Reducing Sensors in Mental Imagery Based Cognitive Task for Brain Computer Interface

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***Abstract* – The performance of mental imagery based brain-computer-interfaces (BCI) can be enhanced by improving Electroencephalography (EEG) signal classification. It is known that the optimal sensors/electrodes for mental imagery applications are the C3, Cz and C4 that are not present in low cost EEG acquisition devices like the Emotiv EPOC+ headset. Hence in this paper a framework is proposed to classify mental imagery tasks using alternative and reduced number of sensors available in Emotiv EPOC+ headset. In this paper four features are extracted from EEG signals which are Band Power (BP), Approximate Entropy (ApEn), statistical features, and wavelet-based features. For classification, Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) are used. 100% cross validation accuracy is achieved by using BP and ApEn features and KNN Classifier with all the 14 electrodes. It is further observed that most of the information necessary for the mental imagery classification is present at the FC5, FC6, P7, P8, AF3 and AF4 electrodes. By classifying the Band Power and ApEn features from the electrodes mentioned above and using the KNN classifier, an average cross validation accuracy of 99.75% is achieved. If the same features from the FC5, FC6, AF3 and AF4 electrodes are classified using KNN, an average cross validation accuracy of 98.55% can be achieved. Hence reduced number of sensors can be used successfully for motor imagery classification. Also based on the model selected, it can be concluded that out of the four mental imagery tasks (LEFT, RIGHT, PUSH and PULL), the PULL mental imagery task is the hardest to be classified, with a classification error of 2.4%.**

Keywords— Mental Imagery, EEG, BCI, Band Power, Approximate Entropy

I. INTRODUCTION

Brain is one of the most important organs in the human body and is made up of three major parts, i.e. cerebrum, cerebellum and brain stem. Cerebrum is the largest among the three, comprising of the left and the right hemisphere which can be further divided into four lobes, which are frontal, parietal, occipital and temporal lobes. When a person is performing a task such as focusing, moving or doing mental calculations, signals travel from neuron to neuron. Although the path travelled by these signals is insulated by myelin, some of the electric signals escape [1]. Electroencephalography (EEG) is a method that detects these escaped signals by placing small metal discs known as electrodes on the scalp [2]. The 10-20 system of electrode placement on the scalp is an international standard introduced by the International EEG Federation. The positions of the EEG electrodes are selected such that all the cortex regions are covered [3]. In this system, all the electrodes are labelled by letters depending on which lobe of the brain it is located (i.e. F – Frontal, C – Central, T – Temporal, P – Parietal, O - Occipital). If an electrode lies in the midline region, it is referred by an additional label 'z'. Moreover, odd numbers and even numbers refer to the left and right hemisphere respectively.

In order to process the EEG signals, they are decomposed into different frequency bands, namely delta (δ), theta (θ), alpha (α), beta (β) and gamma (γ) bands. Among the five frequency bands, delta waves have the highest amplitude and the lowest frequency (1 – 4 Hz). This brain wave is usually observed during deep or dreamless sleep [4]. Next are the theta waves (4 – 7 Hz) which are related to inefficiency, daydreaming and a state between awake and falling asleep [5]. Alpha waves (7 – 13 Hz) are normally found in the occipital lobe of the brain and are generated when the eyes are closed or when a person is in the relaxed state [5]. Beta waves (13 – 30 Hz) are typically found in the frontal and parietal lobes; it characterizes a focused mind [6]. Gamma waves (31 – 100 Hz) are the fastest and have the lowest amplitude as compared to other brain waves. It binds diverse population of neurons together when the brain is processing simultaneous information from different portions of the brain. Therefore, an optimal level of gamma waves is related to good memory while less gamma waves result in learning disabilities. The mu band (7 – 13 Hz) has the same frequency range as the alpha band. The difference between them is that alpha wave is usually present in the occipital lobe whereas mu wave is only found in the sensorimotor cortex where the C3, Cz and C4 electrodes are positioned. Mu wave is "suppressed" or "desynchronized" whenever a person moves or has the intention to move. Hence the analyses of brain waves give insight on different activities occurring in the brain. In this work we aim to propose a framework to classify the mental imagery signals which can be used for brain computer interfaces (BCI). Normally high density EEG headsets are used for accurate classification of EEG signals however we plan to use a low cost headset with fewer electrodes/sensors to achieve the same objectives. In the current study we will use different combination of features and classifiers to come up with a framework for the classification of cognitive tasks with reduced number of electrodes/sensors.

The rest of the paper is organized as follows. In section II we will discuss about previous related work. In section III we will present the proposed method. In section IV, the results will be discussed. The paper will be concluded in section V followed by references.

II. Related Work

The aim of this study is to propose a cost effective and accurate method that is able to interpret the user's mental imagery based on the EEG signals acquired from a low cost EEG acquisition device. In the research conducted by Oikonomou et al. [6] motor imagery based mental tasks were described by the EEG signals obtained from the motor cortex using the C3 and C4 electrodes in the international 10-20 system. In this study, an online accessible dataset, the Dataset 2b from BCI Competition IV was used [7]. The EEG data were obtained from nine subjects when they were performing left hand or right hand motor imagery cognitive tasks. Power Spectral Density (PSD) and Common Spatial Pattern (CSP) features were extracted from the EEG signals. Then, Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) classifiers were used to classify the extracted features. This study showed that the PSD features and SVM classifier gave better classification results.

Gupta et al. [8] conducted a related study using the Dataset 3 (available online) from BCI Competition II [9]. The EEG signals were recorded from 3 subjects using the C3, Cz and C4 electrodes. The subjects were asked to perform left hand or right hand mental imagery tasks when the EEG signals were recorded. The CSP and Approximate Entropy (ApEn) features were extracted and the LDA classifier was used. This research found that the ApEn feature and the LDA classifier is able to achieve an accuracy of 88.43%.

The same dataset was used in the research conducted by R. Chatterjee and T. Bandyopadhyay [10]. They used different combination of features and classifiers to classify the motor imagery signals. Statistical features, wavelet-based features, PSD and Band Power features were extracted, and SVM and Multi-layered Perceptron (MLP) classifiers were used. This research concluded that the combination of wavelet-based features and MLP classifier performs the best with a classification accuracy of 85.71%.

Another study conducted by D. Steyrl et al. [11] suggested that Random Forest (RF) classifier should be considered for BCI applications. In this study, 13 subjects were asked to perform either the right hand or feet motor imagery tasks. EEG signals were recorded and then the signals from C3, Cz and C4 electrodes were used for analysis. This research showed that RF classifier performs better than LDA classifier when CSP features were extracted from the motor imagery signals, achieving classification accuracy of approximately 90%.

N. Prakaksita et al. [12] overcame the shortcoming of Emotiv EPOC device of not having electrodes at the motor region by using EEG signals acquired from the FC5 and FC6 electrodes. By extracting the PSD features and classified them using Neural Network (NN) with Particle Swarming Optimization (PSO), it was able to differentiate between the three motor imagery based mental tasks: tongue, left hand and right hand movements with an overall accuracy of 88.8%.

A similar experiment was conducted by J. Lin and C. Lo [13] in which the subjects performed the same cognitive tasks as in the previous case with some differences as explained. Firstly, instead of only using the FC5 and FC6 electrodes as in the previous case in [12]; two additional electrodes (AF3 and AF4) were used. Whereas for the feature extraction and classification the Wavelet Transform (WT) and SVM were used respectively. The method proposed in this study managed to achieve an accuracy of 85%.

In the study carried out by P. Batres-Mendoza et al [14], time-domain features were extracted from the EEG signals using Quaternion-based Signal Analysis (QSA), followed by Decision Tree (DT), SVM and K-Nearest Neighbour (KNN) classifiers to differentiate between the left and right hand mental tasks. In this study, different combination of electrodes were used and eventually it came to a conclusion that the FC5, FC6, P7 and P8 electrodes combination gave the best results with accuracy of 84.65% using the DT classifiers.

Based on the above studies, it can be concluded that a variety of feature extraction and classification techniques can be used to interpret the motor imagery based mental tasks with slightly varying results. In addition the electrode location also plays an important role in the classification process. In the current study, band power, ApEn, wavelet-based features and statistical features will be extracted from the EEG signals, followed by classification using DT, RF, KNN and SVM classifiers.

III. Methodology

In this section we will discuss the flow of the research. The EEG signal is first pre-processed using EEGLAB to remove artifacts. After that, features are extracted from the EEG signals using the MATLAB software. It is followed by the classification of the extracted features using the Weka software. The flow of the research is illustrated in Fig. 1.

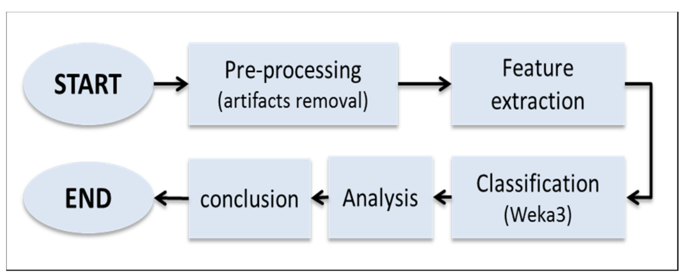

Fig. 1: Generic Flowchart of the Project

A. Description of the Dataset

The EEG data used in this research is obtained from a previous research where a BCI system was developed to control robot using motor imagery [15]. The data was recorded using the Emotiv EPOC headset for 13 subjects. Before performing any mental imagery tasks, the subjects were asked to relax and close eyes for five minutes with the EEG signals being recorded. It is then repeated with the eyes open

Next, the subjects were asked to undergo training of two actions, i.e. mental imagery of push and pull actions on the animated cube displayed on the screen, for three times. After the training, the subjects were asked to apply the mental imagery push action on the animated cube with the EEG signals being recorded for five minutes. It is then repeated by the mental imagery of the pull action. Same procedure was repeated for the mental imagery of left and right actions.

B. Pre-processing of EEG Signals

In this study, the removal of artifacts is performed manually by using an open source MATLAB toolbox known as EEGLAB. Pre-processing stage commences with the filtering of EEG signals from 1 – 30 Hz because frequencies higher than 30Hz belong to the gamma band which is not the band of interest for mental imagery applications. EEG signals obtained are usually noisy with artifacts introduced such as the muscle activity Electromyography (EMG) artifacts, eye movements Electrooculography (EOG) artifacts and interferences from electrical equipment and cables etc. [1].

C. Feature Extraction

In order to identify the neurophysiological phenomenon underlying the recorded brain activity, EEG signals need to be represented in terms of features that describe the information embedded in the signals. In the current study, BP, ApEn, statistical and wavelet-based features are extracted.

The above features are extracted using the sliding window approach as shown in Fig. 2. In this approach, a window of 5-second is used over the EEG signals and the features are computed based on the EEG data within each of the windows [16]. For instance, to extract the ApEn features from a 20 seconds EEG signal, the window starts at t = 0 – 5s. Then, the ApEn feature extraction proceeds with the window from t = 2.5 – 7.5s, if 50% overlapp between the windows is set. Hence, a total of seven ApEn values can be obtained from the EEG signal [17]. For one trial per mental imagery task, the total number of EEG segments generated from a subject with the overlapping ratio of 25%, 50% and 80% is shown in Table I.

1) Band Power:. BP can be calculated by the spectopo() function provided in EEGLAB. The spectopo() function determines the normalized magnitude of EEG signal distributed in the frequency domain, which is known as the power spectral density (PSD) [18]. The output power from the spectopo() function is log-transformed and expressed in decibels (dB) as in (1). Hence, in order to calculate the absolute power at a particular frequency, (2) is used.

$$\text{Power (dB)} = 10\log_{10}(\text{Absolute power}) \quad (1)$$

$$\text{Absolute power} = 10^{\left(\frac{\text{Power(dB)}}{10}\right)} \quad (2)$$

Absolute power of each frequency component in a frequency band can then be computed by setting the lower bound and upper bound of the band, i.e. 1 – 4 Hz (Delta), 4 – 7 Hz (Theta), 7 – 13 Hz (Alpha) and 13 – 30 (Beta). BP is calculated by taking the average absolute power of all the frequency components in the frequency band for one channel (electrode). Above steps are repeated to obtain BP features for all the frequency bands of all channels.

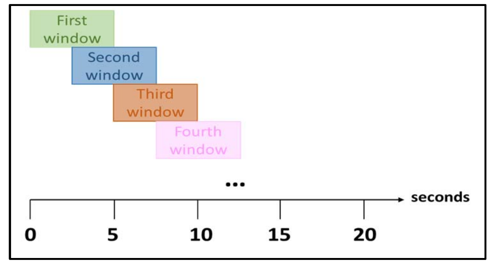

Figure 2: Illustration of the Sliding Window approach

TABLE I: TOTAL NUMBER OF EEG SEGMENTS GENERATED PER SUBJECT FOR DIFFERENT OVERLAPPING RATIOS WITH WINDOW SIZE EQUAL TO 5S AND EEG SIGNAL LENGTH EQUAL TO 20S

Overlapping Ratio	Number of EEG segments generated per class				Total number of EEG segments per subject
	LEFT	RIGHT	PUSH	PULL	
25%	5	5	5	5	20
50%	7	7	7	7	28
80%	16	16	16	16	64

2) Approximate Entropy: ApEn indicates the complexity or regularity of a signal, particularly non-stationary signals like EEG [10]. According to [19], a high ApEn value signifies a signal with random and unpredictable variation. Conversely, a low ApEn value signifies a more regular and predictable signal. The calculation of ApEn values for each channel of the EEG signal is shown below [8], [20], [21].

EEG data from a channel is represented as a sequence of n sample points $X = [x_1, x_2, \ldots, x_n]$. By applying (3), a vector y_i which is a subsequence of X is obtained and a total of n-m+1 of such vectors are found.

$$y_i = [x_i, x_{i+1}, x_{i+2}, \ldots, x_{i+(m-1)}] \quad (3)$$

where i = 1, 2, 3,…,n-m+1, m = number of samples used for prediction, typically set as 2.

Moving on, the distance between 2 such vectors, y_i and y_j is determined to be the maximum absolute difference of their corresponding scalar elements as in (4).

$$d[y_i, y_j] = \max \| y_{i+k} - y_{j+k} \| \quad (4)$$

where k = 0, 1, …, m-1.

For every vector y_i, the correlation integral, $C_i^m(r)$ is calculated using (5). Basically, it indicates the probability that any vector y_j is within r of y_i.

$$C_i^m(r) = \frac{\{\text{Number of } y_j \text{ that satisfy } d[y_i, y_j] < r\}}{n-m} \quad (5)$$

where r is small positive constant indicating tolerance of comparison. According to [8], highest accuracy is achieved when r is set as 0.5 times the standard deviation of the sample points.

Next, a function $\Phi^m(r)$ is defined by calculating the natural log of $C\_i^m(r)$ and then take the average, as shown in (6).

$$\Phi^m(r) = (n-m+1)^{-1} \sum_{i=1}^{n-m+1} \ln C_i^m(r) \quad (6)$$

Repeat steps 1 - 4 by replacing m = m+1. Finally ApEn is computed using (7) as the sample point n is always finite

$$\text{ApEn}(m, r, n) = \Phi^m(r) - \Phi^{m+1}(r) \quad (7)$$

3) Statistical Features: Similar to the extraction of ApEn features, EEG signal from a channel is represented as a sequence of N sample points X(n) = [x_1, x_2, …, x_N]. By applying (8) to (13), six different statistical features are computed from X(n) [10], [22].

Mean:

$$\mu_X = \frac{1}{N}\sum_{n=1}^{N} X(n) \quad (8)$$

Standard deviation:

$$\sigma_X = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(X(n) - \mu_X)^2} \quad (9)$$

Mean of absolute values of first difference:

$$\delta_X = \frac{1}{N-1}\sum_{n=1}^{N-1} |X(n+1) - X(n)| \quad (10)$$

Mean of absolute values of first difference of normalized signal:

$$\overline{\delta_X} = \frac{1}{N-1}\sum_{n=1}^{N-1} |\overline{X}(n+1) - \overline{X}(n)| \quad (11)$$

Mean of absolute values of second difference:

$$\gamma_X = \frac{1}{N-2}\sum_{n=1}^{N-2} |X(n+2) - X(n)| \quad (3)$$

Mean of absolute values of second difference of normalized signal:

$$\overline{\gamma_X} = \frac{1}{N-2}\sum_{n=1}^{N-2} |\overline{X}(n+2) - \overline{X}(n)| \quad (4)$$

where $\overline{X}(n)$ signifies the normalized EEG signal, computed as follows:

$$\overline{X}(n) = \frac{X(n) - \mu_X}{\sigma_X} \quad (5)$$

4) Wavelet Based Features: According to Xu and Song [20], Fourier Transform is an effective way to extract features from stationary signals, but not for non-stationary signals like EEG. Here Discrete Wavelet Transform (DWT) is implemented to express signal in terms of wavelets. It can be executed by using a simple recursive filter as shown in Fig. 3, where h(n) and g(n) represent high pass and low pass filter respectively. In other words, the coefficients Di and Ai are the down sampled outputs of the high pass and low pass filters produced at each decomposition level [23]. The EEG signal acquired in this study is filtered from 1 – 30Hz during the pre-processing stage; the frequency bands obtained at each decomposition level are as shown in Table II. According to the research conducted by [23], the Daubechies wavelet with order 4 (db4) wavelet-based features are able to achieve an accuracy up to 95% if the Gaussian Naïve Bayes (GNB) classifier is used. Thus, db4 wavelet is used in this study and the features extracted are the mean, standard deviation and energy of both D1 and D2 wavelets, which correspond to the beta and alpha band respectively.

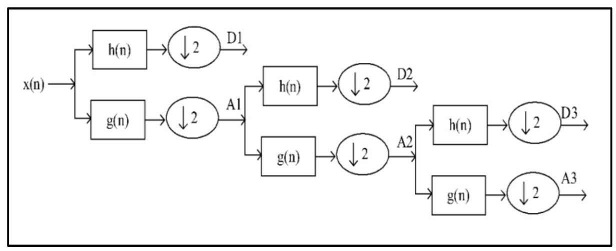

Figure 3: DWT decomposition filter bank

TABLE II: FREQUENCY BANDS AT EACH DECOMPOSITION LEVEL

Signal decomposition	Frequency bands (Hz)
D1	15 – 30
D2	7.5 – 15
D3	3.75 – 7.5
A3	1 – 3.75

D. Classification

Extracted features are used as the input to the classifier. The classification process simply means recognizing the patterns of brain activity and converting these patterns into appropriate commands for the BCI applications (such as wheelchair, or robotic arm) and then perform the desired task based on the commands received [24]. The classification methods employed in this study are DT [25][26], RF [27][28], KNN [30] and SVM [20].

E. Hyperparameters of the classifier

For machine learning, the term hyperparameter is different from the standard model parameters. The standard model parameters are learned straight away during the training of classifiers. On the other hand, hyperparameters are higher-level properties of the model that need to be decided before the training of classifiers. In fact, hyperparameters can only be decided by trying several different values and the one that gives the best results is chosen to be used in the classifier. However, after several attempts, it was found that the default hyperparameter settings in the Weka software actually performs the best for the DT, RF and KNN classifiers.

For SVM classifier, two hyperparameters need to be decided, i.e. Cost, C and gamma. The default setting of these parameters in the Weka software does not perform well with the dataset used in this study. Therefore, a method known as grid search as suggested by Chih et al. [31] is used. Grid search automatically selects the hyperparameters that performs the best for feature classification.

IV. RESULTS AND DISCUSSION

In this section we will discuss the motor imagery classification results. The data is divided into two parts: training set and testing set. The training set is used to train the classifier and the testing set is used to assess the classifier using v-fold cross validation. The v-fold cross validation splits the data set into v subsets of equivalent size. Sequentially, v – 1 subsets are used to train the classifier and the remaining subset is used for testing. Hence, the training and testing of the classifier is repeated for v iterations with a different subset used for testing every time. Finally the results obtained from all the iterations are averaged out to determine the cross validation accuracy (CVA) of the classifier [32]. In this study, 10-fold cross validation is employed as it is the standard evaluation technique commonly used in many researches.

Among all the performance metrics, classification accuracy, p_o is the most straightforward and simplest to understand. Thus, CVA is selected as the parameter to evaluate the performance of the proposed method [32].

$$p_o = \frac{\sum_{i=1}^{M} n_i}{N} \tag{15}$$

where n_i = number of samples classified correctly for each class, M = number of classes, N = total number of samples of all classes.

A. Overlapping of Sliding Window

The sliding window approach is commonly used to extract features from the EEG signal. However, there is no clear guidance regarding the optimum overlapping ratio of sliding window. Therefore, at the beginning of the feature extraction process, band power feature is extracted with different values of overlapping ratio, i.e. 25%, 50% and 80%.

From the experimental results shown in Fig. 4, it can be observed that the highest average CVA is achieved when the overlapping ratio of sliding window is set to 80% or 0.8. The observation holds true for all the four classifiers used in this study. The average CVA obtained using KNN classifier is 58.84%, 67.30% and 95.91% for the overlapping ratio of 0.25, 0.5 and 0.8 respectively. Hence, the overlapping ratio of sliding window is fixed at 0.8 for feature extraction

B. Single Feature Based Classification

The data set used in this study consists of four classes, i.e. LEFT, RIGHT, PUSH and PULL. The average CVA shown in Fig. 5 to Fig. 8 is the overall accuracy of classifying all the four classes using all (14) electrodes. Based on the literature review, the FC5, FC6, AF3, AF4, P7 and P8 electrodes play a significant role in mental imagery applications. Therefore, classification of features using different combination of the electrodes is also performed, in order to reduce the number of electrodes employed for classification.

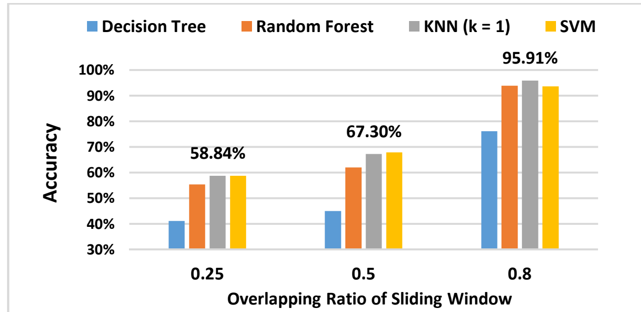

Fig. 4: Average CVA of band power feature extracted with different overlapping ratios of sliding window for all electrodes

1) Band Power Feature: Fig. 5 illustrates the average CVA of BP feature. It can be observed that the DT classifier has the worst performance, giving the lowest accuracy for all combination of electrodes. DT classifies 76.20% of the features correctly. Both RF and SVM classifiers have similar performance and they perform substantially better than the DT classifier, reaching an average CVA of 93.87% and 93.62% respectively using all electrodes available. KNN classifier performs the best with the highest average CVA achieved is 95.91% with all electrodes. Besides, by using only the features extracted from FC5, FC6, P7, P8, AF3 and AF4 electrodes, an accuracy of 92.30% can be obtained.

2) ApEn Feature: From the average CVA of ApEn features shown in Fig. 6, once again the DT classifier performs the worst, with an accuracy of 82.45% with all electrodes. The other three classifiers exhibit good results. RF classifier has slightly lower performance among the three, reaching an accuracy of 98.19% by using features extracted from all electrodes. The performance of SVM classifier is close to KNN classifier, but KNN classifier is still deemed to be the best classifier for being able to classify 99.87% of the ApEn features correctly if all electrodes are used. One thing to be noted is that by only using features from the FC5, FC6, P7, P8, AF3 and AF4 electrodes, an average CVA of 98.67% can be achieved with the KNN and SVM classifiers. Hence, it can be deduced that not all the electrodes on the Emotiv EPOC headset are needed. All information necessary for the mental imagery applications are present in the electrodes mentioned above.

3) Statistical Features: Average CVA of statistical features is presented in Fig. 7. Similar to the ApEn feature, DT classifier is still the worst performing classifier, giving an accuracy of 80% for all electrodes used. The other three classifiers deliver satisfactory results. The performance of KNN and SVM is very close having an accuracy of 95.67% and 94.35% respectively with all electrodes used. RF classifier, on the other hand, has the best performance for all combination of electrodes, except when all electrodes are used. It is able to classify 92.78% of the statistical features correctly if the FC5, FC6, P7, P8, AF3 and AF4 electrodes are used and 95.55% if all the available electrodes are used. In short, it can be inferred that the performance of statistical features is almost identical to band power features in terms of the highest achievable accuracy.

4) Wavelet-Based Feature: Lastly, Fig. 8 illustrates the average CVA of wavelet-based features. As expected, DT classifiers have mediocre performance in this case, with an average CVA of 80.16% by using features extracted from all electrodes. The KNN and SVM classifiers' performance are similar as both of them are able to classify approximately 90% of the wavelet-based features accurately. Among the four classifiers, RF classifier has best performance for attaining an average CVA of 95.07% if all electrodes are used and an accuracy of 88.82% if only the features at FC5, FC6, P7, P8, AF3 and AF4 electrodes are used.

C. ConcludingRemarks

In short, it can be deduced that the best average CVA can be achieved by using all (14) electrodes available on the Emotiv EPOC headset. Hence, an overview of average CVA using features from all the electrodes available is shown in Fig. 9. By classifying the ApEn features using KNN classifier, a CVA of 99.87% is achieved. According to [33], ApEn is an index of complexity for EEG signals. This might imply that the EEG signals of the four mental imagery tasks conducted in this study are very distinct in terms of complexity hence the ApEn feature can predicted the class accurately. In other words, the mental imagery tasks are relatively harder to be carried out as attested by the more complex and irregular EEG signals.

BP features classified by KNN and statistical features classified by RF also perform well as they are able to classify about 96% of the features precisely. The performance of wavelet-based features classified by RF is only slightly lower with a CVA of 95%. This may be due to the fact that the frequency bands decomposed using DWT are approximate in nature. The frequency range of the D2 and D1 wavelets are 7.5 – 15Hz and 15 – 30Hz respectively as shown in Table II. On the contrary, the common definition of alpha band and beta band are 7 – 13 Hz and 13 – 30Hz respectively. This may contribute to the classification error, resulting in lower CVA for wavelet-based features.

The prediction of mental imagery tasks using the features at FC5, FC6, P7, P8, AF3 and AF4 electrodes is viable. This can be proved by the average CVA of 98.67% when classifying ApEn features using KNN and SVM classifiers. There is only a 1.2% drop in accuracy as compared to using all electrodes available. Thus, it can be inferred that most of the information necessary for mental imagery applications is available at the FC5, FC6, P7, P8, AF3 and AF4 electrodes.

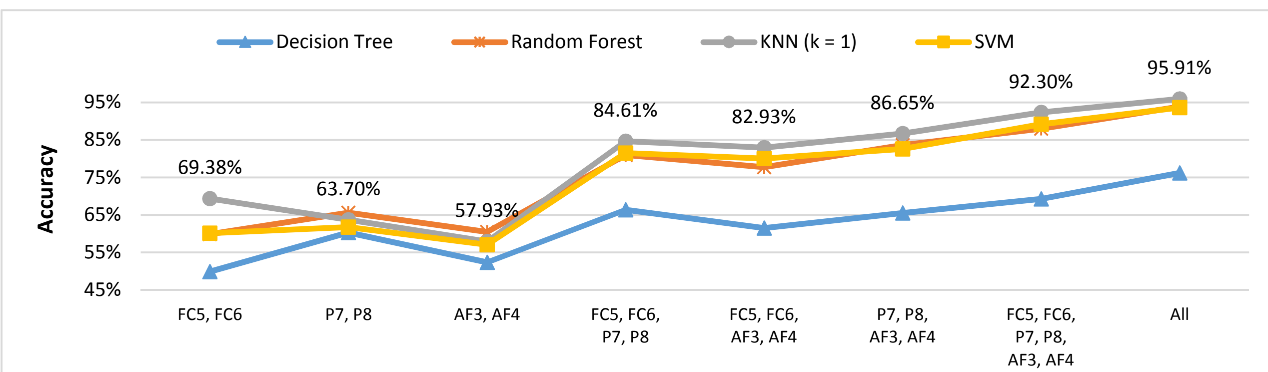

Fig. 5: Average Cross Validation Accuracy of Band Power Features

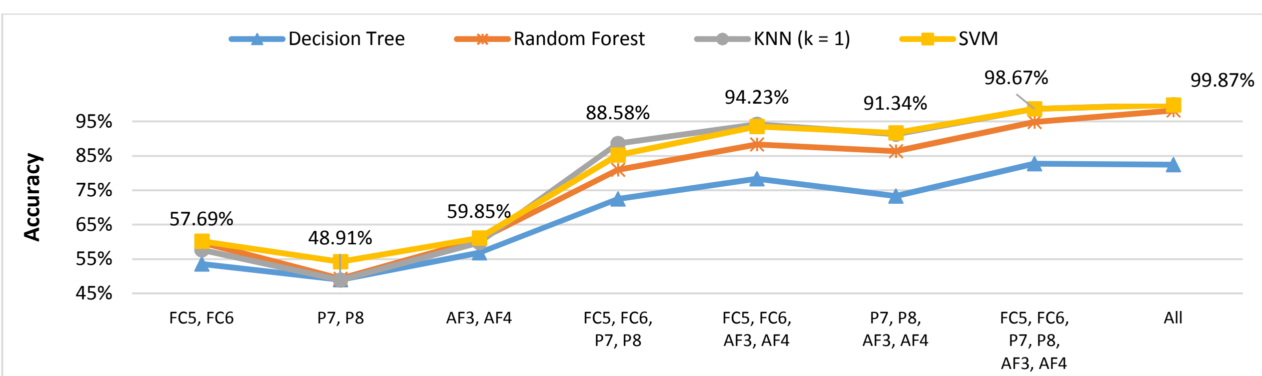

Fig. 6: Average Cross Validation Accuracy of ApEn Features

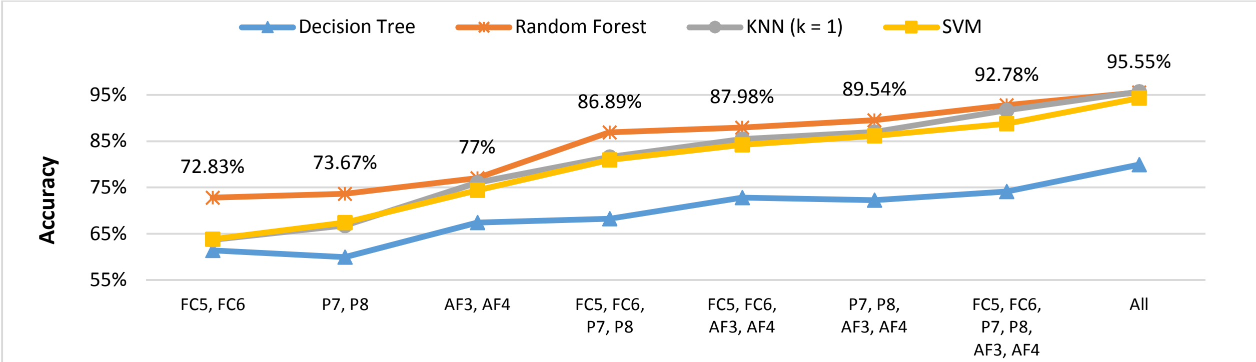

Fig. 7: Average Cross Validation Accuracy of Statistical Features

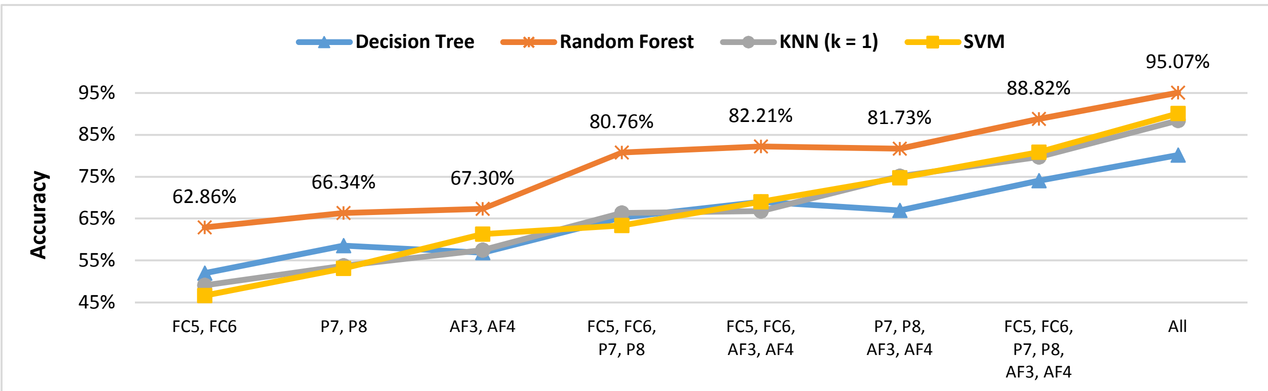

Fig. 8: Average Cross Validation Accuracy of Wavelet-based Features

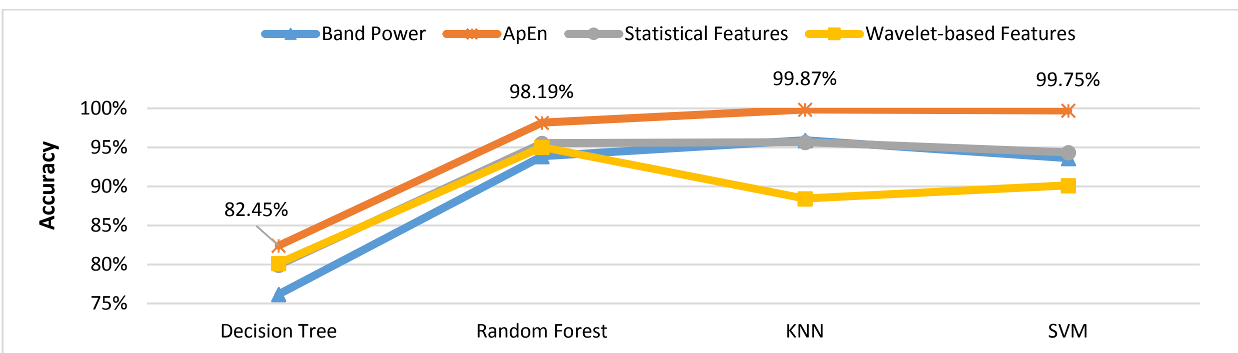

Fig. 9: Overview of average CVA using features from all electrodes available

D. Combined Feature Based Classification

In this section, the mental imagery tasks are predicted based on 11 different combinations of features. The features used in each combination along with the highest achievable average CVA is presented in Table III. It can be observed that all the mental imagery tasks can be classified accurately using Combination 1, which is the combination of band power and ApEn features from all electrodes available. This performance is achieved by using the KNN classifier. It is also worth mentioning that by combining features, an average accuracy of 98% can be achieved with features extracted from all the electrodes available. Although the improvement is marginal to a certain extent, it demonstrates that the combination of features is a possible way to further improve the classification of cognitive tasks.

It should be noted that the 100% cross validation accuracy achieved with Combination 1 opens up new possibilities to explore. Therefore, the combination of Band Power and ApEn features is further studied by classifying these features from different electrode positions.

1) Combination of BP and ApEn Features : From the average CVA of Combination 1 in Fig. 10, it is observed that the DT classifier has the poorest performance with an accuracy of 84.73% with all the electrodes used. The remaining three classifiers perform very well, achieving average CVA higher than 98% for all the electrodes. Among the three top-ranking classifiers, KNN classifier's performance is the most outstanding, reaching an average CVA of 100% if all the electrodes available are used.

Secondly, if instead of 14, only 6 electrodes critical for mental imagery applications, i.e. the FC5, FC6, P7, P8, AF3 and AF4 electrodes are used, the average CVA obtained is 99.75%, which is only a 0.25% drop from the maximum. Thirdly if only four electrodes are used, an average accuracy of 98% can be achieved. By classifying these two features from the FC5, FC6, AF3 and AF4 electrodes using KNN classifier, an average accuracy of 98.55% is obtained, which is only a 1.2% decrease as compared to the six electrodes option. This shows that a more compact and simpler model is feasible with only a marginal compromise in classification accuracy. Hence, classifying BP and ApEn features from the FC5, FC6, AF3 and AF4 electrodes using the KNN classifier is believed to be the best solution for a compact yet accurate model in this study.

However, there is argument that the average accuracy of all the subjects does not precisely reflect the actual performance of the proposed method. This is because of BCI literacy, i.e. the degree to which a person can successfully communicate through BCI varies among individuals. In this case, some subjects may not be able to perform motor imagery even if they are completely engaged in the experiment. Hence, there is a need to further validate the results achieved by the selected model in order to further evaluate this issue.

According to Müller-Putz et al. [34], a proposed method is better than random guessing if it is able to classify 40% of the features from a subject correctly for a 4 classes scenario with less than 10 trials per class. By excluding the results obtained from subjects with accuracy lower than 40%, a more meaningful parameter known as significant accuracy (SA) is obtained. In other words, SA is the mean accuracy for subjects with accuracy higher than 40%. As observed from Table IV, the proposed method is able to classify over 90% of the features correctly for each of the subjects. This indicates that the SA in this case will be the same as the average CVA, thus validates that the proposed method is actually performing well in classifying the LEFT, RIGHT, PUSH and PULL mental imagery tasks.

Hence we can say that the results obtained are within expectations as the reliability of BP and ApEn features has been proven. When these features are used individually, both of them are able to classify from different combination of electrodes precisely. Another way of explaining this phenomenon is that both the complexity and difficulty level of performing the mental imagery tasks varies as each task is distinct and hence eases the process of classification, thus contributing to a higher average CVA.

TABLE III: SUMMARY OF THE HIGHEST AVERAGE CVA ACHIEVED FOR DIFFERENT COMBINATION OF FEATURES USING ALL ELECTRODES AVAILABLE

Combination	Combination of Features				Highest Achievable Average Cross Validation Accuracy
	Band Power	ApEn	Statistical Features	Wavelet-based Features	
1	×	×			100%
2	×		×		96.63%
3	×			×	95.79%
4		×	×		99.87%
5		×		×	99.51%
6			×	×	96.27%
7	×	×	×		99.87%
8	×	×		×	99.63%
9	×		×	×	96.39%
10		×	×	×	99.51%
11	×	×	×	×	99.27%
Average					98.43%

TABLE IV: CVA ACHIEVED BY EACH SUBJECT BY CLASSIFYING THE BAND POWER AND APEN FEATURES USING KNN

Subject	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**S10**	**S11**	**S12**	**S13**
CVA (%)	90.62	100	100	100	100	98.43	100	100	100	96.87	100	98.43	100

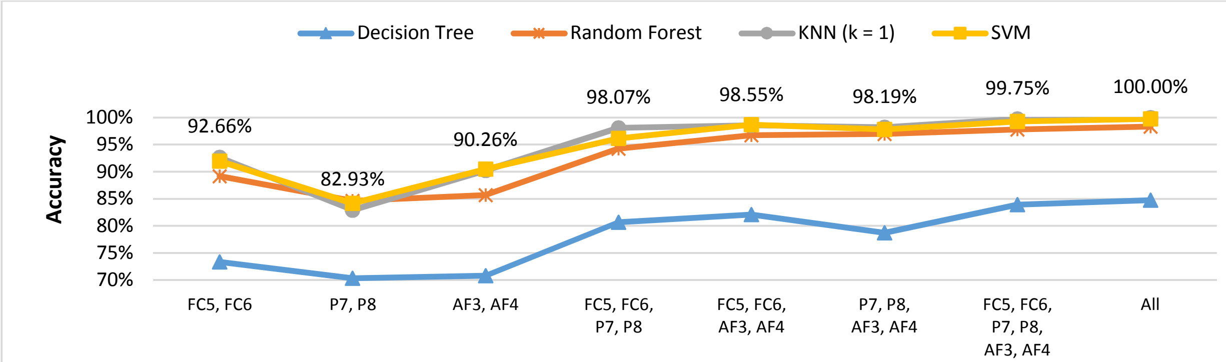

Fig. 10: Average CVA of Combination 1 (Band Power and ApEn features)

2) *Analysis of Mental Imagery Tasks*: As discussed earlier, classifying BP and ApEn features from the FC5, FC6, AF3 and AF4 electrodes using KNN classifier gives very good results in this research. Based on this selected model, a further interpretation is performed to study its effect on the classification accuracy of each mental imagery task.

The average CVA for each of the mental imagery tasks is illustrated in Fig. 11. From the figure, it is found that the RIGHT mental imagery task is classified correctly every time, indicating that it is the easiest to be classified. It is followed by the PUSH and the LEFT mental imagery tasks, with cross validation accuracy of 98.60% and 98.10% respectively. Last on the list is the PULL mental imagery task which has the lowest accuracy among the four cognitive tasks. This can be explained from the perspective of BP and ApEn features. In general, a mental imagery task that is harder to perform requires more power and thus BP is higher. In other words, BP is an indication of the difficulty level of performing a mental imagery task whereas ApEn is the index of complexity for EEG signals. Having the lowest classification accuracy among the four simply means that the PULL mental imagery task is not that distinctive in terms of complexity of EEG signals and the difficulty involved in performing the task.

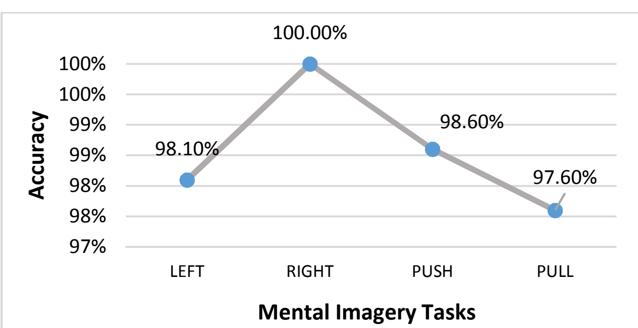

Fig. 11: KNN Average CVA of the mental imagery tasks obtained by classification of BP and ApEn features from the FC5, FC6, AF3 and AF4 electrodes

V. Conclusion

Mental imagery is the imagination of performing a task without executing it in reality. It can be applied in numerous BCI applications. The EEG signals recorded during mental imagery can be represented in terms of features which describe the information embedded within the signals. Classifiers are used to assign a class to the features that correspond to a specific mental imagery task. With the right features and classifier used, the mental imagery tasks performed can be identified accurately and thus applied in BCI.

Through this study, it can be concluded that not all the electrodes available on the Emotiv EPOC+ headset are needed. Most of the information for the mental imagery is present in the FC5, FC6, P7, P8, AF3 and AF4 electrodes. By using the ApEn features from these electrodes, an average CVA of 98.67% can be achieved for KNN or SVM classifier. A drop of 1.2% in terms of CVA is observed if eight electrodes are eliminated. In addition, it is found that the combination of features improves the average CVA. For example, the combination of BP and ApEn features for all the electrodes available using the KNN classifier, an average CVA of 100% is achieved. This combination of features is further studied by classifying features extracted from different pair of electrodes. With these features from four electrodes, the FC5, FC6, AF3 and AF4, an average CVA of 98.55% can be achieved with the KNN classifier; a drop of 1.2%, in average accuracy as compared to six electrodes alternative. It can also be concluded that the PULL mental imagery task is the hardest to classify, with a 2.4% classification error. High BP implies the difficulty involved in performing a mental imagery task and ApEn indicates the complexity of EEG signals.

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