

# A Performance Study of 14-Channel and 5-Channel EEG Systems for Real-Time Control of Unmanned Aerial Vehicles (UAVs)\*

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**Abstract**—Brain-computer interface (BCI), an actively researched multi-disciplinary domain, has completely transformed the approach to robotic control problems. Researchers have focused on developing algorithms that optimize robotic movement to achieve desired trajectories, and it's a general understanding that route optimization problems are difficult to solve mathematically. Humans, on the other hand, tend to optimize their day-to-day activities intuitively. In order to achieve the desired results, the brain exploits a multi-level filtering approach, where the macro features are weighted in the first layer and the microfeatures in further layers. This optimization inside the brain interestingly, leave distinct traces in electroencephalography (EEG) plots. Based on the observations, we propose to use artificial neural networks to classify the EEG data, which intuitively should give a high classification rate, because the human brain also exploits a network of neurons to classify auditory (time-series) and visual (spatial) data. In this paper, we discuss the performances of 14-channel and 5-channel EEG headsets for robotic applications. Data is acquired from 20 subjects corresponding to four different tasks. Using neural nets, we have been successfully able to classify the EEG input into four different classes. We get an overall classification accuracy of 98.8% for 14-channel and 84.5% 5-channel system. As a real-time demonstration of the interface, the predicted class number is sent to a multi-rotor via a wireless link as an appropriate velocity command.

## I. INTRODUCTION

The functioning of the brain has always intrigued researchers and scientists across the world. In the beginning, focal areas of research involved the neurological study of the brain i.e. understanding it's connectivity to the other organs and regulation of functionality of the body. However, the exact functioning of the brain was unclear until the discovery of underlying electrical activity in 1924, when Hans Berger [1] first recorded the human brain activity by means of EEG. Analyzing the traces, he was able to categorize a certain oscillatory activity, now commonly referred to as the 'alpha signals' (8-13 Hz). Interestingly, he correlated the abnormalities in the EEG traces to brain-related diseases. However, it was 53 years later, in 1977, when UCLA Prof. Jacques Vidal realized the potential of Electroencephalography. He demonstrated in an experiment [2], the control of a cursor-like graphical object on a computer screen. He coined the term 'BCI' and is considered as the inventor of brain-computer interface paradigm. Soon after Vidal's work, in 1988, Bozinovski *et al.* [3] reported a non-invasive EEG control of multiple start-stop-restart movements of a physical robot. Brain-computer interfaces, since then have been used

for augmenting, assisting and repairing human cognitive or sensory-motor functions. As opposed to neuroprosthetics, BCIs are not artificial devices implanted in the human body.

The primary reason that BCIs can be aimed at neuroprosthetic applications is the remarkable cortical plasticity of the brain, that signals from implanted prostheses post-adaptation are handled by the brain like natural sensors. In order to implement a BCI-based neuroprosthetic device, it is of utmost importance to ensure a proper classification of the EEG data. Chapin *et al.* [4] demonstrated real-time control of robotic arm using data from the motor cortex.

From the year 2000 onwards, more focus was put on developing algorithms that had improved classification accuracies on EEG data. Qin *et al.* [5] were able to achieve 80% classification rate using a combination of equivalent dipole analysis and cortical current density imaging analysis. Schalk *et al.* [6] developed a general purpose BCI research and development platform, called BCI2000. It has been used to create BCI systems for a variety of brain signals and processing methods. Leuthardt *et al.* [7] demonstrated a novel concept of using the electrocorticographic (ECoG) activity recorded from the surface of the brain. With a training period of 3-24 min, patients were able to master closed-loop control with accuracies in the range of 74-100%. Kamousi *et al.* [8] developed an off-center approach to classification of motor imagery tasks using two-equivalent-dipoles and source analysis. They were able to achieve a classification rate of 80%. Coyle *et al.* [9] describe the construction, principles of operation and implementation of a fNIRS-BCI (functional near-infrared spectroscopy) that exploits motor imagery for control. It's a binary control algorithm with ON/OFF states.

Qin *et al.* [10] later in 2005 suggested a wavelet-based time-frequency analysis approach for categorizing motor imagery tasks. They tested their algorithm on nine subjects and got an overall accuracy of 78%. Lotte *et al.* [11] reviewed and presented briefly some of the commonly used classification algorithms used to design BCIs. They provide guidelines to choose suitable algorithm(s) for a suitable BCI. Cincotti *et al.* [12] predicted that a better classification technique could be achieved by providing the BCI with unmixed activity signals of small cortical regions, which is usually the case in motor-related tasks. They were, however, able to achieve a classification rate of 80%. Later in the same year, Cincotti *et al.* [13] reported a pilot study on BCI as an assistive technology for the differentially abled persons.

An interesting application of BCI is the control of multi-rotor aircrafts because training pilots for RC control is a tedious task. BCIs have the potential to replace RC control

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\* This project was funded by the Defense Development Research Organization (DRDO), Govt. of India

with thought-based control. In the same line LaFleur *et al.* [14] demonstrated a BCI capable of real-time quad-rotor control in 3D space. They were able to achieve 90.5% accuracy in individual subjects at a straight line speed of  $0.69 \text{ ms}^{-1}$ . Kim *et al.* [15] proposed a wearable hybrid interface for influencing the control of quadrotors in 3D space. Their noninvasive model, however, took into consideration eye movements also. Vokorokos *et al.* [16] introduced techniques for noninvasive EEG data collection from a commercially available EPOC headset, manufactured by Emotiv.

After the background work, we realized that there is a lot of scope of improvement in the classification rates and the interface design. In this paper, we not only propose an alternate method to classify pre-processed EEG data using artificial neural networks, but we also implement the classification in a real-time demonstration on multi-rotors. The BCI problem statement doesn't just end with classification; it has to be integrated to a hardware system, only then can the true potential of BCI could be realized. The contributions of this paper are in the same line of thought :

- An EEG classification technique that results in 98% classification accuracy.
- A user-friendly interface which could be integrated with robots of different nature.

## II. METHODOLOGY

A brain computer interface mainly consists of 6 stages : data acquisition, pre-processing, channel selection, feature extraction and reduction, classification and control interface with the external world, as shown in Fig. 1.

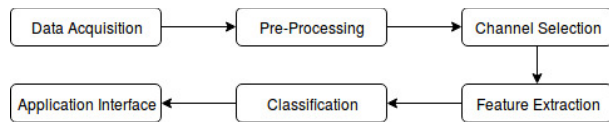


Fig. 1: A General BCI System

### A. Brain Waves and Electroencephalography (EEG)

The electroencephalogram (EEG) is a recording of the electrical activity of the brain from the scalp. The recorded electrical activity of the human brain is very small, usually measured in  $\mu\text{V}$ . A human EEG signal fundamentally comprises of a number of frequency signals classified as:

- **Delta** - Delta band a frequency of 3 Hz or below. These waves are inherently slow but have higher amplitudes. It may occur focally with subcortical lesions and in general distribution with diffuse lesions, metabolic encephalopathy hydrocephalus or deep midline lesions.
- **Theta** - Theta band has a frequency of 3.5 to 7.5 Hz. It is categorized as "slow" activity.
- **Alpha** - This region is localized between 7.5 and 13 Hz and is usually best seen in the posterior regions of the head.
- **Beta** - Beta activity is "fast" activity. It has a frequency of 14 Hz and greater.

- **Gamma** - Gamma signals usually have a frequency range between 25 and 100 Hz, though 40 Hz is typical.

### B. Experimental Subjects

EEG data was collected from 20 healthy subjects for performing four different motor imagery tasks. The subjects belonged to the age group of 22-28 years, excluding two who were above 50. There were 14 male subjects and 9 female subjects in total. Each subject provided a written consent of their willingness to participate in this BCI experiment, verified by the Institute Human Ethics Committee (IHEC) of Indian Institute of Science. Only 3 subjects were previously involved in a BCI related activity, while the others had not been exposed to this field.

### C. Acquisition Protocol

We have designed our own protocol for data acquisition which was followed for all the subjects. Four motor imagery tasks with rest breaks in between were designed so the motor imagery task is reinforced and signals retain sufficient useful information after a tedious acquisition procedure. The acquisition protocol is as shown in Fig. 2

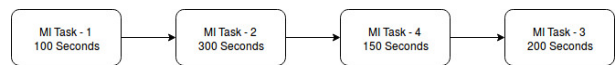


Fig. 2: Acquisition Protocol

Motor Imagery (MI) Task 1 is imagining left hand movement, task 2 is imagining right hand movement, task 3 is imagining left hand movement with finger and elbow movement and finally task 4 is right hand movements with fingers and elbow. The EEG data corresponding to the 4 different motor imagery tasks is depicted in Fig. 3. It becomes increasingly clear from the plot that the variations in the EEG data are prominent and could be extracted provided the algorithm is accurate.

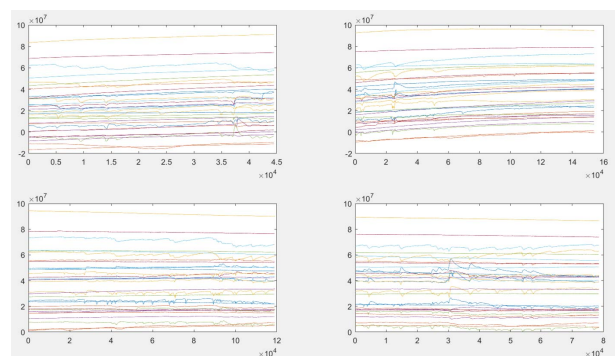


Fig. 3: Amplitude vs. Time Plots of the 4 MI Tasks

We use finger and elbow movements to increase the activations in the sensory-motor cortex as seen in literature survey. The time durations are kept random so the brain does not get used to the tasks repetitive nature which usually results in decreased amplitude of the activation signals as seen by taking real time Fast Fourier Transform (FFT) of the acquired signals, as shown in Fig. 4

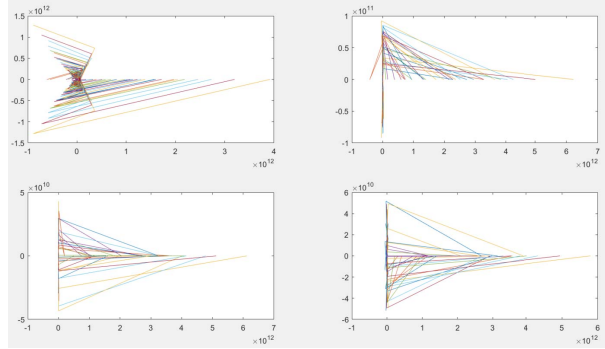
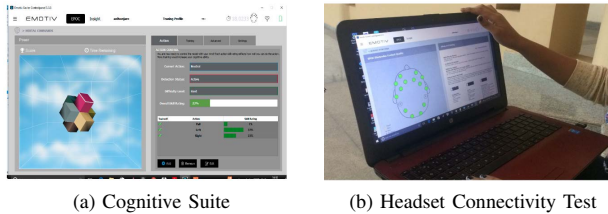


Fig. 4: Amplitude vs. Freq. (FFT) Plots of the 4 MI Tasks



(a) Cognitive Suite (b) Headset Connectivity Test

Fig. 5: Training and Connectivity Testing

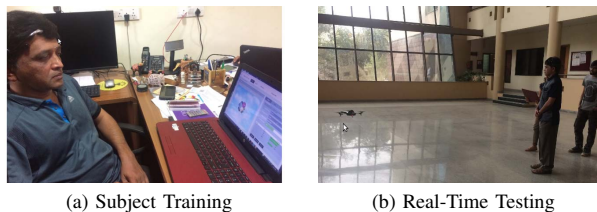
#### D. Subject Training

For an accurate BCI system design, it is very important that the subjects concentrate on a particular task, which would otherwise have a negative impact on the accuracy on the system. Focused thoughts could result in a more localized stream of information in the EEG data.

The subjects in this experiment were trained with the assistance of a cognitive suite shipped along with the Emotiv SDK called *Xavier Control Panel* (Fig. 5a). The connectivity of the headset is also constantly monitored as shown in Fig. 5b. The subject is trained to focus on box movements (which could be up-down-left-right-push-pull etc.), so that he/she can execute the MI tasks with more efficiency. An real-time example of the training and testing procedures is shown in Fig. 6.

#### E. Data Acquisition

In this study, we have used a commercially available non-invasive BCI headsets from Emotiv, called *EPOC+* (14-channel) and *INSIGHT* (5-channel) as shown in Fig. 7. The technical specifications of both the headsets have been mentioned in Table 1.



(a) Subject Training (b) Real-Time Testing

Fig. 6: System Training and Testing Demonstrations



(a) EPOC+ (14-channel) (b) INSIGHT (5-channel)

Fig. 7: Headsets used for experimentation

TABLE I: Headset Specifications

Specification	EPOC+	INSIGHT
Channels	14	5
References	2	2
Sampling Method	Sequential	Sequential
Sampling Rate	128 SPS	128 SPS
Voltage Resolution	0.51 $\mu$ V	0.51 $\mu$ V
Bandwidth	0.21 - 43 Hz	1 - 43 Hz
Connectivity	Bluetooth@Smart	Bluetooth 4.0
Battery	640mAh LiPo	480mAh LiPo

Both the headsets have 2 reference channels each, in the CMS/DR1 noise cancellation configuration. The reference electrodes for EPOC+ are located at P3/P4 locations. EPOC+ has electrodes placed at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 and INSIGHT has electrodes at AF3, AF4, T7, T8, Pz locations as per the International 10-20 system. EPOC+ also has a built in digital 5th order Sinc filter, which allows some basic filtering before the pre-processing takes place. Raw EEG data is acquired from both the headsets using an open-source library called 'emokit', which directly dumps the  $\mu$ V readings from every electrode onto the terminal.

#### F. Pre-Processing and Feature Extraction

The acquisition device is not capable of distinguishing between artifacts and useful data. The recorded activity which is not of cerebral origin is termed artifact and can be divided into physiologic (generated from the subject from sources other than the brain) and extra-physiologic artifacts arise from outside the body (equipment including the electrodes and the environment). Thus preprocessing becomes a necessary criterion before any further computations can be done.

For starters, a high order zero-phase shift band-pass filter is applied with lower and upper cut-off frequencies of 1 Hz and 40 Hz respectively. Eye blinks and other muscle-related artifacts are also filtered. The cornerstone to generate control signals that will facilitate the classification of different mental tasks is to extract the appropriate features from the obtained EEG data. A number of different methods were used to perform feature extraction for various signals such as Discrete Wavelet Transform, Power Spectral Analysis, Time-Domain analysis etc. Our feature vector is dominated by wavelet features as they provide more detailed temporal information about each band of frequencies in the EEG signals.

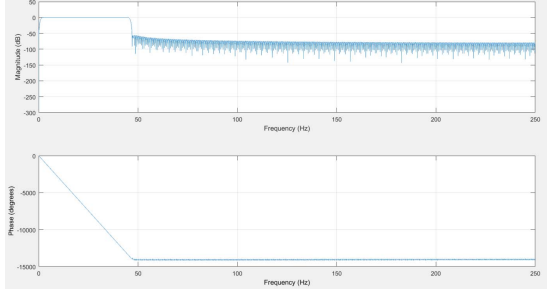


Fig. 8: Zero Phase Shift Band Pass Filter (1-40 Hz)

1) *Wavelet Transform Coefficients*: In this study, we perform a four-level wavelet decomposition with each level having *approximation* (low frequency components) and *detail* (high frequency content) coefficients. The wavelet transform coefficients have been defined by Yohanes *et al.* [17]. It is assumed that the scaling and wavelet functions are given as Haar and Daubechies respectively i.e the basis are known, so the discrete signal  $f[n]$  could be approximated in  $l^2(Z)^1$  as :

$$f[n] = \frac{1}{\sqrt{M}} \sum_k W_\phi[j_0, k] \phi_{j_0, k}[n] + \frac{1}{\sqrt{M}} \sum_{j=j_0}^{\infty} \sum_k W_\psi[j, k] \psi_{j, k}[n] \quad (1)$$

Here,  $f[n]$ ,  $\phi_{j_0, k}[n]$  and  $\psi_{j, k}[n]$  are discrete functions defined in  $[0, M-1]$ . As the sets are orthogonal to each other, we calculate the inner product to obtain the wavelet coefficients :

$$W_\phi[j_0, k] = \frac{1}{\sqrt{M}} \sum_n f[n] \phi_{j_0, k}[n] \quad (2)$$

$$W_\psi[j, k] = \frac{1}{\sqrt{M}} \sum_n f[n] \psi_{j, k}[n] \quad j \geq j_0 \quad (3)$$

where,  $l^2(Z)^1$  is defined as :

$$l^2(Z)^1 = f[n] \sum_{-\infty}^{\infty} |f[n]|^2 < \infty \quad (4)$$

TABLE II: DWT Signal Decomposition Spectrum

Distribution	EEG Band	Bandwidth
D1	Gamma	30-40 Hz
D2	Beta	20-30 Hz
D3	Alpha	8-20 Hz
D4	Theta	5-8 Hz
A4	Delta	0-5 Hz

The DWT coefficients represent the degree of correlation between the analyzed signal and the wavelet function at different instances of time. Therefore, DWT coefficients carry useful temporal information about the transient activity of the analyzed signal, as has been demonstrated by Verma *et al.* [19], where they have used a combination of DWT coefficients and LSSVM (least square support vector machines) to classify EEG data. In contrast to previous methods, our proposed feature fully utilizes the simultaneous

time-frequency analysis of DWT by preserving the temporal information in the DWT coefficients. It was observed that the choice of wavelet function in DWT greatly affects the resulting DWT coefficients. We make use of Daubechies db4 function for wavelet decomposition. The coefficients are defined as follows :

$$C_{x(t)}(l, n) = \int_{-\infty}^{\infty} x(t) \psi_{l, n}(t) dt \quad (5)$$

where  $\psi_{l, n}$  is the wavelet function defined as :

$$\psi_{l, n} = 2^{-(l+1)} \psi(2^{-(l+1)}(t - 2^{-l}n)) \quad (6)$$

After performing DWT, the sub-band energy and entropy are calculated in the following way:

$$ENG_i = \sum_n |C_{x(t)}(l, n)|^2 \quad (7)$$

$$ENT_i = \sum_n |C_{x(t)}(l, n)|^2 \log [|C_{x(t)}(l, n)|^2] \quad (8)$$

The coefficients corresponding to level 4 could be calculated by putting  $l = 4$ . Then the feature vector,  $\vec{F}$  could be defined as:

$$\vec{F} = \{ENG_i, ENT_i\} \quad (9)$$

2) *Differential Entropy*: Differential entropy is a measure of average surprisal of a random variable, to continuous probability distributions which has been defined for EEG based emotion classification by Duan *et al.* [18] as:

$$h(X) = - \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \log \left( \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \right) dx \quad (10)$$

which reduces to :

$$h(X) = \frac{1}{2} \log(2\pi e \sigma^2) \quad (11)$$

where the time series variable X obeys the Gaussian distribution  $N(\mu, \sigma^2)$ . For a fixed length of EEG data, DE is equivalent to the logarithm of average energy in a certain frequency band. The resultant feature vectors for the *INSIGHT* and *EPOC+* have sizes  $80 \times 60$  and  $92 \times 168$  respectively.

### G. Neural Network Model and Testing

The neural network is a relatively simple model, in terms of architecture. It consists of 1 hidden layer (consisting of 25 neurons) and one fully connected layer (FCN) with 4 neurons for 4 classes. The architecture is depicted in Fig. 9. We used a total of 20 samples (all different subjects) for testing the model and the testing accuracy is as high as 88% as seen the confusion matrix plot in Fig. 11, 13 and 14.

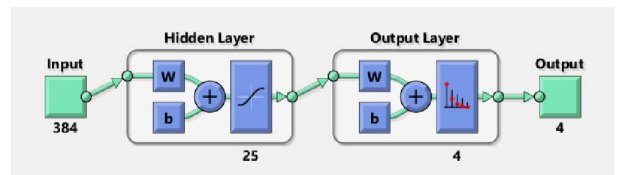


Fig. 9: Neural Network with 25 neurons

While tweaking the neural architecture and the number of neurons, we tested several architectures with multiple layers. We noted the computation time of every architecture in Python using the 'time' library. We tried single hidden layer architecture with 100, 200, 300, 400, 500...and so on neurons, and we observed that the architecture with 500 neurons was an optimal combination of complexity, speed and accuracy. The problem with multiple layered structures was the speed, which we did not want to compromise with. We finalized on the architecture with 500 neurons in the hidden layer with softmax activation function(Fig. 10), which gave remarkable results. As seen in the confusion plots, we have used 15 datasets (15 different subjects) for training, 2 for validation and 3 for testing.

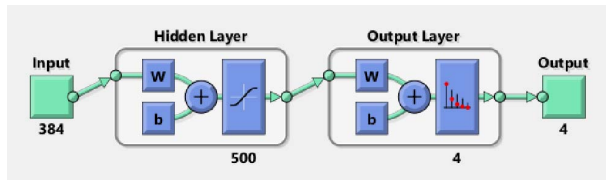


Fig. 10: Neural Network with 500 neurons

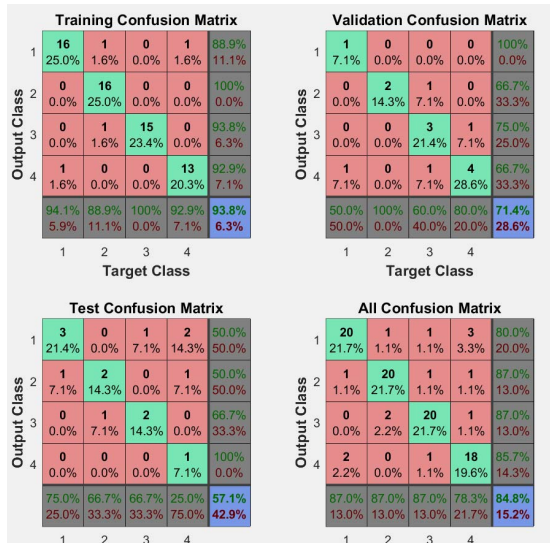


Fig. 11: Confusion Matrix for INSIGHT (5-channel)

### III. EXPERIMENTAL SETUP

The test subject is asked to wear the headset and perform the same mental tasks as were performed previously during data acquisition, for a duration of 2-3 seconds. The time series data so obtained is stored in an array and pre-processed using the techniques mentioned above. The information is then fed to the neural network for classification, which in our case is an integer. The algorithm sends only high level translation and angular velocity commands to the quadrotor platform, in the form of these predicted integers.

Two off-the-shelf quadcopters, AR Drone 2.0 (Fig. 12b) and Parrot Bebop 2 (Fig. 12a), compatible with Python



(a) Bebop 2 (b) AR Drone 2.0

Fig. 12: Testing Platforms

programming language, were used as hardware platforms for algorithm development and testing. WiFi is used for communicating between the systems. Maneuvering the Parrot is handled by an open-source Python library called *python-ardrone*, while we use *bebopautonomy* for the Bebop.

### IV. RESULTS

The respective performance matrices have been tabulated in Table III for 5-channel and 14-channel headsets, for 23 neurons in the hidden layer. The maximum classification accuracy we achieved was 98% when there were 500 neurons in the hidden layer for 14-channel headset data. A video of the same could be watched at the following link : <https://www.youtube.com/watch?v=zt1AdiktwXs>

TABLE III: Performance Evaluation

Metric	EPOC+	INSIGHT
Feature Vector Size	80×60	92×168
Training Samples	60	69
Validation Samples	10	9
Testing Samples	12	14
Accuracy	85.6%	98.2%

The confusion matrices for the training, validation and testing have been plotted and displayed in Fig.11, Fig. 13 and Fig. 14.

### V. CONCLUSIONS AND FUTURE RESEARCH

As demonstrated in the paper, the proposed BCI system is capable of classifying EEG data with an accuracy of 98% in real-time. With an improved neural network architecture, accuracies upto 98.2% can also be achieved, as depicted in the confusion matrix for EPOC+ in Fig. 14. Both 25-neuron and 500-neuron architectures have proven to work in real time due to the availability of high end laptops for computation. However, the biggest challenge with monitoring EEG, is artifact recognition and elimination. There are subject related artifacts (e.g. movement, sweating, ECG, eye movements) and technical artifacts (50/60 Hz artifact, device related artifacts), which have to be handled differently.

The data acquisition protocol, for this study, was carefully designed to get maximum signal to noise ratio and all external disturbances were eliminated such as noise, light and wireless radio-interferences. Sufficient breaks in between sessions were given for the subject to focus and perform



(a) Training and Test Confusion Matrices (b) Validation and All Confusion Matrices

Fig. 13: Confusion Matrix for EPOC+ with 23 neurons



(a) Training and Test Confusion Matrices (b) Validation and All Confusion Matrices

Fig. 14: Confusion Matrix for EPOC+ with 500 neurons

better at the motor imagery tasks. The concept of brain-computer interface is revolutionary in itself, provided the EEG data acquired from subjects is actually the EEG data and not some noise/garbage values. Such a classification model can be implemented to other applications as well. We are working further to make the model more robust in terms of training time and accuracy.

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