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Brain Computer Interface Signals Classification for Right and Left Hands Imagined Movements

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Abstract**:** ***Brain signals are complex and nonstationary, each signal represents an intendent behavior of a user. Brain Computer Interfaces (BCIs) are used to extract and translate these signals. Electroencephalography (EEG) is the common method used for this purpose. Identifying which signal represents which action is important. In this paper, we extracted spatial and spectral patterns for right and left hands imagined movements from EEG signals. We considered only C3 and C4 bipolar channels and band frequency (8-30 Hz) for both alpha and beta. The relevant features classified using Support Vector Machine (SVM) and 9 other common classifiers to compare and contrast classification performances. To ensure classification performance we calculated confusion matrix classes for all 9 subjects from II b dataset. Classification accuracy observed and recorded from all classifiers and 9 subjects. The highest classification accuracy scores for 3 subjects S4, S8 and S9 are (100 %, 89 %, and 71 %) and misclassification scores are (0 %, 11% and 29 %) respectively.***

Keywords: BCI, EEG, Machine Learning, Support Vector Machine, Signal Processing

I. INTRODUCTION

A. Brain Computer Interface(BCI)

Brain-computer interface (BCI) is an external device used to interact with human brain and extract and translate brain generated signals using Electroencephalography(EEG) technique [7], [8]. BCIs history started in 1970s, and was basically used to recognize disabled people's needs [8]. Brain Computer Interfaces (BCIs) act as intermediate between human brain and an external device and establish the link for communication, they are equipped with sensors to detect neural signals. BCIs are the same as other communication and control systems which contain a) input (neural signals) b) translation (processing) c) output (translated behavior) [12]. In Brain Computer Interface the generated neural signals are detected with the help of sensors and then encoded or translated into Electroencephalography (EEG) signals [4]. Brain signals can be extracted from three different recording-positions, therefore the BCIs can be classified as:

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- **Invasive**: The electrodes are implanted inside the brain with the help of surgery, this type is expensive and risky but can provide excellent and accurate data [7].
- **Semi-invasive**: The electrodes are implanted inside the skull with the help of surgery, less expensive and less risky compare to invasive better data quality than non-invasive [7].
- **Non-invasive:** The electrodes are implanted on the scalp surface, this method is used the most because of its less risk and less cost [7].

Electroencephalography (EEG) recording technique is the most common method used in BCIs for extracting the neural signals [10].

B. Electroencephalography (EEG)

Electroencephalography (EEG) is a non-invasive and common technique used to extract neural signals. EEG signals are achieved from the scalp surface by placing the electrodes in particular positions such as C3 left cortex motor for right hand and C4 right cortex motor for left hand with amplitude of (10–100μV) [11]. This method is most commonly used in BCIs and that is because of its less cost and less risk comparably [2] [10]. EEG signals can be further divided into different sub types based on their frequency ranges such as alpha, beta delta, gamma and theta [6]. For right hand and left hand imagined movements we need the first two sub types: alpha and beta with the frequency range of (8-13 Hz) and (13-30 Hz) respectively. Although, EEG signals are touchy with noise, distortion and other artifacts during the recording but still easy to measure [3], [4], [10]. Some BCIs may also use other techniques such as Eelectrocorticography (ECoG) or Electromyography (EMG) to extract neural signals from the brain [3].

C. Machine Learning (ML)

Machine learning is the process of giving the ability to machines such as computers to learn from given data without explicit guides by the user. The process is complex which uses statistics and probabilities to find the best patterns or signals in the data and reach the best solution [21]. Machine Learning can be classified into three categories based on data types, mathematics and computational level:

i) Supervised ML which needs labeled data and further can be classified as a) classification with categorical responses, algorithm examples are: Support Vector Machine (SVM), K-Neighbor Nearest (KNN).

ii) b) regression with continues responses, example Linear Regression.

iii) Unsupervised ML which does not need labeled data, algorithm example is: K-Means.

iv) Reinforcement ML which learns from environment by giving rewards (right or wrong) [21]

The first step in ML is to find the relationships and correlations between the datasets and based on these two factors the machine can predict the unseen observations and find the best pattern [21].

Brain signals are nonstationary and complex, they are usually contaminated with unwanted signals called noise, they vary from one subject to another and one trial to another with high dimensionality. Because of all these variabilities and changes Machine Learning is used to recognize and analyze different mental states from EEG signals [1], [13].

D. Support Vector Machine (SVM)

Support Vector Machine(SVM) is a classifier used to separate linear as well as non-linear data. In SVM the first step is to transform the training data into multi-dimensional space and the second step is to find the proper hyperplane with the help of support-vectors and margins, this means the hyperplane with largest margin comparably. In n-dimensional space infinite lines can be drawn but we search for the one with smallest classification error, this line is called hyperplane and that can be achieved to find the maximum distance between the hyperplanes. SVM can predict both numeric and classification responses [19]. Figure-1 illustrates discriminating the features.

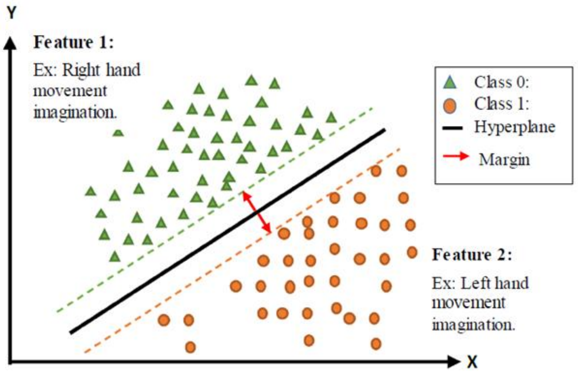


Figure-1: Classifying two mental states with a linear hyperplane using Support Vector Machine (SVM) classifier [21]

Support Vector Machine (SVM) is a supervised machine learning algorithm, very popular used in BCIs for features classification and pattern recognition [2]. The first step is to extract the features and the second step to classify the features into different classes using various classifiers such as Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA) or Support Vector Machine (SVM) [2].

The paper is totally divided into six sections, section I BCI introduction and Machine Learning, section II is Graz dataset 2008 B description, Section III related work, IV Section methodology followed, V Section calculation and performance result and Section VI conclusion of the study.

II. BCI COMPETITION 2008 DATASET IIB

Dataset II b is provided by the Graz University, Medical Informatics Department Austria, and is freely available for the classification problem in Motor Imagery [22]. The data is recorded from 9 different subjects in 5 sessions and consists of two classes: left hand and right hand movements. The first two sessions contain training data without feedback and the remaining three contain training data with feedback. The EEG signals extracted from the brain using three bipolar electrodes or channels called, C3, Cz and C4 where C3 left motor cortex is for right hand movement, C4 right motor cortex for left hand movement and Cz middle motor cortex is for foot movement. Sampling frequency is 250 Hz and Motor imagery interval is 4 to 7 [1][2]. The full description is summarized in Table-1. Pictorial representation for right and left hands imagined movement is shown in figure-2.

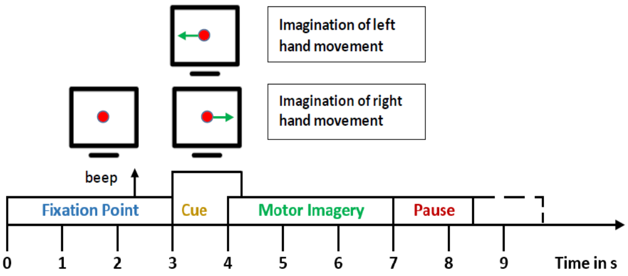


Figure-2: Signals recording paradigm [2]

Table-1: Dataset II b description [2], [22]

Dataset	Graz II b
Number of subjects	9
Number of tasks/classes	2
Number of trials	120
Length of single trail	8
Sampling frequency	250 Hz
Motor Imagery Interval	[4, 7]
Channels	C3 ,Cz, C4

III. RELEATED WORK

Zied Tayeb et al [2], split the data into two parts, training and testing by 80 % and 20 % respectively then for best features selection has applied 6 different classifiers. The 9 subjects are classified into three sub categories based on their classification accuracy:

Bad: S1, S2, S3 and S7 within (60 % to 70 %) classification accuracy.

Good: S5, S6, S8 and S9 within (70 % to 82 %) classification **accuracy**.

Excellent: S4 with (93.75%) classification accuracy.

Fabien Lotte et al [1], used μ (8–12 Hz) and β (16–24 Hz) frequency bands for Motor Imagery (MI) features extraction and two electrodes C3 left cortex for right hand and C4 right cortex for left hand movements. LDA is used for feature classification. Using Common Spatial Pattern, classification accuracy is obtained in the form different versions (73.1 % vs 78.7 % and 77.6 %).

Ernane J.X. Costa et al [14], used Gaussian Representation for feature extraction, left hand and right hand imagination movements, data collected from 10 people, male and female. Classification accuracy recorded at 91%±5.8% for female and 87%±5.0% for male subjects.

G. Pfurtscheller et al [15], used online data from three different subjects with 160 right and left imagination movements at sampling frequency of 180 Hz. The band power for alpha and beta provided in (9-14 Hz) and (18- 26 Hz) respectively. Classification accuracy recoded 80% for all three subjects.

Herbert Ramoser et al [16], considered three subjects S1, S2 and S3 and applied Spatial filtering for extracting single EEG trail. Left hand and right hand motor imagery data recorded and classified. The best classification accuracy noted at (90.8%, 92.7%, and 99.7%) for three subjects respectively.

Yuan Yang et al [17], used F-score and Time Frequency Discrimination Factor (TFDF) with 9 subjects from Graz dataset II a and II b. The features are classified using Linear Discriminant Analysis (LDA). The features are left hand and right hand imagination movements and the channels are C3 and C4. The data is split into 90 % and 10 % training and testing respectively and the band power for alpha and beta is considered at (8-30 Hz). Classification performance recorded for different subjects with S4 the highest accuracy of 95 %.

IV. METHODOLOGY

We process the following main steps in our research methodology to calculate the model accuracy and compare with other's work. Figure-3 illustrates the abstract research methodology for this paper.

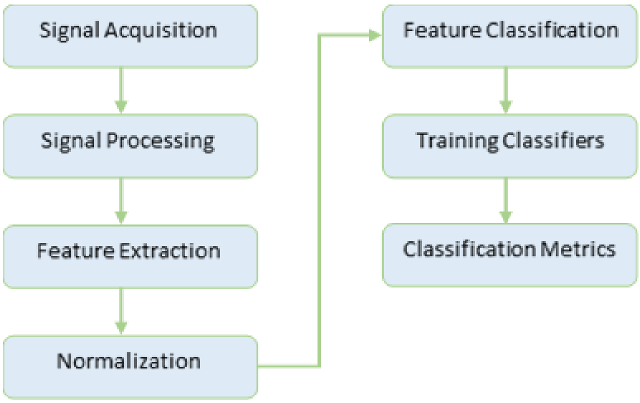


Figure-3: Methodology steps

A. Signal Acquisition

The first step is acquiring EEG signals from the brain and these signals can be achieved in three different ways:

i. **Invasive**: implanting the electrodes inside the brain which provides excellent quality and more accurate signals but expensive and risky [7].

ii. **Semi-invasive**: implanting the electrodes into the skull which provides better quality signals and less risky and expensive compare to invasive [7].

iii. **Non-invasive:** implanting the electrodes on the scalp surface area which provides good signals but less accurate compare to first and second but this method is common because less expensive and less risky [7].

The signals we use from Graz II b dataset is off-line of type iii, means non-invasive and provided by Medical Informatics Department, Biomedical Engineering Institute, Graz University Austria and freely available [2], [22].

B. Signal Processing

A BCI is an external device which is used to extract and interpret electrophysiological signals, these signals are in fact user's intended behavior to show on external world. Every BCI communication system consists of three main steps: a) Input (neural signal) b) Processing (activity performed on signals) c) Output (intended action on external world) [7][8].

The BCI system that recognizes right hand and left hand imagined movements is considered. The two mental states (i.e., right hand and left hands features) are extracted from EEG signals. Both the features are band power and need particular frequency band. For this purpose, two channels C3 left cortex imaginary motor and C4 right cortex imaginary motor for both right and left hand respectively are considered at alpha (8-13 Hz) and beta (13-30 Hz) band power frequencies [1], [6].

C. Feature Extraction

Features extraction means acquiring the relevant data from EEG signals called raw data. These features represent the actual behavior which are wrapped within EEG signals. Right hand and left hand imagery movements are the two features we want to identify and extract from other neural signals. The features may contain unwanted signals (noise) or irrelevant information to be rectified. After extraction the features, they are organized on feature vector [1], [2].

We use two common methods to extract the relevant features (i.e., right and left hands features) out of EEG signal:

- **Spatial pattern:**

These are the features extracted from the brain using electrodes such as C3 and C4 placed in particular positions on scalp surface. Neural signals are recorded using EEG method, different channels used for different type of features. Specifying EEG channels are important [1], [2], [6].

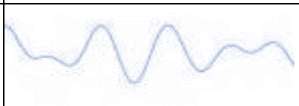
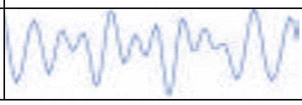
Table-2: Electrode C3 and C4 description [1], [2]

Channel	Position	MI Classes
C3	Left motor cortex	Right hand
C4	Right motor cortex	Left hand

- **Band Power(BP) pattern:**

Brain signals have spectral features, the features need specific band power to identify and extract them. For example, the two mental states (i.e., right and left hands imagery movement features) need alpha and beta (8-30 Hz) band frequency [2], [5], [6].

Table-3: Alpha and Beta BP signals description [6]

Signal	Wave	Band Frequency
Alpha		8-13 Hz
Beta		13-30 Hz

D. Normalization

Before classifying the features, normalization is an important step. Data normalization is the process of arranging the features within a specific range, means large scale data into a small scale such as between (0 and 1). Normalization improves classification performance and accuracy [18].

In this case, we use Min-Max normalization in which the transformation is done linearly [18], the formula is illustrated as:

$$Norm(F) = \frac{(F - \min(F))}{(\max(F) - \min(F))}$$

E. Feature Classification

After extracting the features from EEG signals, we need to classify the features to identify their classes, this process is

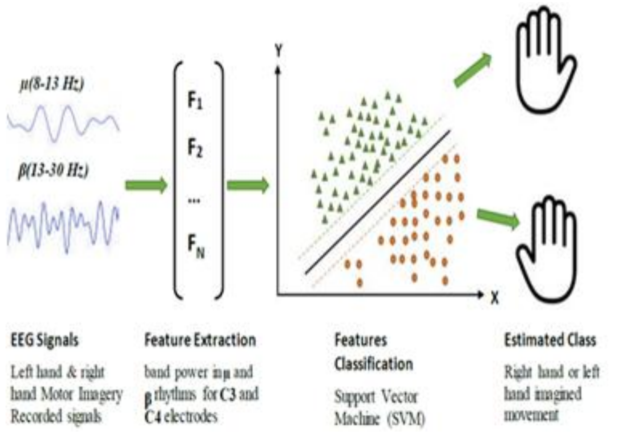


Figure-4: BCI EEG signals classification for right and left hands imagined movement recognition [1].

also known as features translation. In order to classify the features, we used most popular BCI classifier known as Support Vector Machine (SVM) [1], [2]. SVM transforms the features into multi-dimensional space and then classify the features based on largest margin hyperplanes in which the unseen data can be easily generalized [19].

In this case the two mental states split training features into two classes: left hand and right hand features on two sides of hyperplane illustrated in figure-4.

Some BCIs may also use another classifier known as Linear Discriminant Analysis (LDA) [17].

F. Training Classifiers

In order to compare the performance and classification accuracy we use some common classifiers. In first step we split the data into normal training 90 % and testing 10% sets, testing data classified using Support Vector Machine (SVM) and 9 other common classifiers to observe and compare the performance accuracy. In second step the same procedure applied after feature reduction with PCA and LDA and compared the accuracy. In third step we used K-Fold cross validation with K=10. Among all three steps K-Fold with K=6 had great accuracy performance for all subjects. This procedure is applied on all 9 subjects, classification accuracy is observed and recorded individually. The common classifiers used are: Logistic Regression (LR), Forest Classifier (RFC), Decision Tree Classifier (DTC), Gaussian Naïve Bayes (GNB), Multinomial NB (MNB), K-Nearest Neighbors (KNN), Random Gradient Boosting Classifier (GBC), Linear Discriminant Analysis (LDA), Linear SVC (LSVC) and CART. K-Fold cross validation with K=10 is illustrated in Table-4. The best iteration highlighted is K=6.

The result is shown in Table-6. The highest scored observed from GNB 100 %.

G. Classification Metrics

Evaluating a Classifier, accuracy metric is used to observe the performance. But sometimes it is hard to take decision only based on classification accuracy [20]. Confusion matrix can be used to provide a clear picture of data classification. It is n x n matrix used to compare the actual values versus predicted ones. Here we can calculate classification accuracy, classification error, true predictions and false predictions [9]. To ensure EEG signal classification accuracy confusion matrix is conducted Table-5.

Table-4: K-Fold cross validation [2]

1-Fold	Test	Train	Train	Train	Train	Train	Train	Train	Train	train
2-Fold	Train	Test	Train	Train	Train	Train	Train	Train	Train	Train
3-Fold	Train	Train	Test	Train	Train	Train	Train	Train	Train	Train
4-Fold	Train	Train	Train	Test	Train	Train	Train	Train	Train	Train
5-Fold	Train	Train	Train	Train	Test	Train	Train	Train	Train	Train
6-Fold	Train	Train	Train	Train	Train	Test	Train	Train	Train	Train
7-Fold	Train	Train	Train	Train	Train	Train	Test	Train	Train	Train
8-Fold	Train	Train	Train	Train	Train	Train	Train	Test	Train	Train
9-Fold	Train	Train	Train	Train	Train	Train	Train	Train	Test	Train
10-Fold	Train	Train	Train	Train	Train	Train	Train	Train	Train	Test

Table-5: Binary Classification Confusion Matrix [9]

		Predicted Classes		
		Accept: H_0	Reject: H_0	Total
Actual Classes	Accept: H_0	True Positive (TP)	False Negative (FN)	TP+FN
	Reject: H_0	False Positive (FP)	True Negative (TN)	FP+TN
	Total	TP+FP	FN+TN	TP+FN+FP+TN

Classification Accuracy: To calculate model accuracy using confusion matrix then we need four classes (TP, TN, FP, FN), and the formula is:

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (1)$$

Classification Error: Misclassification rate is calculated as:

$$Error = \frac{(FP+FN)}{(TP+TN+FP+FN)} \quad (2)$$

Model sensitivity: It is also known as True Positive Rate, Recall or detection rate indicates how the model sensitively predict true instances.

$$Sensitivity(Recall) = \frac{TP}{(TP+FN)} \quad (3)$$

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Table-6: Subjects and Classifiers performance scores on dataset II b

Classifier / Subject	S1	S2	S3	S4	S5	S6	S7	S8	S9	MEAN
SVC	77 %	59 %	51 %	98 %	**75 %**	69 %	59 %	93 %	77 %	**73 %**
LRC	79 %	57 %	53 %	98 %	70 %	**79 %**	57 %	**94 %**	**77 %**	**74 %**
KNN	71 %	59 %	49 %	97 %	59 %	60 %	59 %	81 %	65 %	**67 %**
NB	81 %	50 %	45 %	98 %	67 %	71 %	55 %	89 %	65 %	**69 %**
LDA	**83 %**	59 %	**55 %**	98 %	73 %	69 %	**60 %**	89 %	71 %	**73 %**
DTC	53 %	55 %	51 %	98 %	68 %	54 %	60 %	72 %	60 %	**63 %**
MNB	62 %	50 %	53 %	**100 %**	63 %	63 %	52 %	89 %	71 %	**67 %**
GBC	75 %	**63 %**	**55 %**	98 %	68 %	73 %	55 %	80 %	77 %	**72 %**
RFC	57 %	54 %	53 %	94 %	68 %	60 %	59 %	85 %	63 %	**66 %**
LSVC	77 %	59 %	51 %	97 %	73 %	67 %	60 %	93 %	73 %	**72 %**
MEAN	**72 %**	**57 %**	**52 %**	**98 %**	**68 %**	**67 %**	**58 %**	**87 %**	**70 %**	**70 %**

Model specificity: also known as True Negative Rate, it is always opposite to model sensitivity which indicates how the model specifically predict true instances.

$$Specificity = \frac{TN}{(TN+FP)} \qquad (4)$$

False Positive Rate (FPR): used to calculate the rate of how the model predict true values incorrectly.

$$FPR = \frac{FP}{(FP+TN)} \qquad (5)$$

False Negative Rate (FNR): used to calculate the rate of how the model predict false values incorrectly.

$$FNR = \frac{FN}{(FN+TP)} \qquad (6)$$

Precision and F-Score can be calculated as:

$$Precision = \frac{TP}{(TP+FP)} \qquad (7)$$

$$F - Score = \frac{2X(Precision\ X\ Sensitivity)}{(Precision+Sensitivity)} \qquad (8)$$

V. ACCURACY CALCULATIONS AND RESULTS

Two mental states (i.e., right hand and left hand imagination movement features) are classified using 10 different classifiers. Classification accuracy and model performance evaluated for all 9 subjects. The best subject among all observed is S4 with highest accuracy 100 % for Multinomial Naïve Bayes (MNB) classifier, the second highest accuracy observed is S8 94 % for Logistic Regression Classifier (LRC) and the third highest accuracy scored by S1 83 % for Linear Discriminant Analysis (LDA).

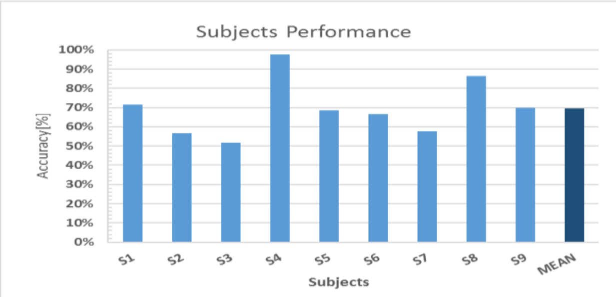

Figure-5: Subjects performance and their mean

Figure-6: Classifiers performance and their mean

Table-7: Classification performance of different subjects using Confusion Matrix

Subject / Metrics	Accuracy	Error	TPR	TNR	FPR	FNR	Precision	F score
S1	62 %	38 %	38 %	85 %	15 %	62 %	71 %	50 %
S2	50 %	50 %	11 %	89 %	11 %	89 %	50 %	18 %
S3	53 %	47 %	25 %	80 %	20 %	75 %	55 %	34 %
S4	**100 %**	**0 %**	100 %	100 %	0 %	0 %	100 %	**100 %**
S5	63 %	37 %	81 %	45 %	55 %	19 %	60 %	**69 %**
S6	63 %	38 %	22 %	100 %	0 %	78 %	100 %	36 %
S7	52 %	48 %	66 %	38 %	62 %	34 %	51 %	58 %
S8	**89 %**	**11 %**	97 %	80 %	20 %	3 %	85 %	**90 %**
S9	**71 %**	**29 %**	54 %	88 %	12 %	46 %	82 %	65 %

The best classifier observed for all subjects is LRC with average value 74 %, the second best classifiers observed for all subjects are SVC and LDA with average value of 73 % and the third best classifiers for all subjects are GBC and LSVC with average value of 72 %. Best average classification accuracy for all 10 classifiers recorded for S4, S8 and S1 with (98 %, 87 % and 72 %) respectively. The highest scores for subjects, classifiers and their averages are highlighted and bolded. Classification accuracy, subjects and their average percentage is shown in Table-6.

Classification performance with respect to different subjects and classifiers visualized as in figure-5 and figure-6.

In order to ensure classification accuracy, we compared actual values and predicted values and calculated different classes such as TPR, TNR, FPR, FNR, classification accuracy, misclassification rate, precision and f-score for different subjects. In this test also S4 scored the highest accuracy 100 % with 0 % classification error and 100 % f-score, S8 scored the second highest accuracy 89 % with 11 % classification error and 90 % f-score and the third highest score recorded for S9 71 % with 29 % misclassification and 65 f-score. Table-7 describes different metrics calculated for different subjects and their scores. Different subject's accuracy, misclassification rate and f-score shown in Figure-7.

VI. CONCLUSION AND FUTURE WORK

In this experiment we considered only two mental states (i.e., right hand and left hand imagined movements) band power features with frequency band μ (8–13 Hz) and β (13–30 Hz) and channels C3 and C4 from BCI Computation 2008 II b dataset. The features extracted from BCI-EEG signals and classified using Support Vector Machine (SVM) and 9 other classifiers to observe and compare classification performances. To ensure classification performance, we also calculated confusion matrix classes as show in Table-7. The highest performance accuracy for all 9 subjects and classifiers observed using K-Fold cross validation with K=6. Classification accuracy recorded for both subjects and classifiers as shown in Table-6 and Table-7. Their accuracy performance is also visualized using graphs as shown in Figure-5, Figure-6 and Figure-7 respectively. Over all, model

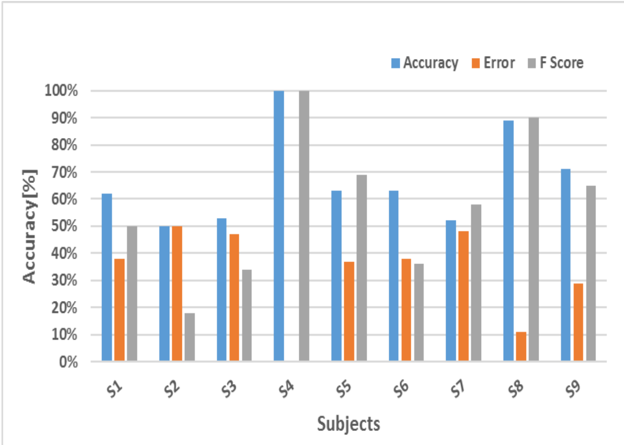

Figure-7: Classification accuracy, error and f-score

performance was good, the highest accuracy scored by S4, S8 and S9 subjects (100 %, 89 %, and 71 %) with classification errors (0 %, 11 % and 29 %) respectively. Future work is decoding of finger forces and grasp movements from Electromyography (EMG) signals and deep learning.

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