

## Performance of channel selection used for multi-class EEG signal classification of motor imagery

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### ABSTRACT

The brain computer interface (BCI) is a system which involves communicating and controlling the machine with the help of brain signal (l'électroencéphalographie EEG), can be used to help people with physical disabilities regain their motor ability. In this paper we investigate the classification of mental tasks based on EEG data for Brain Computer Interfaces, classification of 4 imaginary motor activities (left hand, right hand, foot, tongue) with the BCI competition III data set IIIa. Performance comparisons will be made between different Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), K-Nearest Neighbors (KNN) algorithms of classification using time\_frequency characteristics. This article also shows the influence of choice, number and position of electrodes for each subject (channel selection) were investigated to provide an improvement for the classification accuracy of the algorithm. Results show that using one subset of the channels with positions varied from subject to subject; gave good classification results by comparing it with other research results an average accuracy of 86.06% was observed among all 3 subjects.

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## 1. INTRODUCTION

An brain-computer interface (BCI) provides a new communication channel between the human brain and a computer. Patients who suffer from severe motor impairments may use such a BCI system as an alternative form of communication by mental activity [1] (aim to enable completely paralyzed patients communicating or controlling devices in their environment by mental suggestion ). This system is totally based on the analysis of EEG signals it is the most efficient and widely used recording modality in this system due to its non-invasive measurement procedure, portability and reasonable cost .

Electrical activity inside the brain can be affected by various kinds of actions like movement of arms and legs, as well as visualization, problem solving or even just by imagination. There are variations in the EEG when a person moves his or her hands and legs. Not only that, even when a person tries to imagine such kind of motor movements, then also, there are variations in the EEG signals [2]. There have been a lot of discussions on the imagination of left and right hand movements with many reliable results for its characteristic frequency band and the corresponding cortical activity in the region of cerebral cortex. But the research on the foot and tongue is still limited [3].

A BCI system is represented as a system in a continuous closed, generally composed of six steps [4] : 1. Brain activity measurement, 2. Preprocessing, 3. Feature Extraction, 4. Classification, and 5. Translation into a command and Feedback in Figure 1, steps for feature extraction EEG and classification are very important.

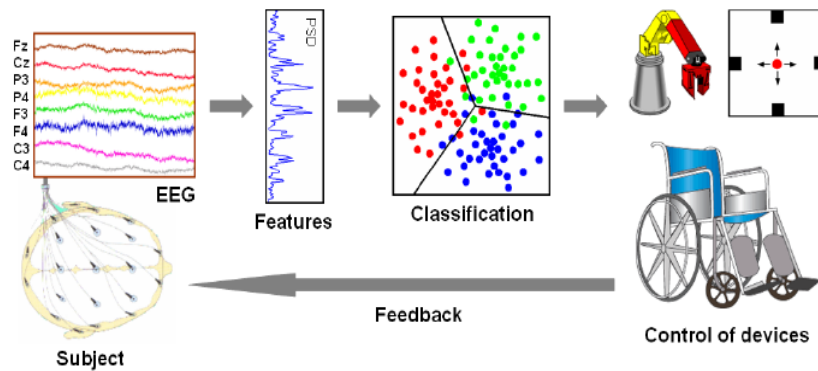


Figure 1. The general architecture of BCI

For the feature extraction process, different methodologies were used to retrieve features in previous studies and these included Sample Entropy [5], Autoregressive (AR) Model [6], band power (BP) [6] Classification of these extracted features was done using various classifiers . A number of linear and nonlinear classifiers have been studied for classification of EEG signals under different conditions like Linear Discriminant Analysis (LDA) [7], Support Vector Machines (SVM) [8], and k-nearest neighbor (KNN) [9-10]. A good classifier should be designed to achieve a satisfactory communication by mental activity [11]. But One major question in classification of EEG signals is the selection of proper electrode positions. Selection of a sub-set of the most distinct electrode positions.

Such as The goal of this study is to show that the position and the number of electrodes applied in a BCI approach of great importance to increase the recognition rate of mental spots. The first goal of our study is to evaluate a variety of classification techniques (SVM , LDA , KNN ) on a dataset using 3 channels (C3, C4, Cz ) only , then Select a sub-set of specifically relevant electrode positions, a good study of the selected features revealed certain electrode positions. The optimal selection is expected to be dependent on the movement tasks and on the individual person. And apply the best method of classification on this sub-set.

The rest of the paper is organized as follows. Section 2 introduces the dataset used in this paper, as well as the proposed approach Section 3 provides the experimental results along with their analysis. Finally, Section 4 concludes the paper.

## 2. RESEARCH METHOD

The proposed model illustrated in Figure 2 represents the overall flow of our work. For this research, the EEG signals were first accumulated followed by data preprocessing. Next, bands of specific frequencies were extracted from the preprocessed data. Subsequently, suitable features were extracted and selected to be fed into the classifier. Finally, classifiers were used to classify these selected features with 10-fold cross-validation.

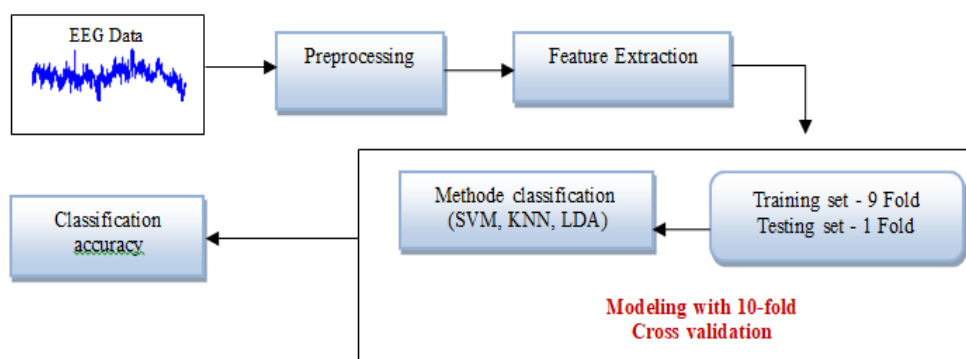


Figure 2. Flow Chart of EEG Signal Analysis

**2.1. Data Description**

The dataset of BCI competition 2003 provided by Graz University of Technology [12] was used in this investigation. From this dataset, the IIIa data, which includes three subjects: k3b, k6b, l1b, were selected to test algorithms. The Graz-BCI system consists of an analysis of motor-imagery-related EEG patterns. When a subject imagines e.g. left hand, right hand, foot or tongue movements, then a transient, locally restricted change in the ongoing EEG is induced. This change is known as event-related desynchronization (ERD) and event-related synchronization (ERS) which can be detected and translated into control signals to the computer. The used amplifier can record 64-channel with a sampling frequency of 250 Hz. Each recorded dataset contains 60 EEG channels; Figure 3 shows the position of each electrode [12].

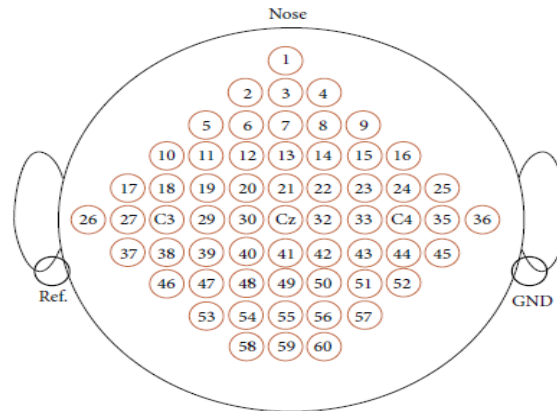


Figure 3. Electrode positions while recording EEG data (BCI competition III data set IIIA)

The training paradigm was a repetition of cue-based trials. The subjects were sat in front of a monitor and asked to perform imagery movements during a given time interval. Figure 4 depicts the timing of the training, each trial began with a blank screen. At time point  $t = 2$  seconds a short acoustic stimulus and across “+” on the screen were given to advise the subject to pay attention.

At  $t = 3$ s the cross was overlapped with an arrow pointing either to the left, right, up or down for 1.25 seconds. According to the direction of the displayed arrow, the subject was asked to imagine a left hand, right hand, and tongue or foot movement, respectively. The movement imagination had to be performed until the cross disappeared at  $t = 7$ s then, a short break with a randomly selected durations up to 2 seconds is considered before starting the next trial [12].

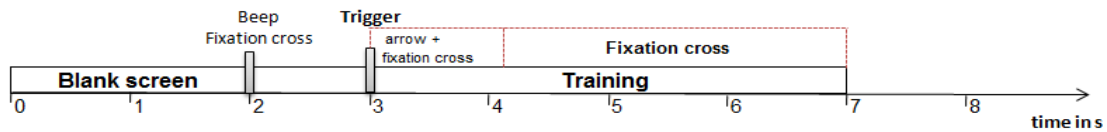


Figure 4. Timing of the paradigm

Datasets were recorded from three subjects (K3, K6, and L1) with different levels of experience in BCI training, subject K3 has much experience relatively to subject L1 where subject K6 is a beginner. Dataset K3 was recorded in 9 training runs whereas K6 and were recorded in 6 runs. Each of the 4 movements was trained 10 times within each run. Table 1 lists the number of the trials in each data set [12]. Original Signal as shown in Figure 5.

Table 1. Number of Trials in Each Dataset

Subject	total	Left	Right	foot	Tongue	note
K3	360	90	90	90	90	Most experienced
K6	240	60	60	60	60	Beginner
L1	240	60	60	60	60	Lessexperienced

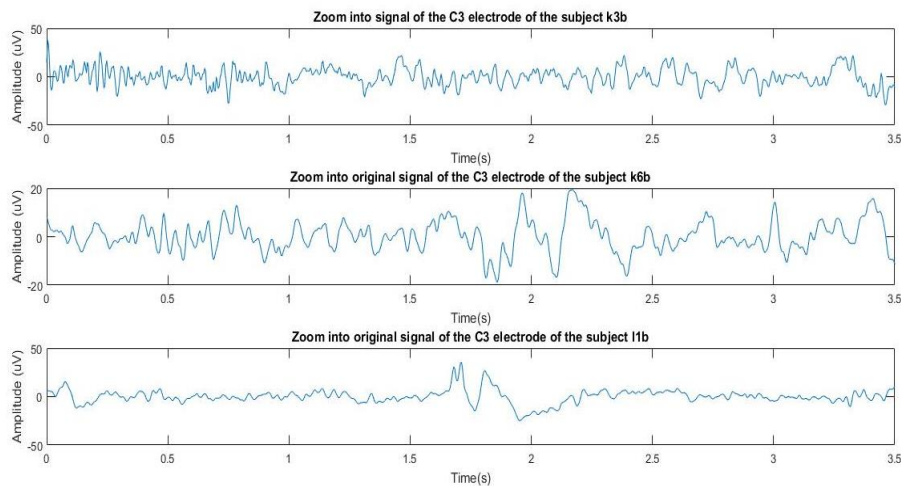


Figure 5. Original Signal

For preprocessing step in description of dataset the EEG signals were filtered between 1 and 50 Hz with Notch filter [12].

## 2.2. Feature extraction

Feature extraction is the collection of relevant information from the signal. In order to select the most appropriate classifier for a given BCI system, it is essential to clearly understand the selected features, what their properties are and how they are used. The aim of this section is to describe the common BCI features and their properties [13]. This step leads to find a better representation of the EEG signal while keeping the most relevant properties corresponding to the performed mental imagery. A robust method based on relative bandpower RBP for extracting the corresponding EEG features.

### 2.2.1 Relative Band-Power (RBP)

An EEG signal consists of several frequency bands named delta, theta, alpha, beta and gamma bands. There is no strict frequency ranges for these different bands, analysis of the EEG signals within these frequency bands presents a gold standard [14].

EEG signal features may be extracted by estimating the power distribution of the EEG in predefined frequency bands. Typically the acquired EEG signal is filtered with the band from 1 Hz to 30 Hz. The acquired signal contains the information required for further analysis. EEG signal analyses are done by extracting parameters in time and frequency domain. For each channel ( 3 canal ,the sub-set of canal) after splitting up the signal into 3 specific bands at (8-12) Hz, (12-20) Hz and (20-30) Hz , the absolute power of each band is calculated the spectrogram is created.

From the spectrogram, the power spectral density is calculated and it is averaged to find the absolute band power values. Relative band power is calculated for each band as a percentage of total EEG activity in the band (1-30) Hz [15].Such features have been successfully used for motor imagery classification.

## 2.3. Classification

The classification procedure includes predicting a confusion matrix model by partitioning the sample data into a training set and a test set, for training and validation respectively, using a technique called k-fold cross validation . This technique randomly divides the data into k equal subset of the data and is repeated 10 times. Each time, one of the k subsets is used as the test set and the other k-1 subsets are put together to form a training set . In this study we investigated three classification methods: LDA, KNN and SVM.

- a) LDA: is a very popular, classical classification method. It is simple to implement and often used as the baseline method for comparison of different classification methods [16].
- b) KNN:is a non-parametric approach, which classifies a given data point according to the majority of its neighbors. The KNN algorithm completes its execution in two steps, first finding the number of nearest neighbors and second classifying the data point into particular class using first step. To find the neighbor, it makes use of distance metrics like euclidean distance [17].

- c) SVM: is a strong state-of-the-art classifier which has demonstrated its excellent generalization properties in various applications, also in the BCI research [18]. Is a supervised binary classification algorithm that finds the optimal separating boundary in hyperplane by maximising the margin of two classes/training data and has great ability in solving high dimension and Non linear features . The standard formulation of SVM can be found in [19].

### 3. RESULTS AND DISCUSSIONS

First, the system performance in terms of precision using electrodes C3, Cz, C4, then a comparison between the selected electrodes was carried. Figure 6 shows the distribution of energy on the electrodes C3, Cz and C4 in the time-frequency domain for the four types of motor imaging for subject K3b.

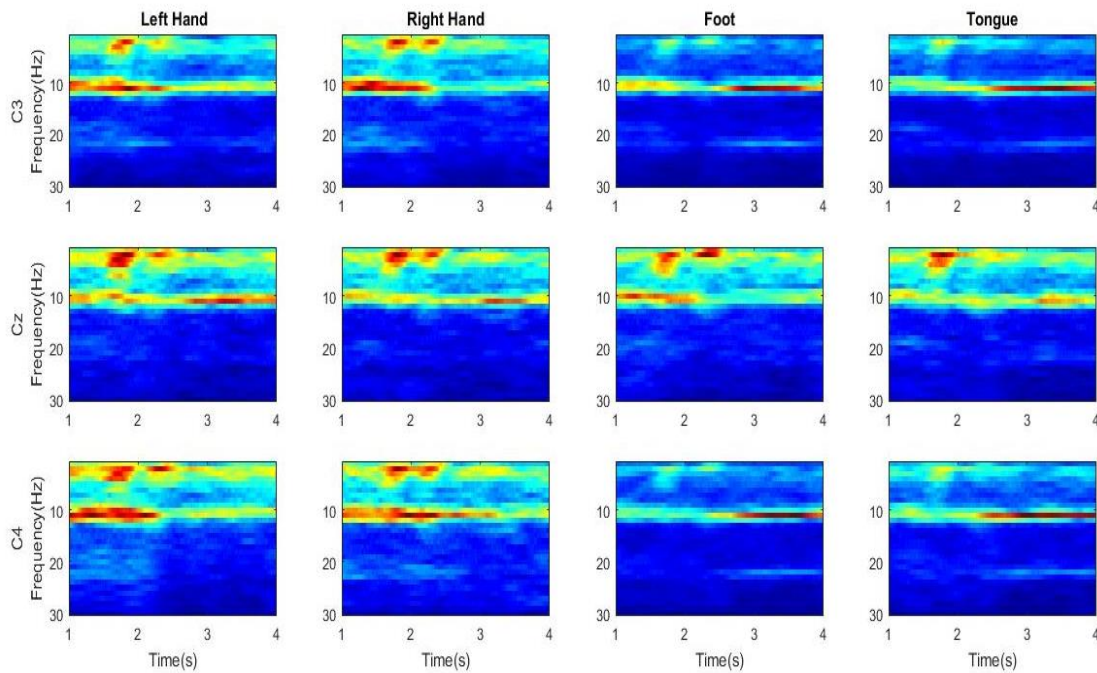


Figure 6. Time-frequency presentation

During a left-hand imaginary movement, on the C3 electrode, the energy was concentrated within 10 to 15 Hz frequency band and keeps the same behavior until the end of the imagination on electrode C4, and within the same band of frequency, the concentrated energy was as the first few seconds. On the contrary, during the movement imagine of the right hand, the energy was concentrated within 10 to 15 Hz frequency band interval on the electrode C3 and for the first seconds, but maintained until the end of imagination on the C4 electrode. For the imaginary foot and long motion, the energy distribution was similar to C3 and C4 electrodes, however, it was different on the Cz electrode.

Table 2 depicts a comparison between the classification accuracies for each subject when three different classification tools SVM, LDA, and KNN were used with 3 canals (C3, Cz and C4) with 10-fold cross validation. Table 3 compares between classification accuracies from each class for each subject using the SVM algorithm who gave better results.

Table 2. Comparison Between Classification Accuracies of 3 Classifiers: SVM, LDA and KNN with 10-Fold Cross Validation

	k3b	k6b	11b	Average
SVM	87,18	75	76,79	81,09
LDA	71,11	32,91	43,33	49,12
KNN	63,05	41,25	42,91	49,07



Table 3. Classification Accuracies from Each Class for Each Subject Whith SVM

	Left hand	Right hand	Foot	Tongue
k3b	93,03	93,03	83	79,66
k6b	75,21	74,78	75,21	74,78
l1b	74,79	77,31	75,21	79,83

### 3.1. Analysis of channel selection

The use of 3 channels has given satisfactory results, the use of 60 channel is not practical Given the length of the execution time. so for improved results we have to select a subset of specifically relevant electrode positions. The channel selection method used to calculate the discriminating power of each channel, for each subject in the dataset.

By presenting the topographies of the 60 channels for each imagined event and each subject as shown in Figure 7. However, due to the invariability between different subjects, the spatial pattern of a given subject is different from other subjects. According to the discriminatory powers of channels, an optimal combination of channels with discriminative powers has been selected.

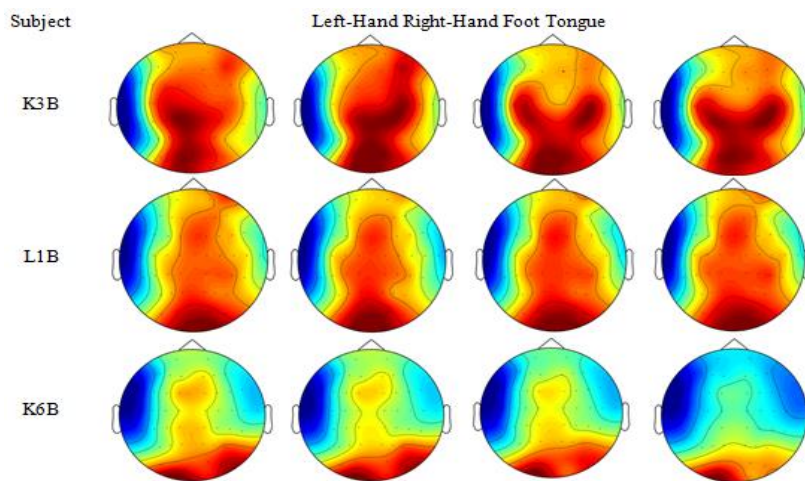


Figure 7. Topographical maps of channels discriminative power distributions for each class and each subject

The channel selection method was used to calculate the discriminative power of each channel for each subject and for each task (class). As shown in Figure 7 for most subjects the channels with high discriminative powers are located in neighboring areas of C3, Cz and C4 electrodes, except for subject “K6B” they are located in the neighboring area of C3 and Cz locations. However, because of individual variability across different subjects, the spatial pattern of one subject is different from the other subjects. According to the discriminative powers of channels, an optimal combination of channels with high discriminative powers was selected.

For individual subject we analyzed the performance of 2 different strategies (i) ranking including channels over the motor cortex, only using a set of three electrodes (C3,Cz,C4), (ii) ranking obtained by channel selection from the data of that subject in Table 4.

Table 4. Channels Selected for Different Subjects

Subject K3b	27,28,29,30,31,32,33,34,35,40,42,48,50,54,56,58,60	17 electrode
Subject L1b	18,27,28,29,38,24,33,34,35,44,31,47,49,51,58,60	16 electrode
Subject k6b	28,14,20,22,30,31,32,40,42,48,50,54,56,57,58	15 electrode

The subject-wise classification of BCI competition III, dataset IIIA through RBP feature extraction method followed by SVM classifier with k (k=10) were investigated as a cross-validation technique. Table 5 shows the multiple class classification accuracies using features selected via canal selection. Classification accuracies from each class for each subject whith svm as shown inTable 6.

Table 5. Accuracy of SVM Classification with 10-Fold Cross Validation

Subject	K3b	K6b	L1b	Average
SVM	92,69	82,98	82,56	86,08

Table 6. Classification Accuracies from Each Class for Each Subject Whith Svm

Subject	Left hand	Right hand	Foot	Tongue
k3b	94,15	94,71	91,09	90,81
k6b	84,89	83,19	73,95	88,24
l1b	79,83	77,73	84,45	89,92

The average performance using a set of three electrodes (C3,Cz,C4 ; Table 2) is cantly lower than the average performance using a set of electrodes find in Table 5. As noted the number of channel and their position differs from one subject to another (depending on the subject and his state of learning experience) we can not choose the same channel combination for all subjects. which proves that a step of channel selection can identify suitable recording sites for individual subjects even in the absence of prior knowledge about the mental task. In this case it is possible to find approximately the number of EEG electrodes necessary for the classification of brain signals without losing substantial classification performance.

We conclude that individual channel ranking is preferable for the experimental. Channel selection can be characterized as an essential step for classification of EEG for BCI system.

When compared with the multiple class classification accuracy from individual algorithms used in this work and other works as detailed in Table 7, it was found that the canal selection for each subject seemed to produce better results.

Table 7. Comparison of Accuracy with other Authors on the Same EEG Dataset

	K3b	L1b	K6b	Average
Hill & Schröder [20]	96,11	64,17	55,83	72,03
Guan, Zhang & Li [20]	86,67	85	81,67	84,44
Gao, Wu & Wei [20]	92,78	78,33	57,50	76,20
Koprinska [ 21]	94,44	78,33	62,50	78,42
Wentrup et al. [22]	94,20	78,60	69,00	80,60
Nos resultat	92,69	82,56	82,98	86,08

#### 4. CONCLUSION

The presented work relates to the feature extraction and classification steps for motor imaging in a machine brains interface system which has been tried to explore EEG signal variations in various types of the imagination of motor movements.

It was observed that the optimal locations for a number of electrodes are slightly different for 3 different subjects. Therefore, the electrode selection must be made for each individual subject to obtain an optimal performance of the BCI (to choose the active electrodes, eliminate the redundand once and reducing the execution tim e).Select a sub-set of specifically relevant electrode positions in an off-line experiment, The optimal selection is expected to be dependent on the movement tasks and on the individual person and his level of learning, This pre selection simplifies the System.

Results of the experiment gave a good classification accuracy when the subjects were studied individually using a different electrode selection for each subject for the feature extraction.

#### REFERENCES

- [1] C. Guger, A. Schlögl, C. Neuper, D. Walterspacher, T. Strein, and G. Pfurtscheller, "Rapid Prototyping of An EEG-based Brain-Computer Interface (BCI) ", *IEEE Trans. Rehab. Eng.*, vol. 9,no.1, 2001.
- [2] S.S.Gupta and S.Agarwal,"Classification and Analysis of EEG signals for Imagined Motor Movements", *Conference IEEE Workshop On Computational Intelligence(WCI): Theories,Applications Ans Future Directions*,14-17 dec2015 .
- [3] D. Ming ,et al,"ICA-SVM Combination Algorithm for Identification of Motor Imagery Potentials", *Computational Intelligence for Measurement Systems and Applications (CIMSA 2010), IEEE International Conference* , pp 92-96,2010.
- [4] D.Trad ,T. Al-Ani , M. Jemni , "Motor Imagery signal Classification for BCI System using Empirical Mode Décomposition and Bandpower Feature Extraction" *Broad Research in Artificial Intelligence and Neuroscience*,vol.7,no. 2,pp. 5-16,june2016.
- [5] H.Jianfeng, X.Dan., M.Zhendong,"Application of Energy Entropy in Motor Imagery EEG Classification",*International Journal of Digital Content Technology and its Applications*, vol.3,no.2, pp. 83-90, 2009.

- [6] G. Pfurtscheller, C. Neuper, C. Guger, W. Harkam, H. Ramoser, A. Schlogl, B. Obermaier, and M. Pregezer, "Current Trends in Graz Brain-Computer Interface (BCI) Research", *IEEE Transactions on Rehabilitation Engineering*, vol. 8, no. 2, pp. 216-219, Jun 2000.
- [7] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, B. Arnaldi, "A Review of Classification Algorithms for EEG based Brain-Computer Interfaces", *Journal of neural engineering*, vol.4, 2007.
- [8] A. Zainuddin, W. Mansor, YK Lee, Z Mahmoodin, "Performance of Support Vector Machine in Classifying EEG Signal of Dyslexic Children using RBF Kernel", *Indonesian Journal of Electrical Engineering and Computer Science*, vol.9, no.2, pp.403-409, Feb 2018.
- [9] E. Setiawan, A. Muttaqin, "Implementation of K-Nearest Neighbors Face Recognition on Low-Power Processor", *TELKOMNIKA (Telecommunication, Computing Electronics and Control)*, vol. 13, no. 3, pp. 949-954, 2015.
- [10] K. Amrizal Abu Nawas, M. Mustafa, R. Samad, D. Pebrianti, N. Abdullah, "K-NN Classification of Brain Dominance", *International Journal Of Electrical And Computer Engineering (IJECE)*, Vol.8, No.4, pp. 2494- 2502, August 2018
- [11] W. Hsu, "EEG-Based Motor Imagery Classification using Neuro-Fuzzy Prediction and Wavelet Fractal Features", *Journal Of Neuroscience Methods*, vol.2, no.2, pp.295-302, 2010.
- [12] G. Pfurtscheller, A. Schlögl, "BCI Competition III 2005: Dataset IIIa and IIIb", 2005. [Online]. Available: [http://www.bbc.de/competition/iii/desc\\_IIIa.pdf](http://www.bbc.de/competition/iii/desc_IIIa.pdf).
- [13] R. Chaudhari, H. J. Galiyawala "A Review on Motor Imagery Signal Classification for BCI", *Signal Processing An International Journal*, vol.11, no.2, pp.16-34, 2017.
- [14] B. Blankertz, et al., "The BCI Competition. III: Validating Alternative Approaches to Actual BCI Problems", *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 14, no. 2, pp. 153-159, 2006.
- [15] F. Howells, V. Deliperi, N. Horn and D. Stein, "Mindfulness based Cognitive Therapy Improves Frontal Control in Bipolar Disorder: A Pilot EEG Study", *BMC Psychiatry*, pp. 1-8, Feb 2012.
- [16] N. Gursel Ozmen, L. Gumusel, "Mental and Motor Task Classification by Lda", *XII Mediterranean Conference on Medical and Biological Engineering and Computing (MEDICOM 2010)*, Chalkidiki, Greece, IFMBE proceeding, pp. 172-175, 27-30 May 2010.
- [17] A. Bablani, D. R. Edla, S. Dodia, "Classification of EEG Data using k-Nearest Neighbor Approach for Concealed Information Test", *8th International Conference on Advances in Computing and Communication (ICACC 2018)*, *Procedia Computer Science*, vol.143, pp.242-249, 2018.
- [18] B. Blankertz, K.-R. Müller, G. Curio, T.M. Vaughan, G. Schalk, J.R. Wolpaw, A. Schlögl, C. Neuper, G. Pfurtscheller, T. Hinterberger, M. Schröder, and N. Birbaumer. "The BCI Competition 2003: Progress and Perspectives in Detection and Discrimination of EEG Signal Trials", *In IEEE Transactions on Biomedical Engineering*, vol. 51, no.6, pp. 1044-1051, 2004.
- [19] C. Cortes and V. Vapnik, "Support-Vector Networks", *Machine Learning*, vol.20, pp.273-297, 1995.
- [20] B. Blankertz, et al., "The BCI Competition. III: Validating Alternative Approaches to Actual BCI Problems", *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 14, no. 2, pp. 153-159, 2006.
- [21] I. Koprinska, "Feature Selection for Brain-Computer Interfaces", *New Frontiers in Applied Data Mining*, Theeramunkong T., et al., editors., Eds. Berlin, Germany: Springer-Verlag, 2010.
- [22] M. Grosse-Wentrup and Buss M., "Multiclass Common Spatial Patterns and Information Theoretic Feature Extraction", *IEEE Trans. Biomed. Eng.*, vol. 55, no. 8, pp. 1991-2000, 2008.

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