A Comparative Study of Motor Imagery (MI) Detection in Electroencephalogram (EEG) Signals Using Different Classification Algorithms

Abstract—**With the advancement of machine learning algorithms, the electroencephalogram (EEG) signal can be highly useful to identify the motor neuron activity (also known as motor imagery, MI event). Depending on the problem and experimental dataset/protocol, researchers use different classification algorithms to classify motor imagery events. Therefore, the selection of classification algorithms for accurate MI detection is significantly important. This paper attempts to provide a brief comparison of the performance of different classification algorithms for MI detection in EEG data. At first, the EEG data of 30 random subjects were collected from a publicly available dataset. Then a combination of time domain and frequency domain features were extracted from the EEG data. Next, the correlated feature selection (CFS) algorithm was used to rank the features based on the correlation. To further reduce the feature set, forward feature selection (FFS) algorithm that was utilized to find out the significant features. For classification, support vector machine (SVM), logistic regression (LR), naïve bayes (NB), and k-nearest neighbor (KNN) were investigated with leave one subject out cross-validation scheme. Finally, the performance of all the classifiers was evaluated using the F1-score. The SVM classifier achieved an average F1-score of 70.26% from 30 subjects' trials. The results suggest that the SVM classifier may perform better than other classifiers. Additionally, the linear kernel of SVM helped to reduce the computational time and complexity of the model. It is expected that the SVM classifier may provide better performance in a wider range of populations.**

Keywords*—*Electroencephalogram (EEG), motor imagery (MI), CFS, classification, f1-score.

I. Introduction

With the progress in machine learning algorithms and innovative solutions, significant researches are being done in diagnosing underlying disease from electroencephalogram (EEG) signal. The EEG signal can be used to interpret and diagnose motor imagery (MI) events, which are mental processes that include imaging gestures without causing real physical movements [1]. However, the MI information may help physically handicapped or elderly people who are confronted with difficulty expressing themselves due to their inability. Therefore, a proper method with appropriate classifier should be developed to detect the MI event that may help to diagnose MI related diseases in human. Towards the development of such method, different classification algorithms were investigated in the MI EEG data.

The recent exercises of machine learning (ML) algorithms exhibited great success in dealing with real-world problems. Analysis of the MI EEG signal is the most trending topic nowadays since it can be useful to diagnose many underlying diseases of humans and help to eliminate them. Researchers had already come up with many potential solutions through the implementation of ML algorithms with MI EEG signals. It is evident from some works of the researchers that the mental practice with MI has a good effect on mental improvement. It is observed that MI events are conducive to activate the brain motor area in stroke patients [2]. In a research [3], the researchers investigated how mental practice with MI events can help in humans' adaptation process. They got the significant result in learning a new sport (golf) through mental practice in combination with physical practice. In a study [4], MI was investigated in multiple sclerosis (MS) patients using functional magnetic resonance imaging (fMRI) by executing behavioural tasks with dominant and non-dominant hands to assess whether anisochrony is associated with disease severity. It was suggested that MI could be helpful as a substitute behavioural marker of MS severity at the early stages of the disease. All these researches are evident that MI can be beneficial to diagnose diseases. Therefore, it is required to implement the MI detection system for the people to get benefitted from their problems.

Implementation of an effective MI detection system is needed for proper MI movement detection. As a result, researchers are working to refine and streamline current machine learning classification algorithms to create a more stable and effective recognition system. By taking this into account, an improved back propagation (BP) neural network (NN) over the traditional BPNN algorithm was proposed in [5], where it exhibited better performance in recognition by solving the low signal-to-noise ratio (SNR) and unclean filtering issues. To improve the classification accuracy, a genetic feature selection algorithm was used in [6] paper along with SVM classifier that was suggested for the application of brain-computer interface (BCI) because of its better classification accuracy. BCI required a minimum of 70% classification accuracy of a subject for communication by BCI. Otherwise, the subject is called BCI inefficiency subject. In a paper [7], researchers acquired better classification accuracy using node degree and clustering coefficient features over typical spatial pattern (CSP) features with the BCI inefficiency subjects. The combination of CSP along with the node degree and clustering coefficient features resultant classification accuracy higher than 70% for a total number of 4 subjects out of 12 subjects. In another research [8], a group of researchers claimed that the empirical mode decomposition (EMD) method could better respond to detecting the mu rhythm during MI left and right-hand movement. For the recognition of the MI hand movements of motor impair person achieved outstanding classifier accuracy using SVM classifier where independent component analysis (ICA) was used to eliminate the noise signal of motor disable person [9]. These existing works exhibit a positive direction toward developing a proper MI event recognition system.

Due to the nonlinear and non-stationary nature of the EEG signal, it is very difficult to find out the proper classification method for the recognition of a specific MI task. A comparative study of different classifiers can assist to find a useful classifier that demonstrates better performance for a specific MI task. In this study, the performances of different classifiers were compared to find out an appropriate classifier that provides a better F1-score with the MI hand movement-related EEG data. To classify the MI data, SVM, LB, NB, and KNN classification algorithms were trained with different kernels. A total of 10 subjects were used to find out the minimum sequenced feature set and validate the extraction process. Twenty subjects were used in the training and testing of the EEG data. The results of the classification models were then analysed to find out the optimum choice of classifier that can perform MI detection accurately.

II. METHODS

A. *Data Collection*

The recorded motor imagery (MI) EEG data of hand movement was collected from a publicly available database known as “GigaDB”. The EEG data were recorded using 64 Ag/AgCl active electrodes where the sampling frequency was 512 Hz. The international 10-10 system was used for recording the EEG data. The EMG data were also recorded with two electrodes by placing on each hand to check the data of actual hand movements. Besides, different noise data, MI and non-MI events, sensor location, etc. also differentiated and stored separately. Each subject's data were stored in different variables inside a MATLAB structure with (.mat) file format [10]. Among the 52 subjects, 30 subjects were selected randomly from the dataset that included only MI left-hand and right-hand movement data. The MI EEG data are the primary concern of this study. The MI experimental setup of the collected data is illustrated in Fig. 1.

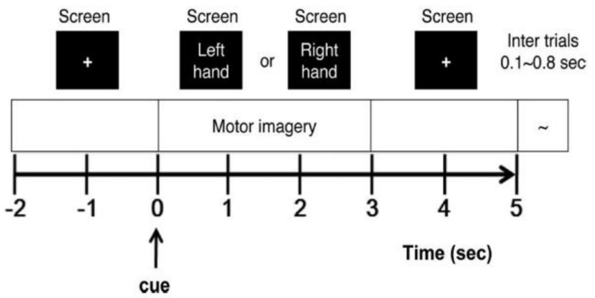

Fig. 1. The scheme of EEG data collection for one trial [10]

In the MI EEG data collection scheme, subjects were asked to imagine the hand movement according to the instructions that appear on a screen. At the beginning of the MI data collection process, a black screen appeared for 2 seconds. Then for the next 3 seconds, MI instructions were appeared to imagine the MI events. After that, a black screen reappeared for the next 2 seconds. A total time duration of 7 seconds described above was counted as one trial. The MI data collection process was completed after 100 times repetition of the trial procedure shown in Fig. 1. Finally, the MI EEG data were recorded for the total time duration of 700 seconds at each electrode [10]. Furthermore, these data were utilized for training with different algorithms and evaluate the performances of the algorithms.

B. *Data Processing and Annotation*

In the beginning, a high-pass filter above 0.5 Hz was used to remove drifts from all the MI EEG trials. After that band-pass filter with 8-14 Hz was used to identify bad trials from all the trials. The complex values of all the trials were replaced by absolute magnitude [10]. The EEG data were successively partitioned into non-overlapping frames. Manual data annotation was performed in order to mark the MI and non-MI event from the EEG data. With the manual annotation process, the MI event of the EEG data was marked and represented with the value “1” for 3 seconds time period of a trial, and the rest of the time of a trial was marked as the non-MI event and represented with value “0”. The annotation reliability was assessed with the kappa coefficient.

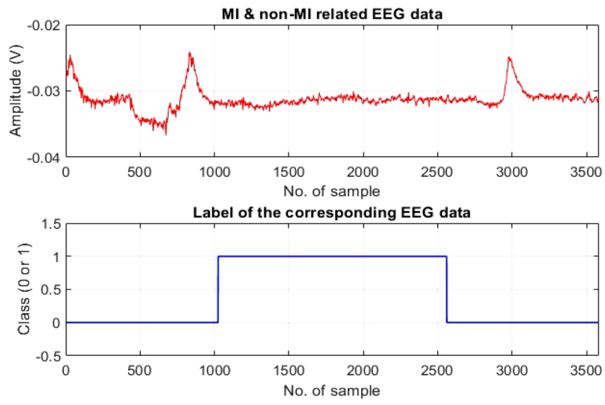

Fig. 2. MI and non-MI event-related EEG data of a trial

The EEG signal of a trial is illustrated at the top of Fig. 2, where it demonstrates the MI and non-MI EEG signal of a subject. At the bottom of Fig. 2, the corresponding EEG data label is provided to understand the portion that contained MI and non-MI event information from the top graph of Fig. 2.

C. *Feature Extraction and Selection*

Feature extraction was used to determine the characteristics of the EEG signal that may help increase accuracy for the identification, reduce dimensions of the EEG data, and generate a feature set from the EEG data [11]. In total, 17 features were extracted from the MI EEG data of each electrode that was the combination of time domain and frequency domain features. These 17 features were represented 700 seconds of sensory data of each electrode of a subject. The feature set data were normalized in the range of -1 to +1 to eliminate data redundancy. The details of the features that were used in this study are represented in Table I.

TABLE I. FEATURES EXTRACTED FROM MI EEG DATA

No.	Feature Description	No. of Electrodes	Total features
1	Mean Value		
2	Median Value		
3	Standard Deviation		

4	Mean Absolute Deviation		
5	Quantile25		
6	Quantile75		
7	Signal Interquartile Range		
8	Sample Skewness	64	17 x 64 = 1088
9	Sample Kurtosis		
10	Spectral Entropy		
11	Peak2Peak Value		
12	RMS Value		
13	Crest Factor		
14	Shape Factor		
15	Impulse Factor		
16	Margin Factor		
17	Signal Energy		

Feature selection algorithms find out the relevant features from a set of features that reduce complexity, computational time, and improve learning accuracy for the training model [12]. Among the 30 subjects, 10 subjects were randomly selected and only utilized for feature selection to maintain reliability. The correlated feature selection (CFS) algorithm [13] was used to identify the relevant features from the extracted feature set that were highly correlated to each other. Afterward, the features that were selected through the CFS algorithm, were ranked with the forward feature selection (FFS) algorithm to acquire the best set of features. Linear discriminant analysis (LDA) was utilized during the FFS process to acquire the ranked features sequence. Finally, the total number of 12 features were selected from 1088 features by following the two stage procedures.

D. *Classification Models*

The four mostly utilized ML classification algorithms namely SVM, LR, NB, and KNN were investigated to detect MI events in EEG data. The classification models are briefly discussed below:

a) The support vector machine (SVM) is a very popular machine learning (ML) technique that can maintain high accuracy with a reduced error rate. Recently, it is widely used for neuroimaging analysis where it exhibited a predictive balance performance. It is a supervised ML technique that has the flexibility to address a range of classification problems [14]. With the SVM, two dimensional problems can be solved by separating the cases using a hyper-line between them where it preserves a maximum distance from two classes. In this work, the SVM was applied with the MI EEG data to check the performance of the two classes problem in this study. A linear kernel was utilized during SVM classification for its simplicity and less complexity.

b) Logistic regression is a supervised ML technique that is widely used for analysing binary classification problems. It has the ability to handle many data mining challenges such as the problems of collinearity, missing data, redundant attributes and non-linear separability, etc. LR follows the same principle of linear regression [15]. Since the LR could introduce the overfitting problem, k-fold cross-validation was applied to eliminate the overfitting problem with the LR classifier.

c) Naïve Bayes (NB) is a simple ML technique to analyze classification problems in an effective and efficient way. NB can be constructed easily and it exhibits good performance in classification. It can outperform the C4.4 decision tree algorithm in the case of ranking [16]. An improved NB was utilized to classify the MI hand movement-related EEG data that competed with other supervised ML techniques in this study.

d) K-nearest neighbor (KNN) is a simplest supervised algorithm that classify new data point based on the similarity of the data points that are the nearest to each other. It has a great use for pattern recognition and categorization [17]. In this study, KNN was applied to the MI data where the value of "K" was set to 100. "K" is the number of nearest neighbors. The labels of the subjects' data were predicted by finding the nearest neighbor class.

E. *Performance Evaluation*

The performance of each subject was evaluated using leave one out cross-validation scheme that was applied with the EEG data during the classification of the models. At the time of the classifier's training process, 6-fold cross-validation was applied to the EEG data. Apart from 10 subjects that were utilized in the feature selection process, the rest of the 20 subjects out of 30 subjects were utilized for train and test the classification models. Among these 20 subjects, 19 subjects were utilized for training the classifier, and the left-over one subject was used to test the performance. The procedure was repeated 20 times and the F1-score of 20 iterations was averaged to obtain the accuracy of classification model performance.

Apart from the F1-score, the assessment of the classification models was also determined using a confusion matrix. The confusion matrix helps to evaluate the classification system by using the actual and predicted classifications data. The classification data were required to be organized in a matrix format [18]. Two-class classifier was used in the classification of this study. The confusion matrix uses some parameters to evaluate the performance of a model. The following parameters of the confusion matrix were used in this study:

[1] Positive (P) defined that the epoch (e.g. data segment) was MI event

[2] Negative (N) defined that the epoch was non-MI event

[3] True positive (TP) defined that the epoch was MI event and predicted as MI event

[4] True negative (TN) defined that the epoch was non-MI event and predicted as non-MI event

[5] False positive (FP) defined that the epoch was non-MI event and predicted as MI event

[6] False negative (FN) defined that the epoch was MI event and predicted as non-MI event

The performances of the models were evaluated using the following performance metrics:

- ***Accuracy:*** a proportion of the total number of actual correct prediction among all prediction. The following equation was used to calculate accuracy:

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

- ***Recall:*** a proportion of the total number of actual positive correct prediction among all actual positive classes. The following equation was used to calculate recall:

$$\mathrm{Re}call = \frac{TP}{TP + FN} \text{..}(2)$$

- ***Precision:*** a proportion of the total number of actual positive correct prediction among all positive prediction. The following equation was used to calculate precision:

$$\mathrm{Pr}ecision = \frac{TP}{TP + FP} \text{...}(3)$$

- ***F1-Score:*** offers the harmonic mean of recall and precision from the test data. It emphasizes on both recall and precision at the same time. It is helpful to evacuate the imbalance problem of recall and precision, and disclose it with a single score. The following equation was used to measure the f-measure or f1-score:

$$F - measure = 2 \times \frac{\mathrm{Re}call \times \mathrm{Pr}ecision}{\mathrm{Re}call + \mathrm{Pr}ecision} \text{.............}(4)$$

III. RESULTS

The result was generated based on the performance metrics such as accuracy, precision, recall, f1-score with SVM, LR, NB, and KNN ML algorithms. These performance metrics were utilized to find out the performance of 20 subjects with leave-one-out-cross-validation. To evaluate the subjects' overall performance, the average (Avg) scores of these 20 subjects are presented in Tables II-V. The standard deviation (SD) was calculated in order to measure the amount of dispersion of these 20 subjects.

TABLE II. THE PERFORMANCE OF THE SUBJECTS WITH SVM

Subject No.	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
1	84.29	90.95	70.33	79.32
2	70.71	63.46	74.67	68.61
3	75.86	83.59	54.33	65.86
4	64.71	56.71	74.67	64.46
5	79.29	71.59	85.67	78.00
6	84.14	80.00	84.00	81.95
7	65.86	58.31	71.33	64.17
8	72.43	66.07	73.33	69.51
9	67.29	57.87	87.00	69.51
10	72.71	62.41	91.33	74.15
11	65.71	56.44	87.67	68.67
12	62.57	54.30	80.00	64.69
13	73.14	62.44	93.67	74.93
14	70.86	61.59	85.00	71.43
15	67.71	62.01	63.67	62.83
16	62.29	54.33	75.33	63.13
17	73.43	69.66	67.33	68.47
18	73.43	64.77	83.33	72.89
19	77.86	69.44	86.33	76.97
20	59.14	51.31	91.33	65.71
Avg	**71.17**	**64.86**	**79.02**	**70.26**
SD	**6.77**	**10.05**	**10.08**	**5.60**

TABLE III. THE PERFORMANCE OF THE SUBJECTS WITH LR

Subject No.	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
1	83.71	91.15	68.67	78.33
2	70.71	63.69	73.67	68.32
3	73.43	84.76	46.33	59.91
4	65.43	58.06	69.67	63.33
5	79.00	76.47	73.67	75.04
6	83.71	79.25	84.00	81.55
7	64.71	61.57	47.00	53.31
8	73.14	68.30	69.67	68.98
9	67.29	57.91	86.67	69.43
10	75.14	65.37	89.33	75.49
11	66.29	57.02	86.67	68.78
12	62.71	54.63	76.67	63.80
13	72.71	63.39	86.00	72.98
14	70.86	63.71	74.33	68.62
15	66.86	63.18	54.33	58.42
16	63.14	55.30	73.00	62.93
17	70.00	74.19	46.00	56.79
18	75.86	70.15	76.00	72.96
19	77.00	67.96	87.67	76.56
20	60.57	52.32	90.33	66.26
Avg	**71.11**	**66.42**	**72.98**	**68.09**
SD	**6.49**	**10.11**	**14.10**	**7.38**

TABLE IV. THE PERFORMANCE OF THE SUBJECTS WITH NB

Subject No.	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
1	79.29	77.98	72.00	74.87
2	74.43	73.91	62.33	67.63
3	75.14	70.86	71.33	71.10
4	64.71	57.10	71.00	63.30
5	71.14	63.24	78.00	69.85
6	83.00	93.30	65.00	76.62
7	65.71	56.91	82.33	67.30
8	72.00	65.76	72.33	68.89
9	67.14	58.14	83.33	68.49
10	72.43	64.66	78.67	70.98
11	52.86	47.43	92.33	62.67
12	61.57	53.51	78.67	63.70
13	66.71	58.40	77.67	66.67
14	71.86	64.51	76.33	69.92
15	62.43	54.71	71.67	62.05
16	54.71	47.83	62.33	54.12
17	71.00	63.90	74.33	68.72
18	70.14	61.29	82.33	70.27
19	73.71	75.22	57.67	65.28

20	60.14	51.99	91.33	66.26
Avg	**68.51**	**63.03**	**75.05**	**67.43**
SD	**7.43**	**10.86**	**8.85**	**4.78**

TABLE V. THE PERFORMANCE OF THE SUBJECTS WITH KNN

Subject No.	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
1	80.43	89.00	62.00	73.08
2	67.43	63.14	57.67	60.28
3	74.57	79.61	54.67	64.82
4	65.57	58.45	68.00	62.87
5	74.14	65.62	83.33	73.42
6	84.71	87.55	75.00	80.79
7	64.29	55.92	78.67	65.37
8	72.00	66.46	70.00	68.18
9	67.43	58.33	84.00	68.85
10	71.71	63.86	78.33	70.36
11	61.86	54.78	63.00	58.60
12	61.14	53.33	74.67	62.22
13	69.43	61.14	78.67	68.80
14	69.71	62.72	72.33	67.18
15	65.86	59.44	64.00	61.64
16	57.14	50.00	59.67	54.41
17	75.00	70.36	72.00	71.17
18	71.14	62.37	82.33	70.98
19	72.14	69.81	61.67	65.49
20	59.43	51.52	90.67	65.70
Avg	**69.26**	**64.17**	**71.53**	**66.71**
SD	**6.69**	**10.53**	**9.74**	**5.80**

Table II-IV illustrate how each subject performed with different ML classification models and provide the average F1-score of each classifier. In terms of accuracy, the highest score was found 71.17±6.77% with the SVM classifier, and the lowest score was found 68.51±7.43% with the NB classifier. The other two classifiers LR and KNN scores were 71.11±6.49% and 69.26±6.69%, respectively. Though the LR classifier provided a higher precision value 66.42±10.11% than SVM, SVM provided a better recall score of 79.02±10.08%. The precision score of NB and KNN was almost close, which were 63.03±10.86% and 64.17±10.53% respectively, but a few numbers of difference could be seen between the recall score of NB (75.05±8.85%) and KNN (71.53±9.74%). On the other hand, the f1-score gradually decreased from SVM to LR (70.26±5.60% to 68.09±7.38%), and NB to KNN (67.43±4.78% to 66.71±5.80%). Subject no. 4, 7, 11, 12, 16, 20 tends to the poor scores in the maximum cases.

The average performances of different classifiers are depicted in Fig. 3 where it exhibits the performances based on four parameters such as accuracy, precision, recall, and f1-score. It is evident from the result (shown in Fig. 3) that SVM performed better than the other classifiers. It maintained the performance with all the parameters of 20 subjects. It has much popularity for its excellent generalization and categorization ability. LR also performed well showed better results than other classifiers except for SVM. Among all these classifiers, the lowest performance had been seen in the KNN classifier with an average f1-score of 66.71%. However, the NB classifier provided the result close to the KNN classifier illustrated in Fig. 3. Fig. 4 describes that the standard deviation of the performance of the subjects. It is evident from Fig. 4 that all the classifiers provide less spread out performances with accuracy and f1-score, and more spread out performances with precision and recall for the subjects. The recall data of the subjects are much spread out with SVM and LR.

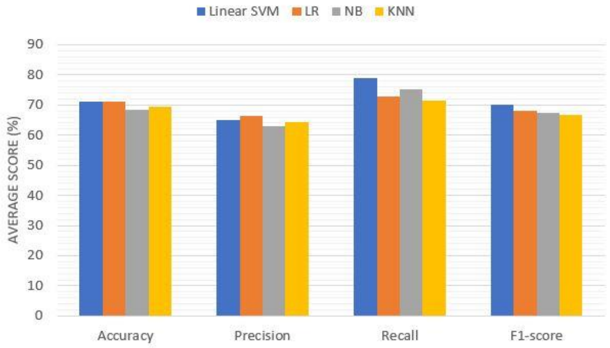

Fig. 3. Average scores with the subjects of different classifiers

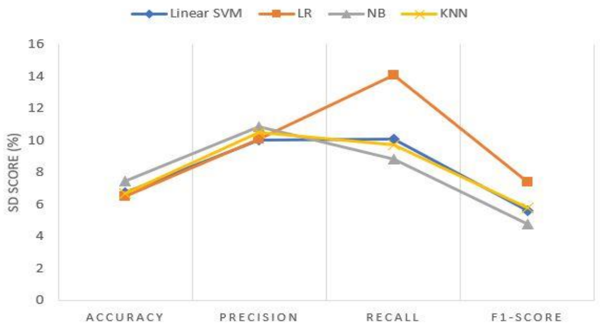

Fig. 4. Average SD score with the subjects of different classifiers

IV. DISCUSSION

The main goal of this work was to contribute towards the development of a MI event detection method in EEG signal as such method can be beneficial for disable individuals. An accurate detection system can enhance the life style of elderly and/or disable persons. Towards that goal, it is essential to extract important relevant information from the data and select a most important features set that may improve the performance of a classifier for detecting MI events in EEG data. Based on the selected feature set, the performance varies with different ML classifiers. This paper aims to provide a comparative analysis and find out the best performance among the most popular ML classifiers in detecting the MI hand movement-related EEG signal.

The subject's performance evaluation process includes SVM, LR, NB, and KNN classifiers. The best results were achieved with an average f1-score of 70.26±5.60% and accuracy of 71.17±6.77% with the SVM classifier. The result of LR provided less score (average f1-score 68.09%) with the subjects than the SVM classifier. Subject no. 3, 7, 15, and 17 is mainly responsible for the decrease of f1-score which is less than 60%. The NB exhibited more spread out results for the subjects where the fluctuation of the results was high with some subjects. This was the main reason for which the average performance of the LR was less compare to SVM. Therefore, it can be said that a lower SD score with the parameters could help to achieve better performances with the subjects. Though the NB classifier was provided less average f1-score and accuracy than the LR classifier, some subjects' result was improved compared to LR. Finally, the KNN provided the lowest f1-score among the classifiers. It is evident from the classifiers' results that SVM provided a more balanced result compared to other classifiers.

With the CFS procedure, 10 subjects were utilized to find out a better feature set. It was observed that the increase in the number of features in a feature set exhibited poor performance of the classifiers. It is expected as highly correlated features may lead to misclassifications. However, a feature set with an optimum number of features (12 features) helped achieve a better result with the classifiers. Though some classifiers provided poor f1-score, particularly, few subjects for which the quality of the data was not uniform. The wider population of the subject's data with the CFS procedure helped to generate better results for the subjects. Therefore, it is suggested from the result of feature ranking, better performance can be obtained if highly correlated features were removed.

The EEG data is very dynamic and unpredictable in nature. In most cases, it showed an imbalanced class problem with classifiers. To eliminate the imbalance class problem, f1-score was measured with the MI EEG data because it can penetrate the extreme values. From the classifiers' results, it was noticed that some subjects provided high accuracy but low f1-score. Therefore, it is suggested to account the f1-score with this category of data to avoid misleading of the subjects' performance. However, the accuracy and the f1-score were both measured in this study to understand the subjects' efficiency from the gap of the performances. One of the limitations of this method was that it was not optimized for the all subjects. Future work can be done including all available subjects. Another future work should be done to explore the effect of electrodes on the subject's performance. Therefore, it will be accounted for in future work so that the classifier can improve the performance and the classifier's computational time can be reduced.

V. Conclusion

This paper compares the four very popular ML algorithms in the case of the detection of MI hand movement-related EEG data. The method was evaluated in a wider range of population and brought success with the model. The highest score of a subject within the classifiers was captured in a range between 76% - 82%. Most of the subjects provide a balanced accuracy and f1-score with the classifiers. The result of the most popular ML techniques provides a better understanding for the detection of the MI EEG signal. The findings may contribute to select proper classifier that may suitable for the communication of the BCI.

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