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ANALYSIS OF MOTOR IMAGERY EEG SIGNAL CLASSIFICATION BASED ON AMPLITUDE-BASED PEAK DETECTION METHOD AND PISARENKO HARMONIC DECOMPOSITION

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ABSTRACT

This paper presents a critical study on EEG Motor Imagery feature extraction techniques using Pisarenko Harmonic Decomposition and Peak Detection algorithm. It was found that the proposed peak detection technique for feature extractions with the KNN classifier was efficient with 95.67% accuracy as compared to 84.56% achieved using feature extraction using Pisarenko's method. Further, feature extraction using the peak detection method with the random forest and gradient boosting with the accuracy of 91.58 and 92.68% is suggested over KNN as the computation time is very high when required to compute the distance of each query instance in KNN.

Keywords: *Motor Imagery, BCI, EEG, Classification, Signal processing, Brain Mapping, Classification, Machine Learning*

1. INTRODUCTION

The Brain-Computer Interface (BCI) is a technology used as an intermediate between the real world and an individual. The study of Electroencephalography (EEG) signals and extracting meaningful information from them defines the sole purpose of Brain-Computer Interfaces. The BCI is capable of converting human brain signals to a system command which can be used to control several devices like robotic arms, text-to-speech monitors, etc. Further, a BCI may be classified into two other forms. The invasive BCI (where electrodes are embedded into the scalp) and the Non-Invasive BCI (electrodes are placed onto the scalp).

Motor Imagery is a mental practice wherein an individual thinks of doing a movement of a certain part of his/her body. The role of BCI and this paper is to identify which part of the body's movement these signals correspond to. A person suffering from ALS might be unable to move his/ her arms, but with proper EEG signal classification, the individual only needs to think of moving the arm and a robotic arm attached to his/her body that would simulate the movement.

Motor imagery-based EEG signals have been significantly helpful for people with motor deficiencies by providing medical rehabilitation functions. However, due to EEG signals' non-stationary, non-linear, poor signal-to-noise ratio, and other features, numerous preprocessing, feature extraction, and multi-mode classification challenges remain. Practical BCI systems are thus few.

2. LITERATURE SURVEY

There have been numerous studies on feature extraction techniques used worldwide for the classification of EEG like the Band Powers (BP)[1], Power Spectral Density (PSD) values[2][3], Adaptive autoregressive (AAR), an autoregressive (AR) parameters[4][5]. Time-frequency features [6] and inverse model-based features [7] [8] [9], and Amplitude values of EEG [10].

Kant et al [11], presented a study on EEG feature selection on motor imagery dataset using a wavelet transformation-based approach. BCI 2003 competition motor imagery dataset was used to extract the alpha frequency band which was later analyzed using wavelet-based time-frequency analysis. Features such as Shannon entropy, wavelet energy, log energy, skewness, kurtosis were extracted and from symmetrical electrodes placed over the motor cortex, which were later used to evaluate the model using SVM and KNN classification techniques. The highest classification accuracy of 86.4% was obtained using SVM.

Rahman et al [12], presented a study on the potentiality of using motor imagery events from the prefrontal cortex for motor planning classifications. The dataset was collected from the prefrontal cortex using 16 channel fNIR device for two classes (right-hand movement and left-hand movement). In total 30 trials were done for each participant. Extracted features were classified using KNN and ANN classifier and the highest accuracy of 82% were obtained using KNN and 92.5% using ANN.

Ha et al [13], proposed a CapsNet (Capsule network) based motor imagery EEG classification technique. The study uses BCI competition IV 2b dataset obtained from nine subjects during a two-class (right hand and left hand) motor imagery task, sampled at 250 Hz. The EEG signals were then band-pass filtered between 0.5 Hz to 100 Hz and then notch filtered at 50 Hz. The signals were first transformed in 2D images using average accuracy of g short-time Fourier transform and later fed to the CapsNet model, achieving average accuracy of 78.44% in contract to highest accuracy of 72,28% using traditional machine learning techniques.

Farooq et al [14], presented a comparative study on multivariate EEG signal classification techniques for motor imagery-based classification. The dataset was obtained from four healthy subjects (three males and one female) using 14 channels Emotive headset. The data consist of 4 trials sampled at 128 Hz. The dataset was then decomposed to obtain a beta band and filtered using tenth order Butterworth notch filter later the dimension of data is reduced using PCA and features were extracted using ICA. The highest accuracy of 80.5% was obtained using the KNN classifier.

Xu et al [15], presented a wavelet transform-based motor imagery feature extraction technique using time-frequency images obtained by combining EEG data from three channels (C3, Cz, and C4). The study uses dataset III of BCI competition II consisting of 280 trials of 9 seconds, and dataset 2a from BCI competition ćô recorded from nine subjects and having 6 runs with 48 trials each. The dataset was filtered to remove unrelated frequency components and then trained on a 2-layer convolution neural network. The highest accuracy of 92.75% was achieved.

The human brain produces biosignals that have recognizable features which can be used to design interfaces in supporting prosthesis, orthosis, and exoskeletons. There have been several studies on comparing and analyzing the features in these bio-signals but the acceptance of these analysis is still uncertain. One of the major reasons could be the lack of information to suggest the possible combination of feature selection and feature classification models. Our study compares 2 major feature selection models with the combination of various machine learning approaches. The retrieved feature vectors were utilized to distinguish between two classes of motor movement. The study of different classifiers for feature sets is discussed based on the classification rate. Further, we suggest the implementation of assistive devices with the combination of feature selection and classification model that gives the best performance in assisting people with motor deficiencies.

3. METHODOLOGY

When designing a BCI system, a few critical properties of these features have to be considered [16] such as Noise and Outliers: Since BCI signals have a very poor signal-to-noise ratio, the extracted features also contain the noises. High Dimensionality: While extracting the feature vectors from the EEG signals, it is expected to be in high dimensionality before we concatenate the individual features into a single feature vector that is extracted from several channels and at various times segments [17]. Time information, it is necessary to have specific event-related time information for each of the activity patterns in our brain. Non-Stationary: The EEG signals vary from time to time and specifically over the sessions. Small training sets: Since EEG signals training process is time-consuming [18], the training sets are proportionately small. Hence such issues need to be addressed for better classification performance.

Human brain
EEG chann

Figure 1. Basic Steps Involved In EEG Classification

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This section explains our approach for EEG Motor Imagery feature extraction techniques using Pisarenko Harmonic Decomposition and Peak Detection algorithm from data collection to data pre-processing and feature engineering followed by a comparison of various classification models on the pre-processed data.

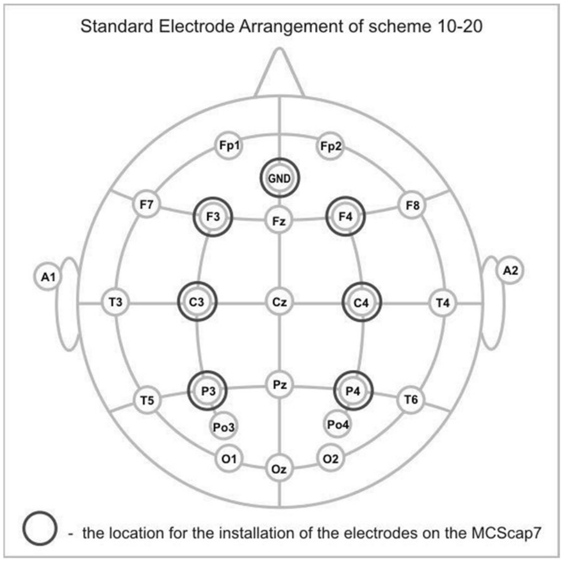

Figure 2, EEG Channel Placement On The Human Head

Figure 1, States the steps involved in achieving classification, the brain activities produce electrical signals which are acquired by the sensors, and further preprocessing is done to remove the artifacts from the signals. The filtered signals are analyzed to extract certain features such as amplitude that reflect the specified actions of a BCI user. Further, these features are used with desired classification algorithms.

3.1 Dataset Acquisition

The experiment conducted in the study uses the publicly available motor imagery dataset obtained by NUST. The dataset is composed of a range of biomedical electrode recordings from the central lobe of a subject of 21 years old male, right-handed with no known medical conditions. The EEG signals were recorded during random hand movements with eyes closed. The dataset consists of data from 19 channels corresponding to the following electrodes: FP1, FP2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, FZ, CZ, PZ; which were based on Standard arrangement of electrodes in an international 10-20 scheme (Figure 2), sampled at 500 Hz.

A standard arrangement of electrodes in an international 10-20 scheme is shown, which lies between the distance of human nasion and the lowest point at the back of a skull. Several parts of the brain serve several distinct functions. The 10/20 system defines the exact positioning of electrodes on these parts of the brain to capture the signals through various channel placements on the human scalp. Only channels, c3 and c4 were of our interest as they have the most predominant motor activity [19][20].

3.2 Data Pre-processing

Pre-processing is done to remove the artifacts from the signals. Among the several channels available in the data, channels C3, Cz, and C4 were selected as these channels have the most predominant motor activity for the left and right hands [21]. The channels were low pass filtered at 64Hz using a 2nd order Butterworth filter [22]. The first-order band-pass filter is converted to a second-order filter by the addition of an RC network [23] by allowing the only low-frequency signal to pass. It is always desired that in a Low-pass filter, the gain is high in case of cut-off frequency at the stopband and for a second-order Low-pass filter the frequency response rate is 40dB/decade.

3.3 Feature Extraction using Pisarenko's Harmonic Decomposition

Pisarenko's method or Pisarenko harmonic decomposition is one of the eigenvectors-based feature extraction approaches which mainly utilized to evaluate power spectral density (PSD). Such eigenvector-based methods are useful to determine the frequency and power of signals from artifact-dominated readings [24]. This ability of the Eigen decomposition to even correlate artifact-corrupted signals is at the heart of such approaches. In the presence of white noise, this technique assumes that a signal, x(n), is made up of p complex exponentials (Figure 3).

$$A(f) = \sum_{k=0}^{m} a_k e^{-j2\pi f} \quad \dots\dots\dots (1)$$

In the above equation, the coefficient of the equation is denoted by 'ak' and the order of eigenfilter for the model is specified by 'm'.

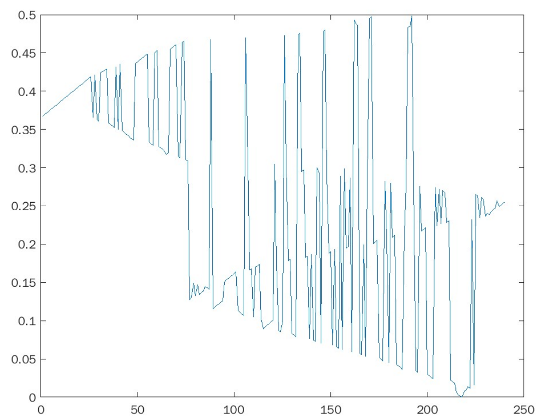

Figure 3. Sinusoidal Frequency Component Using Pisarenko's Technique

The Pisarenko technique estimates the signal's PSD, 'P' or the position of the frequency estimation function's peaks (or the pseudo-spectrum) from the eigenvector corresponding to the lowest eigenvalue using the signal desired equation as follows:

$$P = \frac{1}{|A(f)|^2} \quad \dots\dots\dots \ (2)$$

3.4 Feature Extraction using Peak Detection

Pre-processed data is then utilized in the feature extraction step to extract the peaks of the signal using the peak detection algorithm with a delta value of 50. The peak detection method can be considered as a feature extraction technique that extracts various frequency peaks from the EEG data using the window search method.

Peaks in the EEG data are identified using the window search approach by evaluating a moving rectangle along the curve. Two points are considered on the rectangle. On the input signal curve, P1(x1, y1) and P2(x2, y2) are identified, where x1 and x2 are the x coordinates of the rectangle's bottom left and bottom right corners, respectively. The biggest of the two numbers y' is obtained by comparing the values of y1 and y2 as in (Equation 3).

$$y' = y_1 > y_2 \,?\, y_1 : y_2 \quad \dots\dots\dots \ (3)$$

The local maxima of the curve, indicated as yLocalMax, is the greatest height y of the curve between the points P1 and P2 (Equation 4). After that, compute the difference between the local maxima and y'. After then, the difference is compared to the rectangle's height (Equation 4).

$$Difference = y_{LocalMax} - y' \quad \dots\dots\dots \ (4)$$

In the case of a negative peak, the lesser of the two y values (y") is taken into account (Equation 6), and yLocalMax, is deducted from the y" (Equation 7).

$$y' = y_1 < y_2 \,?\, y_1 : y_2 \quad \dots\dots\dots \ (6)$$

$$Difference = y'' - y_{LocalMax} \quad \dots\dots\dots \ (7)$$

The height of the rectangle encompassing the downward curve is then compared with the 'Difference'. Using channels C3, C4, and Cz, different peaks were identified for both the classes (i.e., right-hand movement and left-hand movement).

Figure 4, depicts the peaks (marked in blue) detected in the signals acquired from channels, C3 and C4 for both left and right-hand motor imagery using the peak detection algorithm with a delta value of 50. Further, these peaks are used as selected features for classification purposes.

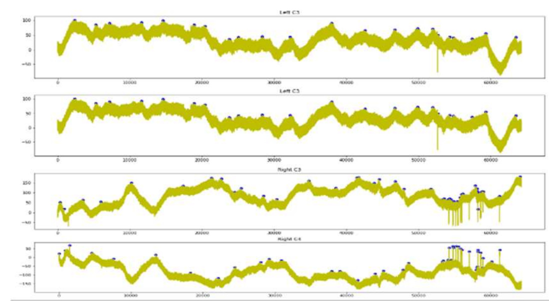

Figure 4, Detected Peaks In The Left C3, C4, And Right C3, C4 Of The Dataset

In total 65 peaks were detected using the peak detection algorithms, 43 of which were from the 0th class, 22 from the 1st class among them. Out of the total 65 detected peaks, random 45 samples were selected as training class and 20 samples for the testing. The 45 training samples had 30 samples from the 0th class and 15 samples from the 1st class and among the 20 test samples had 13 samples from the 0th class and 7 from the 1st class.

3.5 Classification Models

The classifier uses the independent feature to predict the class of given input. In this study, we used the following classification techniques to illustrate the usability of the proposed technique.

3.5.1 K-Nearest Neighbour Classifier (KNN)

K-Nearest Neighbours (KNN) is a standout among the most fundamental yet basic classification algorithms in Machine Learning [25]. It has a place with the administered learning space and finds extreme application in design acknowledgment, information mining, and interruption recognition. With KNN we consider cost as a mixture of time and some memory. KNN requires intensive memory to store all data points. It uses the Euclidian distance [26] to calculate the nearest of the k neighbors (Equation 8, 9).

$$d(p,q) = d(q,p) = \sqrt{(q1-p1)2 + (q2-p2)2 + \cdots .. + (qn-pn)2} \quad \ldots \ldots \ldots (8)$$

$$d(p,q) = d(q,p) = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2} \quad \ldots \ldots \ldots (9)$$

Where d(p,q), denoted the Euclidian distance between an input vector p and the nearest neighbor q or vice versa. One of the drawbacks of this algorithm is that it is very sensitive to the dimensionality of the feature set [27,28].
Steps for classification include:
Step 1. Store training samples in a list that contain a tuple(x,y)
Step 2. Calculate Euclidean distance d(a[i],p) where p is the unknown data point.
Step 3. Make a set of the smallest distances obtained.
Step 4. The one with the majority of hits is the label.

3.5.2 Random Forest

It is a supervised learning approach, meaningful by its name in randomizing the creation of forests. The Random Forest algorithm has many trees connecting to forests and their outcomes, as a large number of trees can be found in a forest, a more precise outcome is expected. It works by constructing a larger number of Decision trees allowing the method of classes for the prediction of individual trees which is the classification and regression technique [29,30].
The class which gets the highest number of votes by the Decision Trees is the Decided Class. Random decision forests clarify Decision Trees' process that is misclassified with their training sets 221. Random Forest finds the root node and distinguishes the component hubs running haphazardly making it distinct from the random decision tree [31].
The random forest's ultimate output is generated by collecting the majority of the outputs from every tree in the forest for some input vector x', as indicated in equation (10), where B is the bagging constant.

$$\hat{f} = \frac{1}{B} \sum_{b=1}^{B} f_b(x') \quad \ldots \ldots \ldots (10)$$

It produces reliable results since it can aggregate the output from numerous decor-related trees.

3.5.3 Gradient Boosting (XgBoost)

Gradient boosting machines are a group of effective machine-learning strategies that have demonstrated significant accomplishment in an extensive variety of functional applications [32,33]. They are profoundly adaptable to the specific needs of the application, such as being learned for various loss functions [34]. Gradient boosting involves three elements:
i. Boosting the loss function.
ii. Predicting a weak learner.
iii. Minimizing the loss function by using an additive model for the weak learners.

3.5.4 Support Vector Machine (SVM)

Support Vector Machine is a supervised learning approach widely used in classification problems. It separates the input with the linearly separable dataset using a Decision Boundary with a maximum margin [35]. The most favorable Decision boundary (Hyperplane) can be found as:

$$w.x_i + b \geq +1, if y_i = +1 for x_i \ having the class +1 \ldots \ldots \ldots (11)$$

$$w.x_i + b \leq +1, if y_i = -1 \ for \ x_i \ having \ the \ class -1 \ldots \ldots \ldots (12)$$

For each data composed of n vectors xi; whereas yi indicates whether the elements belong to the class as +ve or -ve, xi is associated with the value of yi .

3.5.5 Decision Tree

At its most basic level, a decision tree is a tree with a condition or statement and two branches that are either true or false or 0 or 1; those branches can be expanded to match a more sophisticated question [36]. Formally defined, a decision tree is a supervised learning technique that uses a non-parametric model to operate on labeled data.
The objective is to learn basic decision rules from data characteristics to construct a model that predicts the value of a target variable. A decision tree can be considered as an approximation to a piecewise constant [37].

3.5.6 Artificial Neural Network (ANN)

An artificial Neural Network is made up of artificial neurons known as nodes, which are linked units. Typically, these neurons are grouped into

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layers. At different levels, different modifications can be applied. These are trained by analyzing instances with known input and framing probability-weighted connections between the two as a consequence [38]. The input layer is a hidden layer that may contain several layers, and the output layer is the three layers that make up an ANN. The core of neural net training is backpropagation [39]. It fine-tunes the neural net's weights based on the epoch's mistake (iterations). So, it's all about feeding the loss backward to make the neural network forecast better.

4. RESULTS

Several classifiers were trained and tested for this prepared dataset. Table 1, below shows the accuracy comparison of the various classifier using Peak detection and Pisarenko's Method for feature extraction. It was found that KNN offered the highest accuracy of 94.5%, Random Forest and other tree-based classifiers achieved around 91.58%, KNN, though achieving higher accuracy is however not much used in EEG classification due to its high memory usage and laziness. Other classifiers were also used and the accuracy offered was just normal.

Table 1. Table Depicting The Accuracy Scores Of Various Classifiers

Algorithms	Accuracy	
	Peak Detection	Pisarenko's Method
Random Forest	91.58 %	89.46 %
KNN	94.50 %	84.56 %
XgBoost	92.68 %	86.45 %
Decision Tree	89.78 %	84.36 %
ANN	86.24 %	81.62 %
SVM	67.56 %	69.45%

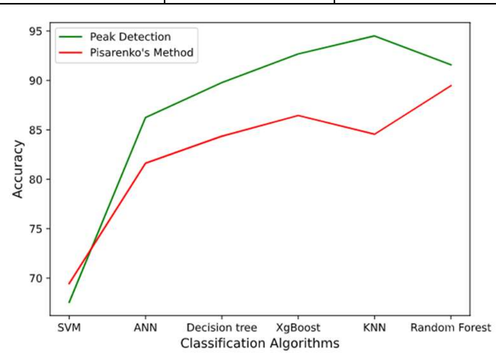

Figure 5. Line Plots Of Various Classifiers Used Vs The Accuracy Scores Of Individual Classifiers

The above line graph in Figure 5, draws the variations in achieving the classifier accuracy on different classification algorithms among which KNN has the highest of 94.5% and SVM with the lowest of 65.35% using Peak detection algorithms, and Random Forest has the highest accuracy of 89.46% and lowest accuracy of 69.45% achieved by SVM using Pisarenko's Method.

4.1 Performance Measure

Classification performance was calculated by considering precision, recall, and F1 score.

Table 2 Performance Measure

		Predicted	
		Positive	Negative
Actual	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TP)

Table 2, describes the calculation of performance measure with True Positive meaning yes, the samples are correctly classified, True Negative are predicted as No, and False Positive and False Negative means the samples are incorrectly classified.

a) Precision is calculated with the ratio of True positive with Total Positives.

$$\frac{TP}{TP+FP} \cdots \dots \dots (13)$$

b) The recall is the ratio of True positive with Total classified

$$\frac{TP}{TP+FN} \dots \dots \dots (14)$$

c) The F1 score is a weighted average of the precision and recall scores. In relation to a specific positive class, the F1 score combines precision and recall [40].

$$F1 = 2\frac{(Precision * Recall)}{(Precision + Recall)} \dots \dots \dots (15)$$

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Table 3, Performance Evaluation For Pisarenko's Method

Algorithm	0 Class			1 Class		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
Random Forest	0.87	0.96	0.91	0.95	0.83	0.88
K Nearest Neighbour	0.85	0.85	0.86	0.83	0.83	0.83
Gradient Boosting	0.81	0.96	0.88	0.94	0.74	0.83
ANN	0.82	0.84	0.83	0.80	0.78	0.79
Support Vector Machine	0.75	0.65	0.70	0.63	0.73	0.68
Decision Tree	0.85	0.85	0.85	0.82	0.82	0.82

Table 4, Performance Evaluation For Peak Detection Method

Algorithm	0 Class			1 Class		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
Random Forest	0.92	0.92	0.92	0.86	0.86	0.86
K Nearest Neighbour	0.93	1	0.96	1	0.86	0.92
Gradient Boosting	0.92	0.92	0.92	0.86	0.86	0.86
ANN	0.86	0.87	0.86	0.84	0.82	0.83
Support Vector Machine	0.69	0.85	0.76	0.5	0.29	0.36
Decision Tree	0.92	0.92	0.92	0.86	0.86	0.86

Table 5 presents a comparative report for with the various methods used to detect Motor Imagery EEG signals for Left/Right hand classification and being compared to the proposed method to detect the EEG signals using peak detection technique with an improvement in the achieved accuracy as compared to one achieved using Pisarenko's method for feature extraction phase and classified using same set of classification algorithms, as shown in Table 3. Upon calculation of performance measure, we observed higher precision and recall for KNN in both the classes using peak detection method. Similarly, XgBoost had the second-highest precision and recall value followed by Random Forest. Since KNN has

Table 5, Comparison Table With Existing Results

Paper	Title	Methods Used	Accuracy
Kant et al [11]	Wavelet transform based approach for EEG feature selection of motor imagery data for brain computer interfaces	Wavelet transformation based approach is used for feature extraction and SVM and KNN is used for classification	86.4 %
Ha et al [13]	Motor Imagery EEG Classification Using Capsule Networks	Short-time Fourier transform is used for feature extraction and Capsule Network (CapsNet) is used for classification.	78.44 %
Farooq et al [14]	Motor Imagery based Multivariate EEG Signal Classification for Brain Controlled Interface Applications	Independent Component Analysis (ICA) and Principal Component Analysis (PCA) is used for feature extraction and KNN is used for classification	80.5 %

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Proposed Peak detection Method	Comparative Study of EEG signal classification based on amplitude-based peak detection method and Pisarenko Harmonic Decomposition using Motor Imagery Dataset	Peak detection technique in signals is used for feature extraction KNN, Gradient boosting and Random Forest is used for classification	94.5 % using KNN and 92.68 % using XgBoost

higher time complexity and higher memory requirements [22][24], we suggest using Random Forest and Gradient Boosting (XgBoost) for classification using our peak detection method for better performance.

5. CONCLUSIONS

Motor Imagery EEG signal detection is a difficult research subject in the Brain-Computer interface systems. Focusing on the accuracy and feature selection requirements suitable for classification models, this paper studies the EEG signal datasets of Left & Right-hand movement. The Pisarenko Harmonic Decomposition method & Peak detection method were applied to consider the features in the recorded and filtered EEG signal and put to test with various machine learning classifiers for comparison. The Peak detection algorithm shows promising results as compared to Pisarenko Harmonic decomposition method. The KNN model, though offering higher accuracy (94.5%), is not considered suitable in the EEG classification domain because it is a non-learning model. Therefore, Random Forest and gradient boosting seem to be the optimal choice for the same. This classification could be applied in various EEG-based hand prosthetic robotic arms to assist people with motor deficiencies.

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