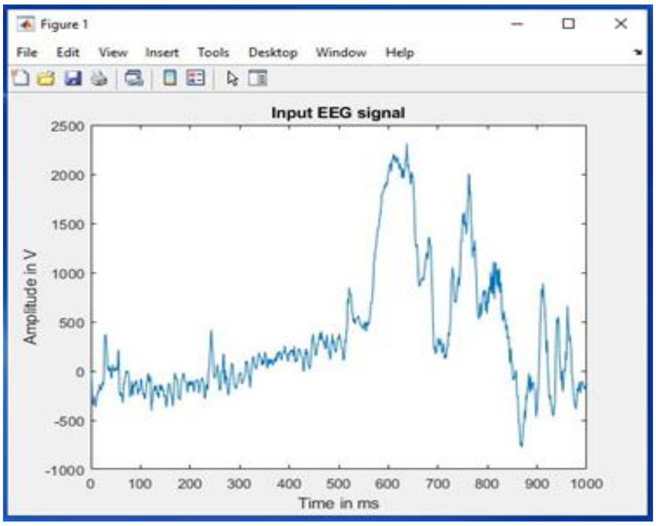

Fig 11: Input EEG Signal of subject f

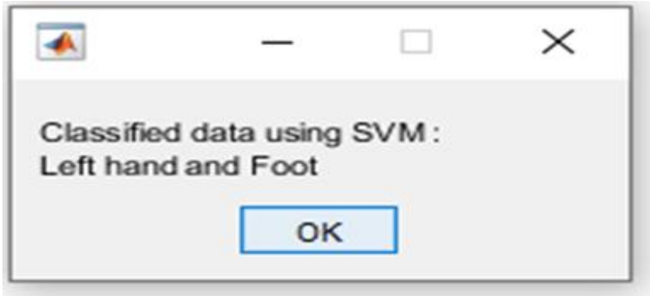

Fig 12: Message box generated for subject f after applying SVM Classifier

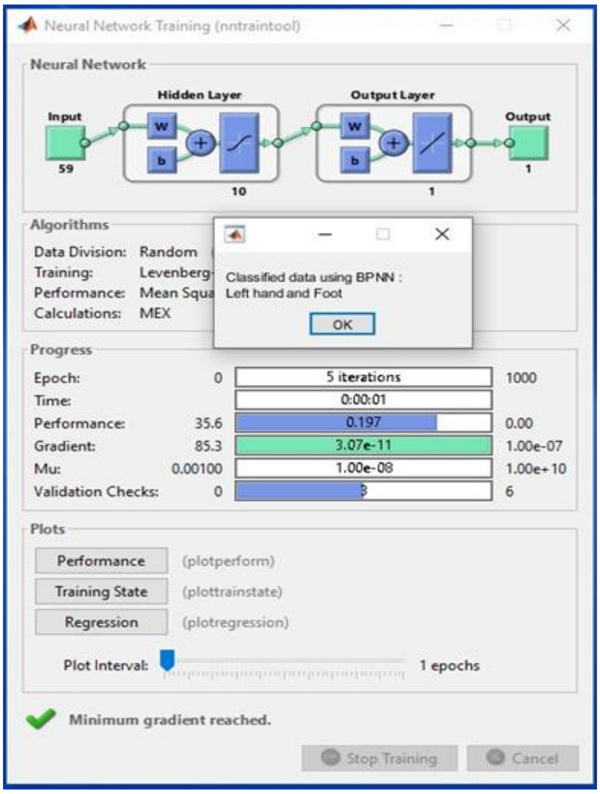

Fig 13: Message box generated for subject f along with neural network toolbox after applying BPNN Classifier

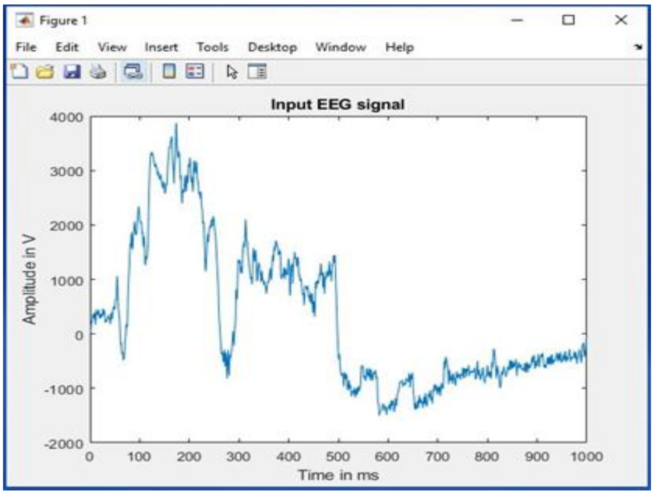

Fig 14: Input EEG Signal of subject g

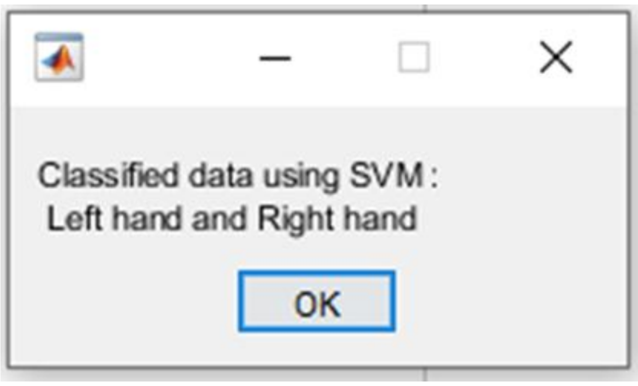

Fig 15: Message box generated for subject g after applying SVM Classifier

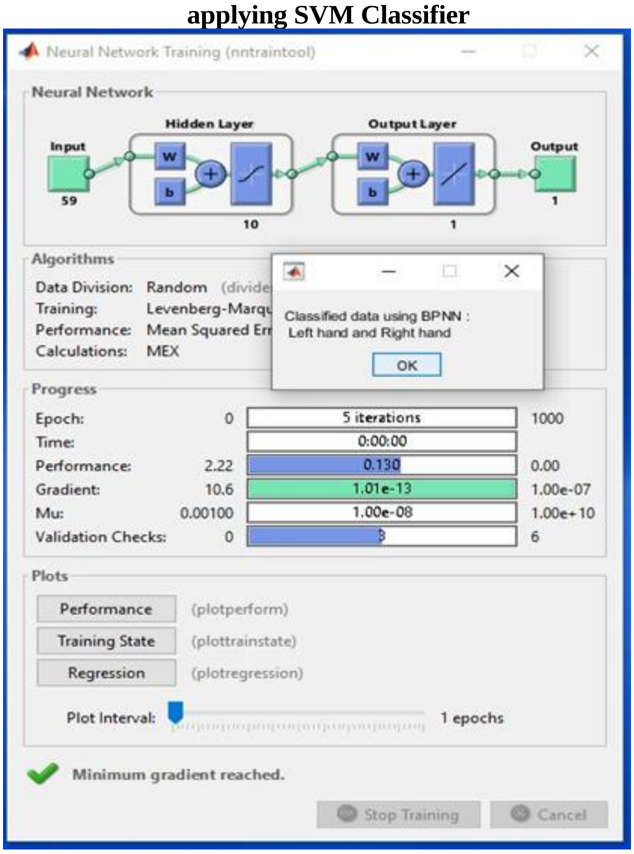

Fig 16: Message box generated for subject g along with neural network toolbox after applying BPNN Classifier

V. CONCLUSION AND FUTURE WORK

Research work focused on EEG signals classification for left hand, right hand or foot movements, in view of a particular set of features. Results were obtained for classifying the type of movements (left hand, right hand or foot) using classifiers namely SVM, BPNN for four subjects (a, b, f, g). EEG data acquired from the BCI Competition IV, Dataset1 for left hand, right hand, or foot movements were analyzed using EEGLAB, an open source toolbox running under MATLAB. The analysis results represent visualization of channel data (scroll), channel location and spectrum of activity. In future, intend to gain EEG signals, perform the classification technique and employ them in designing a thought controlling wheelchair.

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