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Classification Algorithms of EEG Signals based on Motor Imagery

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ABSTRACT

This paper proposes a method for processing motor imagery-based Electroencephalography (EEG) signals to generate precise signals for Brain-Computer Interface (BCI) devices used in rehabilitation and physical treatments. BCI research is mainly used in neuroprosthetic applications to help improve disabilities. We analyze EEG data from seven healthy individuals using 59-channel caps. The signals are down-sampled to 100 Hz after pre-processing to remove artifacts and noise by using Filter Bank Common Spatial Patterns (FBCSP). EEG features are extracted using the Fisher Discriminant Ratio (FDR). A comprehensive comparison of classification methods is conducted, encompassing statistical techniques, machine learning algorithms, and neural network-based models. Specifically, Linear Discriminant Analysis (LDA) and K-Nearest Neighbors (KNN) are evaluated as statistical classifiers; Support Vector Machine (SVM) is used for the machine learning approach; and Radial Basis Function (RBF), Probabilistic Neural Network (PNN), and Extreme Learning Machine (ELM) are explored as neural network models. Model performance is validated using K-fold cross-validation and confusion matrix analysis. Among all evaluated classifiers, the ELM model—implemented as a single-layer neural network—demonstrates superior classification accuracy, suggesting its strong potential for real-time BCI applications in neurorehabilitation.

1. Introduction

Brain-computer interface (BCI) research has significantly advanced in recent years, with a primary focused on neuroproteins applications aimed to restoring lost functions such as vision, hearing and movement as well as assisting in the rehabilitation of individuals [1]. Brain activity can be monitored through various neuroimaging invasive and non-invasive techniques [2]. Among the non-invasive techniques, EEG has emerged as one of the most widely used due to its high temporal resolution, affordability, and ease of use [3].

EEG signals play a crucial role in diagnosis and treatment of neurological and neurodegenerative disorders [4]. However, despite their clinical importance, EEG recordings are often contaminated by various artifacts and noise sources which significantly compromise signal quality and hinder accurate interpretation [5]. The primary sources of the artifact are muscular activities, blinking of eyes during the signal acquisition procedure, and power line electrical noise [6]. Many signal processing methods have been introduced to mitigate these artifacts [7], including regression [8], blind source separation [9], and FBCSP [10].

In addition to pre-processing, the extraction and classification of EEG features are fundamental steps in EEG signal analysis. Although EEG signals inherently contain neural information, this data must be effectively categorized to be meaningful and actionable. Many

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studies have been devoted to improving EEG classification techniques. For instance, Khosla et al. [11] conducted a comparative analysis of EEG signal processing and classification approaches, while Lotte et al. [12] provided a comprehensive review of classification algorithms used in BCI systems. More recently, Aggarwal et al. [13] and Altaheri et al. [14] have explored machine learning and deep learning models, respectively, to enhance EEG classification accuracy. All these works produce precise, reliable, and accurate signals [15]–[17].
Various classification strategies have been applied in this domain, including statistical approaches, machine learning techniques, and neural network-based models. As for statistical methods, LDA [18] and KNN algorithm [19] can be mentioned. LDA makes models of the probability density function and KNN assigns a feature vector to a class based on its nearest neighbours [20]. Based on machine learning methods, Genetic Algorithm (GA) [21], Inductive Logic Procedures (ILP) [22], and SVM [23] are widely used for EEG classification. For example, Lokman et al. proposed a feature selection method based on GA to identify optimal features for decoding finger movement-related EEG signals [24]. Methods such as RBF neural network [25], ELM [26], and PNN [27] can be considered as the main neural network algorithms used for EEG classification.
In this study, EEG signals from seven healthy subjects are pre-processed using FBCSP to reduce noise and artifacts. Feature selection is performed using the FDR method, and the trials are classified using three approaches: a statistical classifier, a machine learning-based method, and a neural network-based model. Classification performance is evaluated using cross-validation (K-fold) and confusion matrices. Notably, the one-layer neural network demonstrates superior performance compared to the other methods.
The findings of this study highlight the importance of selecting an appropriate classification algorithm for accurate EEG signal decoding. In particular, the results suggest that the ELM algorithm is a highly effective and efficient choice for classifying simple EEG signals due to its strong performance and generalization ability.

2. Experimental Procedures

In this section, the experimental steps of EEG signal processing are discussed, from the initial stage of raw data collection and pre-processing, to the separation of frequency ranges necessary for rehabilitation and physical treatments, and finally to the feature extraction stage, which prepares the EEG signal for classification purposes. The classification approaches will be discussed in detail in Section 3. Figure 1 shows the overall block diagram of EEG signal processing.

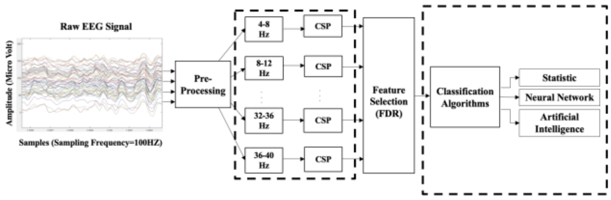

Fig. 1. Overall EEG signal processing.

2.1. Subjects and EEG Recordings

In this study, EEG signal has been collected from seven healthy individuals using a 59-channel cap, resulting in 59 EEG signals extracted from different points of the head. The signals were band-passed, filtered with a frequency between 0.05 and 200 Hz , and digitized at 1000 Hz with 16 bits. Recordings were performed using Brain-Amp MR plus amplifiers and an Ag/AgCl electrode cap. In this work, data were collected based on the data presented in [28].

2.2. Pre-processing

When collecting EEG signals from the brain, the electrodes used may interfere with each other and generate noise in the signals. Additionally, the data collected from the brain may not originate directly from it, which is known as artifacts. These artifacts can be physiological, generated from parts other than the brain, or non-physiological, caused by external factors. Proper pre-testing or examination design measures can help reduce physiological artifacts. Therefore, EEG signals may be contaminated by noise and artifacts from external sources, requiring pre-processing to remove them. To achieve this, we used the common average reference filter. This filter eliminates common noise across all electrodes, such as power-line interference, by subtracting the average signal from all channels, and emphasizes actual local brain activity while reducing bias from a single physical reference electrode. This filter functions as an upper-bound filter and is formulated as follows.

$$x_i^{CAR}(t) = x_i(t) - \frac{1}{C}\sum_{j=1}^{C} x_j(t) \tag{1}$$

where x_i^{CAR} is the value of the signal after going through the filter, x_i is the initial value of the signal, and C is the number of channels and electrodes.

2.3. Frequency decomposition

After removing the destructive effects of noise and artifacts from the EEG signals, which was done in the pre-processing step, these signals were divided into different frequency bands using FBCSP. FBCSP is a tool that automatically identifies the most discriminating frequency bands of EEG signals for tasks such as motion imagery classification. By combining these bands with spatial filtering, the accuracy of the BCI is significantly increased. The FBCSP algorithm combines the filter bank framework with the CSP algorithm. Therefore, using the CSP algorithm, from each frequency band, the EEG data are spatially filtered, and using a mutual information-based criterion, the most distinctive features are selected. The FBCSP algorithm consists of the following steps:
1- Spectral filtering: In this step, the EEG data is decomposed to nine equal bandwidths by using a filter bank. The higher frequencies (20Hz - 40Hz) can be used for rehabilitation and physical treatment purposes. These frequencies are derived experimentally.
2- Spatial filtering: This step uses the CSP algorithm to separate the data having coverage over each other and

divide them into two groups. Considering $x_b \in R^{n \times s}$ representing single-trial EEG going through the b_{th} band-pass filter, where *s* and *n* are the number of measurement samples and, the number of channels, respectively. The CSP matrix linearly converts x_b to Z_b spatially filtered as follows:

$$Z_b = W_b x_b \tag{2}$$

where W_b indicates the CSP matrix, and it is calculated by solving the following eigenvalue decomposition problem:

$$C_{b,1}\, W_b = (C_{b,1} + C_{b,2})\; W_b D \tag{3}$$

where $C_{b,1}$ and $C_{b,2}$ are the average covariance matrices of the band-pass EEG signal, and *D* is the diagonal matrix containing $(C_{b,1} + C_{b,2})^{-1} C_{b,1}$ eigenvalues. Usually, to filter spatially, only the highest and lowest eigenvalues, which are the first and the last m rows W_b, are used as the most discriminative filters.

3- The m pairs of CSP features corresponding to the i_{th} trial from the b_{th} filter are derived as:

$$f_{b,i} = \log \frac{diag(Z_{b,i} Z_{b,i}^T)}{tr(Z_{b,i} Z_{b,i}^T)}. \tag{4}$$

$f_{b,i} \in R^{1\times 2m}$ and $Z_{b,i}$ are the first and the last m row of the Z_b. Due to using the nine frequency bands, the i_{th} trial feature vector is:

$$F_i = [\, f_{1,i}, ..., f_{9,i} \,]_{1\times 18m}. \tag{5}$$

Remark 1. We selected $m = 2$, which means that two pairs of spatial filters are used.

Using this algorithm, we obtained a set of features that are ready to be processed by a classifier; however, it is necessary to select a subset of these features that are more effective on the signal characteristics. FDR is an effective feature selection method, which we will discuss in the next sub-section.

2.4. Selection of the most valuable features

After the extraction of the trial feature matrix, choosing the most valuable features is vital, and to do so, the FDR algorithm is used as follows:

$$FDR = \frac{(m_1 - m_2)^2}{S_1 - S_2} \tag{6}$$

where, m_1 and m_2 are the average of the features between class 1 and class 2, and S_1 and S_2 are their variance. By calculating the FDRs, they can be organized, and then the largest FDR indicates the signal with the most valuable feature.

3. Classification Approaches

In the previous section, the pre-processing and processing steps of the signal were discussed, and the most valuable features were extracted. By extracting the valuable data, the EEG signals are ready for classification. For this aim, three approaches, including statistical techniques, machine learning, and neural networks are used, and each approach is explained in more detail in the following section.

3.1. Statistics approaches

Statistical approaches are generally characterized by a probabilistic model that, rather than providing a classification, they calculate the probability of belonging to each class. Two main algorithms are used as statistical approaches in this work which are LDA and KNN, which are further defined as follows:

1- Linear Discriminant Function Analysis: The basic idea behind this method is to determine if the groups are different based on the mean of a variable and then use that variable to predict group membership. In other words, in LDA, the primary purpose is to seek those linear features that reduce the dimensionality and simultaneously preserve class separability [15].

2- K-Nearest algorithm: This method is a nonparametric approach classifying a given data point based on the majority of its neighbours. It consists of two main steps: first, finding the number of nearest neighbours, and second, classifying the data point in a specific class [17].

3.2. Machine learning approaches

Machine learning mainly focuses on automated computational methods by learning a task from several examples. The goal of machine learning when it comes to classification purposes is to create classified expressions that can be understood by humans easily. As with statistical approaches, background knowledge may be used in development, but operations are performed without human intervention.

The algorithm used in this paper regarding the machine learning approach is SVM. SVM is used to construct the optimal hyperplane with the most significant margin for separating data between two groups. For our two-dimensional data, a single hyperplane is enough to divide the data into two groups. Therefore, we use a kernel with a linear function in SVM to transform the data into a space where the two groups are linearly separated.

3.3. Neural Network approaches

Generally, a neural network consists of layers of interconnected nodes where every single node generates a nonlinear function of its input. To mimic human intelligence, neural network methods combine statistical techniques with machine learning. Since, this is performed unconsciously, there is no accompanying capability to clarify the learned concepts to the user [29]. The standard neural network algorithms used in this work are RBF, PNN, and ELM, where each can be defined as follows:

1- Radial Basis Function Networks: This network consists of three layers, with the middle (hidden) layer nodes being Gaussian functions. RBF networks are feed-forward and are good candidates for approximation problems, since they have faster learning capabilities compared to other feed-forward networks [23].

2- The Probabilistic Neural Network: PNN can be seen as a reformulation of kernel discriminant analysis. When there is an input, the first layer calculates the distance between the information and the input vector using learning. The second layer creates a probabilistic vector, and finally, a transfer function in the output of the second layer is constructed by choosing the highest probability and a positive value for the goal class, and a negative value for other classes is assigned [25].

3- Extreme Learning Machine: The obligation to repeat the neural network approaches makes the algorithms extremely slow; however, ELM has a single hidden layer on its structure and can select the input weights and hidden layer basis randomly and a much faster learning speed and better performance are obtained since it can reduce the risk of network being trapped in local optima [24]. In the simulations, we considered the ELM structure with one hidden layer consisting of 15 nodes.

Table 1 is provided to compare the mentioned classification algorithms and examine the advantages and disadvantages of each method.

Table 1- Comparing the classification algorithms

Classification method	Advantages	Disadvantages
KNN	- simple, - no training phase, - suitable for non-linear data, [30]	- slow prediction, - poor scalability with data, - sensitive to noise and feature scaling, - poor for high-dimensional EEG, [12]
LDA	- fast training and prediction, - high interpretability, - suitable for limited data, [31]	- Assuming the limitation of linear separability of the data and their Gaussianity - fails in complex nonlinear EEG patterns, [32]
SVM	- resistant to overfitting, - efficient for nonlinear EEG signals, - high accuracy, [33]	- slow to train (does not scale well with data), - sensitive to hyperparameters, - difficult to interpret, [34]
RBF	- superiority for complex nonlinear features of EEG signals, [35]	- extremely slow training, - sensitive to the parameter of step size, - probability of overfitting, [36]
PNN	- fast prediction, - noise-resistant, - providing probabilistic outputs, [37]	- memory-based (stores all training data), - slow training with large datasets, - less scalable, [38]
ELM	- extremely fast training (single-step computation), - scalability, - efficient for small data sets, - efficient for real-time BCI, [39]	- low interpretability (black-box model), - sensitive to initial random weights, - underfit probability for highly complex features, [40]

4. Validation Methods

In order to validate the three approaches studied in the previous section, we use two methods for validating the results: the K-fold algorithm and the table of confusion. In the K-fold method, all subsets except one- used in the testing phase for validation- are used for training. This method is repeated K times (K-fold), where each subset is used once for testing. Then, the cross-validation algorithm compares the result of the test classifier with the state of the original test features for validation, and this method is repeated several times, each time transmitting a vector into the test classifier. Finally, the results are averaged to produce a single overall classification accuracy, as follows [41]:

$$accuracy = \frac{1}{k_{\max}} \sum_{k=1}^{k_{\max}} [\frac{M(k)_{correct}}{M_{total}}] \times 100\% \tag{7}$$

where M_{total} is the total number of vectors to be classified, $M(k)_{correct}$ is the number of correct vectors in k iteration, and $k_{\max}$ is the number of folds.

The confusion table method is a table with two rows and two columns that reports the number of true positives, false negatives, false positives, and true negatives. This method provides a more accurate analysis than the K-fold method, especially when the data set is unbalanced. For evaluating the confusion matrix, one of the most informative measures is the Matthews correlation coefficient (MCC) [42].

5. Results

In this section, the accuracy of the results obtained from three classification techniques, including statistical, artificial intelligence, and neural network are calculated and then validated using the K-fold method and the confusion matrix. The outcomes of these approaches are compared, and the most suitable algorithm is selected. Various metrics such as sensitivity, specificity, precision, negative predictive value, MCC, F1 score, and accuracy are computed to validate and compare the performance of each algorithm. We chose K=10 for k-fold cross-validation since it balances computational efficiency with the reliability of the results. Thus, at each iteration, each fold containing 10% of the data represents a test sample, and finally, after sufficient iterations, the results are averaged. The validation results for the KNN algorithm are illustrated in Fig. 2. The results for precision are obtained higher than other methods for nearly all cases, resulting in the highest average for all cases. Sensitivity has the lowest value among the five cases, leading to an average of 77.14. The validation methods and subjects in Fig. 3 illustrated for LDA are considered the same as indicated in Figure 2. The average value of negative predictive is 82.2%, the highest value for the five subjects. The average accuracy validation result for the LDA algorithm is 80.14%. The lowest value of validation methods for half of the cases with the lowest average is specificity, with a value of 80%.

The SVM algorithm's validation results are shown in Fig. 4. It is seen that the average precision is 81.76% for all subjects. For case c, the specificity and sensitivity are both 82%. The average precision value is also reported as 80.16%, surpassing other validation methods. For the same number of subjects and validation methods, for the RBF algorithm, the validation results in Fig. 5 indicate an average accuracy of 78.42%. The negative predictive value, with an average of 80.55%, has the highest value for all cases except for case b. The normalized average values for MCC and F1 score are 0.577 and 0.77, respectively. Sensitivity with an average of 78.14 has the lowest average value compared to other validation methods. The validation results for PNN method are shown in Fig. 6. Considering the validation methods and the number of subjects, the same as previous algorithms, the obtained results for negative predictive have the highest average for four cases, with an average of 80.57%. The validation results for sensitivity, with an average of 78.57% have the lowest value among all the validation methods. The lowest value for both MCC and F1 score, with averages of 0.586 and 0775 respectively, is for subject b, and the highest value is for subject d. For the same validation methods and subjects, the validation results for the ELM algorithm in Fig. 7 indicate an average accuracy of 80.92%. The average precision value is 83.93%, having the highest value among other methods for six subjects. In comparison, sensitivity has the lowest value for nearly all subjects except case E, with an average of 79.42%.

According to the results of validation shown in figures 2 to 7, it is concluded that ELM is more accurate compared to the other methods of classification evaluated above. In Fig. 8, the accuracy of all methods is tabulated. The results show that ELM performed better compared to other methods, while LDA performed second best in terms of MCC, sensitivity, and negative predictive value. KNN performed worst among all of the validation methods. PNN and RBF performed nearly equally, with PNN showing a slight edge in certain validation methods. Therefore, it is concluded that ELM outperforms other classification methods. Conversely, KNN consistently yields the lowest average values across all validation approaches employed in this study. Nevertheless, methods with proven stability, such as LDA and SVM, are typically preferred for practical implementations.

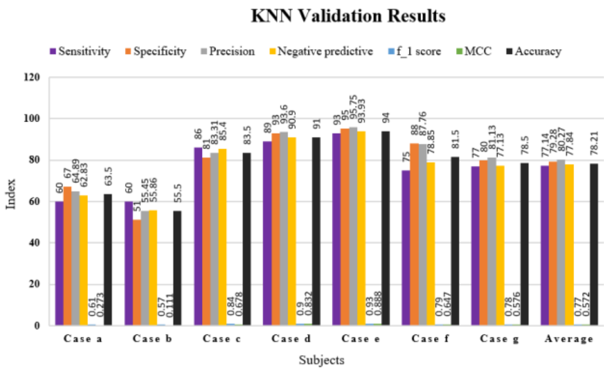

Fig. 2. The validation results for the KNN algorithm.

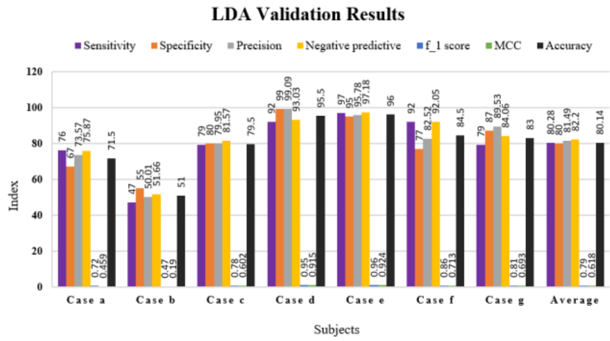

Fig. 3. The validation results for LDA algorithm.

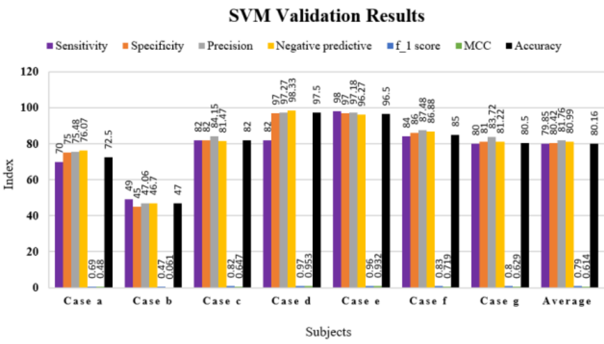

Fig. 4. The validation results for SVM method.

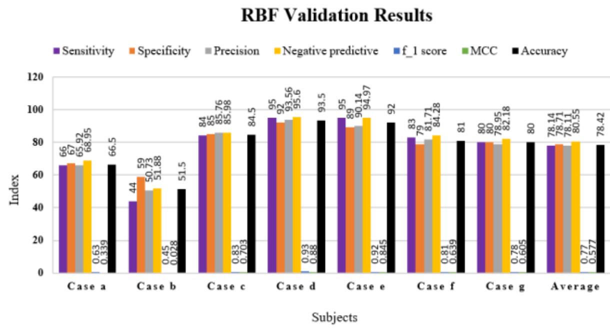

Fig. 5. The validation results for RBF method.

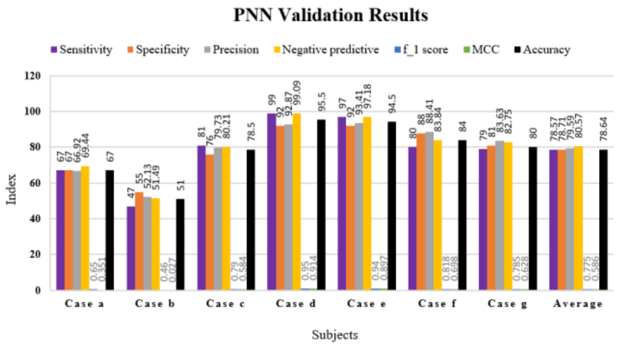

Fig. 6. The validation results for PNN method.

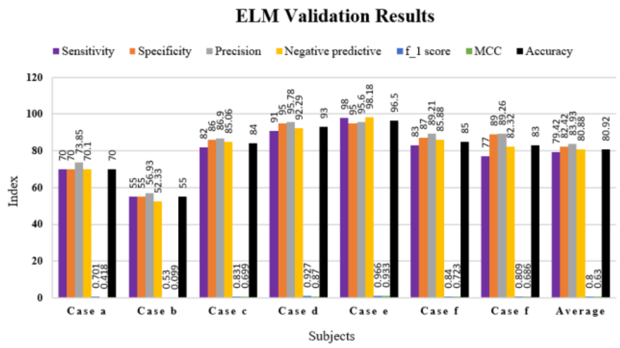

Fig. 7. The validation results for ELM method.

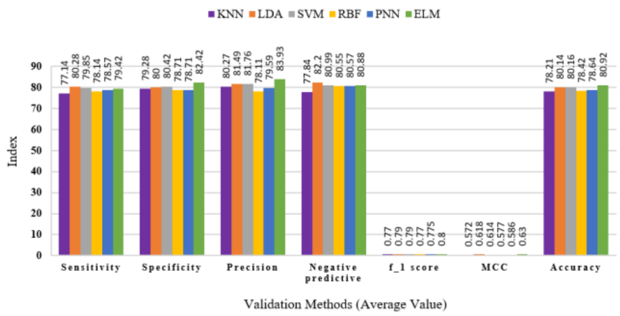

Fig. 8. The average values of validation methods obtained from KNN, LDA, SVM, RBF, PNN, and ELM algorithms.

6. Discussion and Conclusion

In this paper, our primary objective was to classify EEG signals from seven individuals accurately to obtain well-classified signals suitable for a BCI system. We aimed to determine which classification method yields the most accurate results. The EEG data used in our study were provided by [28] and consisted of data from seven healthy participants. The data were recorded using a 59-channel cap and down-sampled to 100 Hz. Pre-processing included initial low-pass filtering using a Chebyshev Type II filter of order 10 with a stopband ripple of 50 dB down and a stopband edge frequency of 49 Hz. Subsequently, the mean was calculated for blocks of 100 samples. The experiments were run in Matlab 2020b on a computer with two cores, 2.7 GHz CPU, and 8 GB RAM. Our study aimed to compare the accuracy of three different classifiers in classifying EEG signals while keeping other signal factors constant. These classifiers included statistical methods, neural networks, and machine learning techniques. The main findings of our research can be summarized as follows:

1- Among the statistical algorithms, LDA demonstrated superior performance to KNN, with accuracy rates of 80.14% and 78.21%, respectively.

2- When comparing the neural network-based algorithms, ELM outperformed the others with an accuracy of 80.92%, while PNN and RBF achieved accuracy rates of only 78.64% and 78.43%, respectively.

3- Comparing the three approaches, ELM demonstrated the highest superiority over other algorithms, achieving the highest accuracy. In the machine learning category, SVM was the second most accurate classification method, with an accuracy rate of 80.16%. Among the statistical approaches, LDA outperformed the remaining algorithms, while KNN showed the lowest accuracy among all the proposed methods.

Based on the results, ELM outperformed both statistical and neural network approaches in accuracy. ELM's superior performance can be attributed to its rapid training, robust conclusions, global applicability, and strong classification capabilities [43]. On the other hand, the results indicated that KNN performed less effectively compared to the different algorithms, since the performance of the KNN algorithm is influenced by various factors, such as distance metrics and the choice of k-value, which can significantly impact the classifier's performance. Therefore, further investigation of these factors is necessary when designing EEG signal classifiers to improve accuracy. As also mentioned in the study [44], the results of the multi-channel analysis indicate that KNN did not perform quite well in this matter [44]. The accuracy obtained for SVM, which leads to better results compared to KNN, is consistent with [45]-[48]. In addition, SVM also outperforms LDA, which can be attributed to the computational requirements of the LDA algorithm. In LDA, calculating the weight factors requires the estimation of the inverse of the covariance matrix. As a result, in cases involving higher-dimensional data with limited samples, the estimations of the covariance matrix and its inverse are less accurate and affect the overall performance of LDA [44], while the SVM algorithm does not depend on the covariance matrix and its inverse [49]. Additionally, the results of our work on the superiority of ELM compared to SVM and LDA are consistent with the results provided in [50]–[54]. In [50], which dealt with the classification of motor imagery EEG signals in a BCI system, a BCI competition dataset and a band-power feature extraction were used in experiments. The experimental results showed that the ELM method can obtain higher mutual information and classification accuracy with medium time consumption, compared with the LDA and SVM methods. [51] used a feature extraction algorithm based on the discrete wavelet transform and CSP methods in combination, which simultaneously utilized time-frequency domain information as well as space domain. The classification results of extracted features using LDA, ELM, and SVM methods showed that ELM has higher classification accuracy and a faster learning rate. [52] has proven that the ELM method is more efficient than SVM for various pattern recognition applications, since in this method, in addition to minimizing the training error, the output weights norm is also minimized without the need for iterative tuning. In [53], phase features were proposed to be used in motor imagery classification. A surface Laplacian filter was applied to remove the background, and a genetic algorithm was used to select sub-features. The results showed that classification by ELM performed better than classification with LDA. [54] proposed a novel semisupervised locality-preserving graph embedding model for learning a low-dimensional embedding. Experimental results showed that their proposed approach achieves higher classification performance compared to benchmark methods such as LDA and SVM on various datasets.

Since RBF requires high-dimensional subsets for better performance, it can be concluded that it is improper for methods with few features [55]. Furthermore, PNN inevitably increases the classification time, decreasing its usefulness in real-time applications [56].

While this study demonstrates the superiority of ELM in accuracy, its critical advantage for real-time BCI applications lies in its computational efficiency. ELM trains several times faster than traditional iterative methods (e.g., SVMs, deep networks) due to its single-step solution. On the other hand, due to its single-layer structure and simplicity, the ELM method is compatible with EEG signals, which are signals with low complexity. EEG signal features (e.g., band-power shifts) often require less hierarchical abstraction than image/video data, making ELM's fast and shallow processing sufficient for key discrimination patterns. Unlike Convolutional Neural Networks (CNNs) or Long Short-Term Memorys (LSTMs), which require large data sets, complex training, and heavy resources for hierarchical spatio-temporal modeling, ELM offers real-time adaptation with minimal latency, which is crucial for real-time BCI applications. Also, unlike CNNs or LSTMs, ELM avoids costly backpropagation and hyperparameter tuning. Thus, these features of speed, simplicity, small sample efficiency of ELM, and consequently minimal resource requirement make this method suitable for EEG signal classification and BCI applications.

It is worth noting that although ELM is superior in speed and simplicity for small and feature-based EEG datasets, deep learning methods are more suitable for raw signal modeling despite higher computational cost. In other words, the use of hybrid or deep models may be preferred in richer multi-modal tasks [57].

Future work should rigorously benchmark ELM against CNNs, LSTMs, and hybrid models (e.g., CNN-LSTM) in terms of accuracy, training speed, use of various datasets, and resource utilization for BCI tasks. This will determine whether ELM is efficient enough or whether deeper models—despite their higher complexity—justify their cost for critical real-time performance gains. In addition, the small sample size of this study limits statistical power and carries the risk of overfitting. Also, reliance on a single dataset restricts generalizability across different EEG paradigms or populations. These constraints motivate future studies and validation in larger groups and multiple datasets.

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