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Improving Generalization of Motor Imagery EEG Model using Unsupervised Clustering Approach

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Abstract— ***Motor imagery electroencephalograph is nonlinear, nonstationary and high dimensional in nature. Due to which, the prediction of existing classification model across multiple subjects is limited. To improve the performance of the existing classification models across multiple subjects, a new preprocessing approach is presented in this paper. A hybrid feature selection approach is introduced to select the optimal number of channels followed by clustering. Clustering helps to explore shared brain activity patterns and their relationships to outside factors by detecting similar clusters among different subjects. In this study, four different classifiers are used to classify motor imagery electroencephalograph data. The proposed approach yields an accuracy of 99.6% using ensemble technique. Significant improvement is seen in the Logistic Regression. The results in this study indicate that generalization of motor imagery electroencephalograph across multiple subjects is possible using our proposed approach.***

Index Terms— ***Machine Learning, Brain Computer Interface, Electroencephalograph, Feature optimization, Clustering***

I. INTRODUCTION

Motor Imagery (MI) classification has received considerable attention in recent years but nevertheless confronts many difficulties, including multi-person and multi-class classification. The previous research work addressed the challenges like the limited availability of Electroencephalograph (EEG) training data and the high dimensional nature of EEG data. Another major challenge in MI classification is the non-stationary nature of EEG data[1][2][3]. This non-stationarity characteristic signifies that the temporal and spectral characteristics of the EEG signal vary with time. The individual differences in EEG lead to a loss of generalizability for classification systems across subjects (inter-subject task) and across different sessions for the same subject (intra-subject task). The traditional approach is to train new models using EEG data of each subject, which is very computationally very costly.

So far, numerous research efforts have been dedicated to accurately classifying MI data[4][5]. But none of them thoroughly investigated the crucial data structure that captures the real distribution of EEG samples. Machine learning models are data-driven, meaning that classification performance is determined by the data quality and how the training data is used to train the model. An EEG data set may contain amplitude values with varying frequencies, ranging from resting to super active. Suppose the training data for different frequency classes is not balanced. In that case, the classification model will show high accuracy for a specific class with a higher ratio than the other classes. Since EEG signals are highly non-stationary, varying from session to session and subject to subject, the model fails to generalize unseen data. This is due to the fact that the underlying data distribution structure is typically unavailable beforehand. Finding intrinsic patterns in EEG data could provide model learning more background knowledge and improve neural pattern decoding.

As a result, unsupervised techniques, such as clustering, are required to explore the intrinsic patterns present in EEG. With the increasing number of EEG signals without labels, clustering EEG signals is becoming an effective new technique for Brain Computer Interface (BCI) applications.

The conventional methods for analyzing EEG data rely heavily on the experimenter's capacity to remove outliers and identify peaks and waves that correspond to various neural processes because the EEG signal is typically high dimensional and noisy.

Unsupervised learning techniques has the ability to identify groups of subjects who share common MI EEG features. These methods do not use models that have been trained on labelled datasets, in contrast to supervised learning methods. Instead, they produce dense clusters of samples in a high-dimensional environment. There are two clustering algorithms: hierarchical and partitional clustering[6]. Hierarchical clustering creates a cluster hierarchy by dividing large clusters into multiple smaller ones, then combining the smaller clusters at their nearest centroid [7]. Conversely, the data collection is divided into a set of discontinuous groups using partial clustering, which lacks a hierarchical structure [8]. In this paper, we consider hierarchical and partition clustering algorithms to solve the problem of cross-subject EEG variation data.

To summarize, we investigate whether unsupervised clustering can be used to investigate cross-subject classification while achieving a degree of accuracy. Thus, in this article, we hypothesize that:

1. The performance of the MI classification in the case of cross-subject scenarios can be improved using methods for unsupervised clustering techniques.
2. How performance depends upon feature selection

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Vol 10, Issue 8, August 2023

algorithm used?

3. Classification accuracies are determined by the type of clustering technique used.
4. A hybrid feature selection approach is proposed as a preprocessing step.

This paper is divided into five sections. Section II discuss the related work. The proposed methodology is discussed in section III. Methodology is shown in section IV. The experimental verification and result analysis are discussed in section V. The results are discussed in section VI, and the conclusion is given in section VII.

II. RELATED WORK

To the best of our knowledge, multi-trial EEG clustering research is challenging because of its peculiarities and challenges. Very few studies are found in this domain[9][10]. Numerous research initiatives have been made to date to develop Common Spatial Pattern (CSP) variations that will increase the accuracy of reading EEG patterns. A filter bank CSP (FBCSP) [11] has been created to optimize the retrieved CSP features from several filter bands by utilizing the mutual information between the features. An extension of FBCSP called discriminant FBCSP (DFBCSP) [12] has been additionally developed to incorporate Fisher's ratio into the most discriminative filter bands, improving the separability of CSP characteristics between classes. Additionally, for better pattern separability, a sparsity-constrained filter band common spatial pattern (SFBCSP) [13] has been created. It explores a condensed set of multi-bands CSP features. There are few further CSP variations in the literature [14]. Although each of the aforementioned methods has demonstrated some promise in terms of enhancing the decoding accuracy to varied degrees, none of them has successfully investigated the crucial data structure that accurately captures the real distribution of EEG samples. Given that the distribution structure of data is typically unknown beforehand due to the fact that EEG signals are extremely nonstationary and exhibit significant trial-to-trial changes, a model created in this manner is likely to reduce learning performance[15]. However, to our knowledge, this is the first comprehensive analysis between classification and preprocessing + classification on MI EEG dataset. Further, we have also proposed a hybrid feature selection approach to select the optimal features.

III. PROPOSED APPROACH

In this section, we illustrate the proposed approach of this paper. The framework starts with a hybrid feature selection technique, followed by clustering. Finally, we adopt various classifiers to classify the trained EEG features.

A. Feature selection in the MI EEG dataset

One of the most challenging aspects of BCI is that it is individual-dependent. The solution to this issue is to use as many electrodes as possible. Using many electrodes, however, introduces additional issues, such as low classification accuracy, high computational complexity, and lengthy setup time in the case of BCI. Consequently, this means that channel selection is critical for EEG signal classification. The metaheuristic algorithms choose the ideal choice from a list of potential solutions based on a random search space. The problem can be defined in terms of its cost function, which is a function built using values from the search space as inputs and evaluates solutions. In order to find the best possible solution, a metaheuristic algorithm seeks a solution that satisfies the constraints of the cost function. According to the issue at hand, the optimal use of a cost function is to either maximize or minimize the aim. Each metaheuristic algorithm has two stages, such as exploration and exploitation. Maintaining a balance between these two phases is crucial for finding a global optimum and avoiding local optimums. Various scholars have proposed different meta-heuristic algorithms, such as [16]–[20] etc. To boost the effectiveness of metaheuristic algorithms, hybrid metaheuristic algorithms are suggested [21]–[24]. For the most part, metaheuristic algorithms that

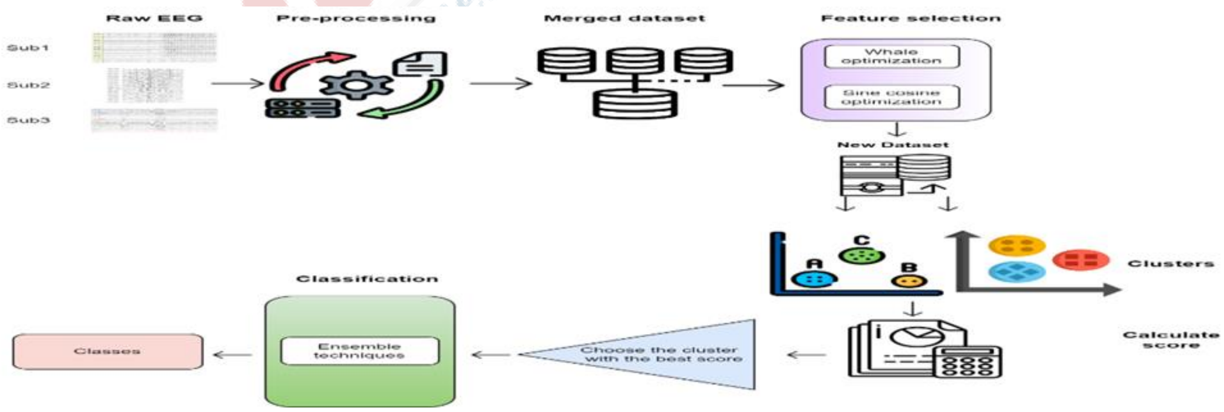

Fig 1. Proposed Framework for MI EEG classification

solve optimization problems combine two or more metaheuristic algorithms. Utilizing each algorithm's benefits

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while minimizing each algorithm's disadvantages is the main goal of hybrid metaheuristic algorithms. The balance between exploitation and exploration is typically applied in hybrid metaheuristic algorithms. Hybrid metaheuristic algorithms are suggested to balance these two phases because, as already mentioned, some algorithms perform well during exploration and exploitation. On the other hand, these algorithms have a significant convergence/accuracy trade-off[25]. This chapter combines two feature selection techniques: Whale optimization algorithm(WOA)[26] and sine cosine optimization algorithm(SCA)[27].

The use of the WOA algorithm has some disadvantages. Although it is efficient at locating the best solutions and has a straightforward implementation, it occasionally has difficulties locating solutions during exploration. The exploration stage of the algorithm is crucial for accelerating convergence and avoiding local optimum situations. As a result, algorithm performance is significantly impacted by exploitation. Trigonometric sine and cosine functions are used to enhance the SCA's exploration and exploitation phases. The algorithm has some drawbacks despite being straightforward to use and requiring few parameters. The drawbacks include poor exploration, low precision and slow convergence in some optimization problems. As an alternative, the SCA algorithm makes complex computational efforts to find an ideal and effective solution in areas of the search space that are not optimal.

B. Clustering techniques

As the number of unlabeled EEG signals increases over time, EEG clustering is emerging as a crucial new method for BCI applications. One of the most significant choices in cluster analysis is selecting the right cluster number. Different approaches to figuring out the ideal number have been proposed. Unfortunately, there aren't many studies on clustering unlabeled EEG time series except [28] [29][9]. They used an optimal objective function to find the cluster centroid on cross-correlations between candidate EEG trials and the cluster centroid. In this paper, we used two clustering algorithms: k-means++ and Fuzzy c means.

C. Machine learning models used for classifying MI EEG signals

This section presents a summary of machine learning models i.e., approaches that have been used in this paper for classifying MI EEG signals as shown in Fig. 1. In our work, 10-Fold cross-validation is used for validating the data. To evaluate the effectiveness of the predictions made by machine learning models, we used accuracy, precision, recall and F1 score. Models used include: Logistic Regression, Random Forest, Decision Tree and Ensemble Learning. Various studies [30][31][3] have explored the ensemble approach, several classifiers have been used for the classification of MI EEG signals but none of these have achieved good results. Zenobi et. al. [32] proposed an ensemble learning which takes the advantage of multiple classifiers. Mistake made by one classifier is compensated by another classifier.

IV. Evaluation Methodology

This section introduces the evaluation metrics used in our work to assess the quality of the clusters generated and the performance of the machine learning models on those clusters.

A. Metrics for assessing the quality of clusters generated

The clustering quality of the clustering algorithms is reflected in the compactness and scatter of the clusters. In light of these findings, we examined the three clustering quality measures: Silhouette score, **Calinski-Harabasz Index and Davies-Bouldin Index**

V. Experimental Verification and Analysis

This section presents the dataset description, experimental configuration, and the results of our proposed clustering-based ensemble technique.

A. Dataset Description

To find out how cognitive measures affect MI BCI performance, the Department of Cognitive Science and Artificial Intelligence at Tilburg University in the Netherlands conducted experiments. The 57 subjects (36 women and 21 men) who made up this dataset were recorded using the 16 electrodes (F3, Fz, F4, FC1, FC5, FC2, FC6, C3, CZ, C4, CP1, CP5, CP2, CP6, T7, and T8) suggested by the

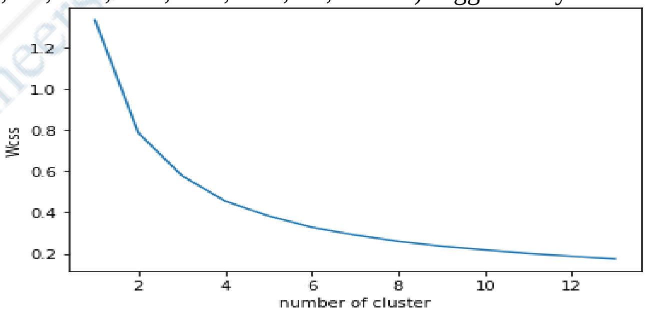

Fig. 2. Silhouette method to find an optimal number of clusters

10-20 system. However, we only used a dataset of 3 subjects for our research. The participants were instructed to visualize the movements of their left and right arms throughout the experiment. Four different runs of 40 trials each for each class were sampled at a rate of 250 samples per second. The total number of features is 18, where 0 denotes the first feature, and 17 is the last. As a result, a 17× S matrix with S standing for sample count is created as the entire training dataset.

B. Experimental configuration

This study used an Intel Core-i5 (2.60 GHz) computer with 8 GB of RAM for the experiments. In order to implement the

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Vol 10, Issue 8, August 2023

suggested method, we used the machine learning library sci-kit-learn and the Python programming language. To develop a generalized model which can work across more than one subject, we combined the datasets of different subjects into one. We conducted our experiment in three folds. In the first fold, we used feature selection techniques to remove the redundant features and select the most optimal ones only. The number of features selected by proposed hybrid feature optimization algorithms is shown in Table. I. After finding the most relevant features, we use two different clustering techniques in the second fold. The scores obtained are shown in Table II. We choose clusters with the highest scores. Finally, we use our proposed ensemble model in the third fold. Additionally, we contrast the clusters of our proposed ensemble model with some machine learning classifiers. The classifiers used are Logistic Regression, Random Forest, and Decision Tree.

C. Result

To gain insights about the impact of the clustering on the classification of MI EEG data, we compared classification with the feature selection + clustering + classification framework. We first evaluate MI EEG data using machine learning models. No pre-processing is done. Simultaneously, we select optimal set of features using a proposed hybrid model. After selecting the features, clustering algorithms are applied. The quality of the clusters generated by different clustering algorithms is assessed in the third step.

- Results obtained by machine learning models without pre-processing step: In this work, we applied Logistic Regression, Random Forest, Decision Tree and Ensemble technique using voting classifier on MI EEG dataset of three subjects. The results obtained are shown in Table I.

Table I. Shows the performance of the machine learning models without preprocessing

S.NO.	Machine learning models	Accuracy	F1-score	Precision	Recall
1.	Logistic Regression	53.75%	53.6%	53.7%	53.5 %
2.	Random Forest	95.97%	98%	96%	98%
3.	Decision Tree	98.7%	98%	99%	98%
4.	Ensemble technique	99.2%	99.3%	99.2%	96%

From the table, it is evident that the highest accuracy is achieved by ensemble technique. Logistic Regression showed worst performance. But the aim of our work is to analyze whether feature selection + clustering as a preprocessing step affects the classification performance or not.

- Features selected by Proposed hybrid feature optimization technique: To conclusively demonstrate the effectiveness of a reliable feature selection technique, we use hybrid feature selection technique called Whale Optimization Sine Cosine Algorithm (WOSCA) on the combined dataset of MI EEG. The number of features selected is shown in Table II.

TABLE II. Shows the optimal features selected

S.NO.	Feature Selection Algorithm	Total number of features	No. of Features selected	Features selected
1.	WOSCA	18	5	['timestamp', 'C4', 'CP6', 'F3', 'FC6']

From the Table II, it is evident that the hybrid feature selection technique selects total 5 features out of 18. Therefore, we will use only these features and remove the redundant ones.

In k-means++, three parameters influence the quality of the clusters generated. The three parameters include: distance measures, initial value of clusters and the number of clusters.

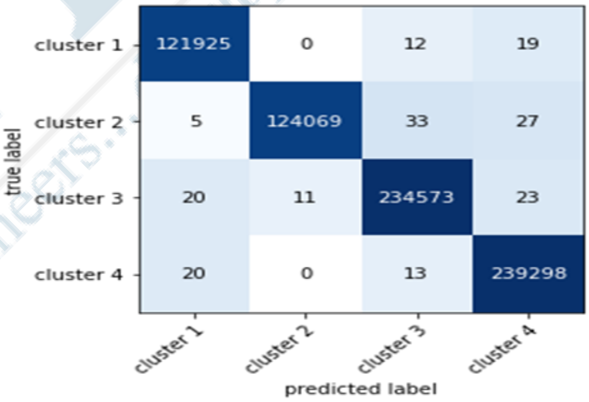

Fig. 3. Confusion matrix obtained using hybrid feature selection and k means++ technique.

The last two parameters are the most important hyperparameters. If we are able to initialize the values of clusters properly and select an optimal number of clusters to group the data points, then we achieve clusters with the best quality. In our work we initialized the clustering algorithm by using hybrid feature selection method. The proposed hybrid approach is successful in obtaining a set of optimal features. For finding the number of clusters in k-means++, we use silhouette method as shown in Fig. 2. It can also be used to find the consistency and the quality of the clusters generated.. In our method we found k=4, an optimal number of clusters for k-means++ whereas k=3 for Fuzzy c means clustering. From Table III, it is evident that the score obtained using k-means++ is 0.45. This means that the clusters are consistent and densely populated. The fuzzy c-means process

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Vol 10, Issue 8, August 2023

involves an additional parameter, commonly referred to as the fuzzifier, in contrast to k-means clustering. A data point is assigned fuzzy memberships to all clusters rather than being directly allocated to a cluster. As a result, it is feasible to reduce the impact of data items that are not part of a specific cluster, such as data points that are situated between overlapping clusters or data points brought on by background noise. Consequently, the cluster analysis becomes significantly more accurate with the addition of this new parameter. In our work, we obtained a silhouette score of 0.0006 using Fuzzy c-means clustering algorithm.

From the Table III, it is evident that the silhouette, **Calinski-Harabasz** score and **Davies-Bouldin Index** obtained using k-means++ algorithm is better than Fuzzy c-means algorithms on MI EEG dataset.

TABLE III. Shows the Scores obtained by different clustering algorithms

S.NO.	Clustering algorithm	Silhouette score	**Calinski-Harabasz** score	**Davies-Bouldin Index**
1.	k-means++	0.45	318767	0.851
2.	Fuzzy c-means	0.0006	1.44	0.89

We calculated classification accuracies on MI EEG dataset using feature selection followed by clustering. For classification, we used the same classifiers. The results obtained are shown in Table IV and the best results are highlighted in bold. The Table IV clearly yields that the accuracy achieved after applying preprocessing step is better than without using any pre-processing step.

TABLE IV. Shows the performance of the machine learning models using k-means++ as clustering algorithm

S.NO.	Machine learning models	Accuracy	F1-score	Precision	Recall
1.	Logistic Regression	99%	98.9%	99%	99%
2.	Random Forest	98.5%	98.3%	97%	98.4%
3.	Decision Tree	98.9%	98.9%	98%	98.9%
4.	Ensemble technique	99.6%	99.6%	99.2%	99.6%

Table IV illustrates the accuracy achieved by machine learning models when the features of MI EEG dataset were selected by the proposed hybrid feature selection method followed by k-means++clustering. Significant improvement can be seen in case of Logistic Regression. The best accuracy is achieved by ensemble learning.

TABLE V. Shows the performance of the machine learning models using Fuzzy c means as clustering algorithm

S.NO.	Machine learning models	Accuracy	F1-score	Precision	Recall
1.	Logistic Regression	33%	32.04%	33.5%	33.5%
2.	Random Forest	97%	96.6%	97.5%	97.4%
3.	Decision Tree	98%	98.1%	98%	98.2%
4.	Ensemble technique	99.3%	99%	99%	99.1%

VI. Discussion

To have a comprehensive impact of the feature selection and clustering on the classification performance, feature relevance and generalization, we compared the two pipelines-classification without preprocessing and classification with preprocessing. Feature selection can help in identifying the most relevant features present in MI EEG dataset. By comparing classification results with and without preprocessing (feature selection + clustering), we can get insights into which features are significant.

In this paper, we evaluate the generalization of the classification models. By combining the datasets of more than one subjects, we aim to introduce subject independent framework. In this way, a model trained on the data of one subject can be used on all other subjects as well. To demonstrate the impact of preprocessing on MI EEG dataset, we first classified MI EEG dataset without using any preprocessing technique using four different classifiers: Logistic Regression, Random Forest, Decision Tree and Ensemble technique. The classification comparison is shown in Table I. The results demonstrate that the ensemble technique outperformed the other three methods. However, logistic Regression performed very poor achieving an accuracy of 53.75%. To show the efficacy of pre-processing on MI EEG data, we also computed the classification of four different classifiers with the selected EEG channels followed by clustering. The feature selection is done using a proposed hybrid approach called WOSCA. The number of features selected are shown in Table II. Out of 18, the proposed hybrid approach selected 5 features. For clustering, we used k means++ and Fuzzy c means algorithm. The optimal number of clusters in k-means++ is found to be 4 where as in case of Fuzzy c means it is 3. The algorithms are successful in grouping similar EEG signals irrespective of the subject. The quality of the clusters is assessed using three different scores: Silhouette score, **Calinski-Harabasz** score and **Davies-Bouldin Index** as shown in Table III. It is evident from the table that k-means++ forms better clusters than Fuzzy c-means. The classification performance after preprocessing is shown in Table in Table IV. It is clear from the table that the classification accuracy is improved. By using only significant features, the model is able to generalize well on the unseen dataset. However, significant improvement can be seen in the Logistic Regression where the classification accuracy has increased from 53.7% to 99% using K means++. Surprisingly, the classification performance of Logistic Regression using hybrid feature selection and Fuzzy c means clustering degraded as shown in Table V. Therefore, after comprehensive analysis, it is clear that preprocessing improves the classification performance of MI EEG data.

VII. CONCLUSION

Unsupervised EEG clustering is a difficult but important task because there is an increase in unbalanced EEG data. In case of multi-subject EEG, clustering can help in identifying common intrinsic patterns. Inter-individual variability occurs due to the differences in the anatomy of brain. Moreover, removal of redundant features is a very crucial step in the classification of MI EEG data. It is because unnecessary features from noise, electrode disturbance etc degrade the performance of a model. Therefore, our work proposes a supervised approach to MI EEG classification. A data preprocessing workflow is introduced that can be applied to multisubject MI EEG datasets. It is done in order to explore the intrinsic structure captured by the proposed preprocessing step. For choosing the best features, we proposed a hybrid feature selection method. It is followed by clustering. From the results, it is evident that the proposed preprocessing approach have a significant impact on the performance of the classification models. Our approach is able to enhance the classification accuracy from 53.7% to 99% using Logistic Regression as classifier and 99.2% to 99.6% using an ensemble technique.

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