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EEG Signal Classification in BCI Using New Evolutionary Optimization of Instantaneous Frequency Features

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ABSTRACT

Brain-computer interface (BCI) systems, a branch of human-computer interaction (HCI), are normally adopted to create a direct communication pathway between the brain and external environments. Existing BCI methods struggle to deal with high-dimensional EEG features and computational complexity. This paper introduces a new feature optimization strategy for this struggle, called Evolutionary Strategy for Feature Selection with Dimension Reduction (ES_FSDR), in the EEG classification model. The ES_FSDR employs machine learning techniques to select the most related features by a new representation of evolutionary strategies in a subset of features and hybridize them by reducing the features' dimensions for the least amount of complexity and efficient operation for this subset of features, which consequently affects the EEG signal classification performance.; this strategy is applied to instantaneous frequency features in signal processing. This strategy aims to learn robust and meaningful feature representations for the BCI classifiers. ES_FSDR is particularly useful in EEG no stationary signal processing situations involving numerous features and high dimensionality. Individually, participants completed five different mental activities while 15 EEG channels were chosen to create a baseline. Mental tasks include "dynamic imagery," e.g., hand motor imagery (HAND), feet motor imagery (FEET), and "non-dynamic imagery," e.g., mental word association (condition WORD), mental subtraction (SUB), and spatial navigation (NAV). Both within-day analysis and between-day offline modeling investigated classification of five distinct mental task imagery from nine users with disability central nervous CNS system impairment for the available dataset from BNCI Horizon 2020. Findings demonstrate how effectively the suggested model increases accuracy obtained using multi-classification in the dataset within a day, which is around 98.31%. And between a day dataset, the results are around 95%. Moreover, the model that is suggested outperforms the classifying accuracy compared with other different performance methods.

1. INTRODUCTION

Certain mental activities have an exact and predicted effect on spontaneous electroencephalogram (EEG) rhythm alterations. This indicates that a person can produce unique EEG patterns on their own, regardless of sensory input. Such EEG patterns are recognized by brain-computer interfaces (BCIs), which then use them to trigger actions. For an overview of BCI technology, see the studies [1-3].

Nature is our constant source of inspiration for our research. Since humans acquire a significant amount of information through their eyesight, scientists are interested in learning more about the neurological processes in the brain and the regions involved. Since imagination is a cognitive tool humans possess, it makes sense that BCI technologies would seek to leverage any opportunities to improve the brain's ability to communicate with the computer it controls. For this reason, we continue to investigate the potential applications of visual imagination in BCI systems. With positive outcomes, several different BCI control techniques investigations have effectively concentrated on evoked potentials, including the SSVEP control method and P300 [4, 5] or on event-related potentials such as the application of motor imagery technique [6-8] within the creation of several valuable applications [9, 10]. And mainly used to modulate EEG patterns for the participants to use the EEG signals for exoskeleton control in rehabilitation applications [11, 12]. Each of these instances demonstrates the rapid advancement of BCI technology about motor signals.

"The manipulation of visual information that comes not from perception but from memory" is one definition of visual imaging as another control BCI technique [13]. The ability to detect and classify mental imagery for visual imagery would make it easier for a BCI to be used in more applications like classifying shapes [14], classifying 12 different images of objects [15, 16], classifying different pictures of words from daily life [17, 18], Decoding Visual Images for Controlling Drone Swarm Formation [19], which could benefit individuals with mobility issues by enabling them to overcome physical limitations and perform artistic works or explore their creativity [20-23].

In the field of BCI, the main goals are to develop new applications for augmentative communication and support people with functional limitations who have lost their ability to move their body bodies [24-29], Our objective in conducting this research experiment is to show how compelling mental tasks imagery in the creation of Brain-Computer Interface (BCI) systems using EEG signals and its use in studies classification mental tasks that incorporate both "dynamic imagery" for motor imagery tasks and "non-dynamic imagery" for non-motor (cognitive) imagery tasks.

This work's remaining sections are arranged as follows: Several variations on the theme are discussed in Section 2. Section 3 provides an explanation of our methodology for the proposed model using a new feature optimization method (ES_FSDR). Section 4 presents the results and directions. Finally, Section 5 presents the conclusions and future work.

2. RELATED WORK

The proposed method [30] addressed the challenge of high-dimensional EEG feature spaces by combining feature extraction and selection methods to enhance mental imagery for the classification of motor imagery (MI) tasks. A high-dimensional feature vector is then created by combining the retrieved features. To reduce dimensionality while preserving discriminative features, three feature selection techniques are employed: Multi-Subspace Randomization and Collaboration-Based Unsupervised Feature Selection (SRCFS), Minimum Redundancy Maximum Relevance (mRMR), and Correlation-Based Feature Selection (CFS).

The selected characteristics are supplied into classifiers, such Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), and Multi-Layer Perceptron (MLP) for MI task classification. Among these, the SRCFS method combined with the LDA classifier demonstrates superior accuracy on benchmark datasets.

The use of the study [31] modified binary grey wolf optimization (GWO) and wavelet packet decomposition for classifying mental imagery for motor imagery signals has been studied. Researchers have seen positive outcomes in terms of categorization accuracy for two subjects by combining these two approaches. Still, the accuracy rate for every subject was left out.

In the study [18], the research explores a hybrid approach combining convolutional neural networks (CNNs) and genetic algorithms (GAs) for mental imagery for visual imagery EEG signal classification. EEG features were extracted using Power Spectral Density (PSD) within the alpha frequency range and formatted into matrices to emulate image data for CNN input. GAs optimized neural network hyperparameters, including layer configurations, activation functions, and training parameters. The classification performance was compared across CNN+GA, SVM, LDA, and RF, with CNN+GA achieving the highest accuracy and demonstrating significant potential for mental imagery-based BCI systems.

In the study [19], the research examines the use of mental imagery for visual imagery in EEG-based BCI to control swarm drone formations. Six subjects performed four visual motion imagery tasks—Hovering, Splitting, Dispersing, and Aggregating—using a 64-channel EEG system. Data were preprocessed using band-pass and notch filters and the Common Spatial Pattern (CSP) technique, which focuses on the alpha band (8–13 Hz), was used to extract features. Classification was performed using various models, including LDA, SVM, and ensemble methods, with LDA achieving an average classification accuracy. This approach highlights the potential of visual imagery for intuitive drone swarm control.

In the study [16], the research utilizes a public EEG dataset to classify mental imagery for visual imagery (VI) and visual perception (VP) utilizing Black Hole Algorithm (BHA)-optimized CNNs. EEG signals were collected using a Brainvision actiCHamp amplifier EASYCAP with 64-channels., following standard preprocessing methods, including filtering, normalization, and Independent Component Analysis to remove artifacts.

The CNN architecture, which autonomously extracts features from EEG data, was optimized through BHA to identify the best structure for classifying EEG signals. The framework also explores transfer learning to reduce user training fatigue by leveraging VP data to classify VI signals, thereby demonstrating its feasibility for brain-computer interface applications.

In the study [32], this research investigated the impact of individually adapted mental imagery tasks examines the functionality of EEG-based brain-computer interfaces (BCIs) for those with severe disorders. Participants completed five mental activities in two different sessions, including non-motor imagery, word association, mental subtraction, spatial navigation, and motor imagery of the hand and feet.

EEG signals were recorded using a 30-channel setup, with preprocessing to remove artifacts and optimize signal quality. Common spatial patterns (CSP) and Fisher's linear discriminant analysis (LDA) were employed for feature extraction and classification, respectively. The research demonstrated that user-specific task combinations significantly enhance classification accuracy by evaluating the variability of classification performance within and between days. The findings support the importance of personalized task selection for improving BCI accessibility and reliability for end-users with functional disabilities.

Prior studies have mostly concentrated on using different machine learning and deep learning techniques, numerous features extracted from the signal, and its many dimensions problem was used either by feature selection methods or by dimension reduction methods with or without pre-selection of EEG signals channels in mental imagery.

Our working idea is to enable the EEG signals to classify mental task solutions by addressing this problem by proposing a new feature evolutionary computational optimization method: Evolutionary Strategy includes Hybrid (camping) Feature Selection with Dimension Reduction (ES_FSDR) methods. This proposed strategy has the potential to impact the EEG classification model performance significantly, which is especially true when the dimensionality reduction is within a pre-selected feature set -at the individual level - of signals by evolutionary methods for representing individuals and development operations initially based on instantaneous frequency features by processing the signal for pre-selected channels. This improves the fitness of the selected individual for EEG signal classification.

3. METHODOLOGY

The operational framework by offline modelling of our model for classifying signals generated by various mental tasks is shown in Figure 1. It provides a thorough explanation of the main procedures followed in the present research; the steps are as follows:

Step 1, the pre-processing procedure for multichannel EEG recordings, involves choosing the specific channels, bandpass filter was utilized to determine the 8–35 Hz frequency band of the EEG signal, segment the EEG data into trials based on event trials for participants, and normalize each segment.

Step 2, the EEG signal trials are decomposed into subsets using a filter bank, which dissects the signal into its frequency components through Gabor filter banks. Instantaneous frequency features are extracted from each subset using the Hilbert transform (HT) approach.

The remaining steps are for the proposed Evolutionary Strategy (ES_FSDR) to optimize the features of the EEG signal. Because the main contribution of it considers many sides in the same strategy by integrating the feature selection with dimensionality reduction at the chromosome (solution) level with machine learning techniques, thus, the solution becomes stronger. As different to what is typically occurring at the population level, these methods consider one-sided of feature selection or dimension reduction (e.g., genetic algorithms).

Step 3: Select potential features using the individually evolutionary selected subset to derive an optimal feature vector for each participant's trials.

Step 4, the final reduced feature vector, obtained by using the reducing dimensions technique, plays a crucial role in the subsequent classification process.

In Step 5, the classification process, such as LDA, SVM, and MLP classifiers, values this selected feature subset's fitness.

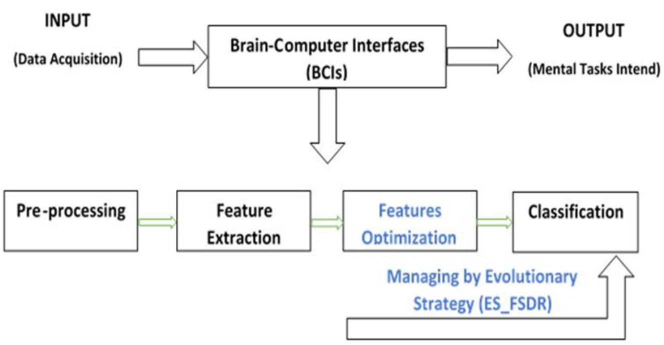

Figure 1. Framework of our model for the classification of mental tasks EEG signals

3.1 Dataset description (participants and recordings)

EEG data from nine disabled users (Seven women, aged between 20 and 57, median age 38, SD=10) were collected over two days for five mental tasks. The tasks comprised mental word association (condition WORD), subtraction (SUB), spatial navigation (NAV), right-hand motor imagery (HAND), and foot motor imagery (FEET). Experimental details are provided in Figure 2. Each session had eight runs with 40 trials per class per day. A run had 25 cues, with 5 for each task, presented randomly.

EEG was captured using 30 scalp electrode channels following the international 10-20 system. Electrodes were positioned at channels AFz, F7, F3, Fz, F4, F8, FC3, FCz, FC4, T3, C3, Cz, C4, T4, CP3, CPz, CP4, P7, P5, P3, P1, Pz, P2, P4, P6, P8, PO3, PO4, O1, and O2.

The g.tec GAMMAsys system is incorporating g.LADYbird active electrodes were employed to acquire data, uses 256 Hz as the sample frequency.

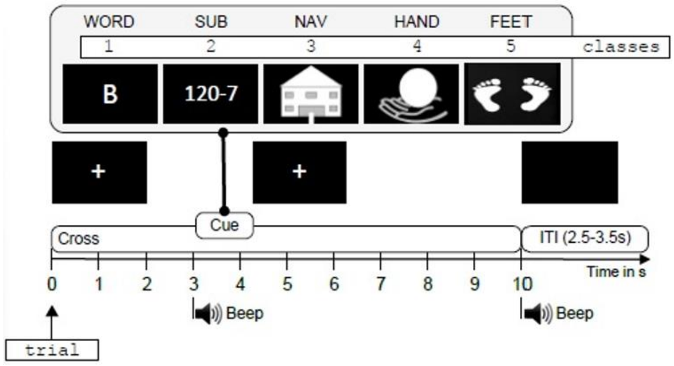

Figure 2. The experimental technique involves motor and non-motor imagery tasks

The experimental paradigm involves imagery trials lasting 10 seconds with a cross at t = 0 sec. Participants focus on the cross without moving their eyes. A beep at t = 3 sec grabs attention, followed by a graphical cue at t = 3-4.25 sec. The second beep at t = 10 sec ends the trial. Inter-trial intervals of 2.5-3.5 sec occurred. The subjects were told to move during ITI and avoid moving during imaging. A 4-second blank screen was displayed at the start and finish of runs [33].

3.2 Pre-process the EEG signals

The EEG data were somewhat pre-processed by filtering from 0.5 to 100 Hz using a notch filter at 50 Hz when we collected them [34].

The first stage in this process in our research was channel selection, which aimed to reduce the time and computational complexity [35-53], reduce setup time in specific applications, and develop a channel selection mechanism for activities of mental tasks imagery, hence decreasing the amount of over fitting that will result from the use of unrelated channels. By the employment of 15 channels, we choose P7, P5, P3, P1, Pz, P2, P4, P6, P8, PO3, PO4, O1, O2 F3, and F4. Most of these electrodes on the occipital region of the skull are driven by the observation that this specific area is intricately linked to the process of human visual perception [18, 47]. Additionally, some electrodes from the sensorimotor region, which are strongly connected to the brain for movement imagery-based BCI [31, 33].

A bandpass filter was utilized to eliminate noise from the original EEG signal. Because the raw EEG commonly contains various types of artifacts such as eye blinking, sudden sound, muscle and body movements, and environmental noises. Moreover, specific narrowband components of the EEG signal are particularly responsive to certain tasks. Hence, it is not unexpected to observe the utilization of certain sub-bands instead of the entire EEG bandwidth. Thus, this study concludes that the wider 8-35 Hz EEG signal frequency range is appropriate for the job. Related research indicates that 7 Hz to 36 Hz is when most of the brain activity related to movement imagining activities takes place [30, 35]. This frequency range is the region in which noticeable effects occur during visual tasks [18, 36].

Our experimental approach for the broader 8-35 Hz frequency band involved primarily four corresponding narrowband signals notably the low-beta (13-22 Hz), high-beta (22-35 Hz), and Mu-band (8-13 Hz). Then, we divide the signal into fixed-size segments, creating and averaging periodograms for each segment. Segments are normalized to zero mean and maximum absolute value to remove bias and scale differences and then saved as frames.

3.3 Feature extraction

Feature extraction is a key part of any BCI system. In actual production and life, most of the signals are not stationary and nonlinear. For no stationary processes, instantaneous frequency is a feature that cannot be ignored [37]. A filter bank of bandpass filters is used to produce a single-valued frequency signal by dissecting it into its frequency components [38]. Gabor filter banks are utilized for their smoothness and optimal compactness in both temporal and frequency domains.

The real signal is transformed into the complex domain to create the analytic signal, which is then built for each band pass output waveform. This method is used because it allows the real input to be described in terms of its instantaneous frequency [39]. Given a real input signal s[n], mathematically speaking, it's the formula for computing an analytical signal is:

$$s^{[n]} = s[n] + jH\,[s[n]] = s[n] + js^{[n]} \tag{1}$$

where, $s^{[n]}$ is the quadrature signal, and s (t) is the linear operator Hilbert transform (HT). We used this transform because it is helpful in the analysis of non-stationary signals. It may describe frequency as a rate of phase change, allowing it to fluctuate with time. We used the instantaneous frequency of the EEG signal. Phase f (t) can be computed using the EEG and analytical signals as direct computation of the signal's instantaneous frequency (IF) from phase yields the following results [38]:

$$f\,[n] = \frac{1}{2\pi} \cdot \frac{d\phi[n]}{dt} \tag{2}$$

3.4 Feature optimization

EEG signals frequently contain useless information due to their complexity and the use of several electrodes in their collection. One of the most important tasks in BCI is discarding such information. The performance of a BCI system is directly affected by its features, and recent research has concentrated on developing new or better methods. Due to their enormous dimensions and low feature effectiveness, there are many extracted features from the multiband that are not advantageous for classification and add to the computational complexity, which lowers performance. In actuality, certain trials usually degrade the efficiency of machine learning algorithms.

To address this problem, the proposed evolutionary strategy (ES_FSDR) is applied to feature optimization. Evolutionary Computation (EC) is an efficient and intelligent optimization methodology inspired by the behaviors of some organisms and the mechanisms of biological evolution [48].

3.4.1 Evolutionary computing (EC)

Evolutionary computation (EC) is one computational intelligence model used to mimic the phenomenon of biological evolution. Genetic algorithms (GA), evolutionary programming (EP), evolution strategies (ES), and genetic programming (GP) are the four algorithms that make up EC at the moment. In research on self-adapting control, American researcher Holland proposed GA in the 1950s. In the 1950s, the American researcher Holland proposed GA. In the 1960s, American researcher Fogel developed EP to study the finite-state machine of artificial intelligence. ES was developed by German researchers Rechenberg and Schwefel to handle numerical optimization problems simultaneously. In order to study the automatic design of computer programs based on the GA, the American researcher Koza proposed GP in the 1990s.

Although different scholars proposed the four algorithms for various purposes, their computing processes are similar and can be described in steps as follows.

a) One group of initial feasible solutions are created;

b) The properties of the initial solutions are evaluated;

c) The initial solutions are selected according to their evaluation results;

d) The next generation of workable solutions can be obtained by conducting evolutionary operations on the chosen solutions;

e) The computation will end if the workable solutions found in the previous phase are able to satisfy the requirements. If not, the computation process goes back to step b and the workable solutions found in the previous step are used as the beginning solutions.

Generally speaking, EC is a global optimization method that possesses the following features:

(i) The process starts from a group rather than a single point;

(ii) The search process only uses the objective function;

(iii) The search process uses the random method.

As a result, this approach offers the following benefits: It is (i) incredibly flexible and applicable to a wide range of problems; (ii) capable of solving highly nonlinear and nonconvex problems; and (iii) has a high degree of plasticity and ease of deserialization.

In essence, A typical complex optimization is figuring out a geometrical constitutive model. One well-liked global optimization method for figuring out the geomaterial constitutive model is EC [51].

The general pseudo code for Proposed Strategy, as in Figure 3.

Proposed evolutionary strategy (ES_FSDR) for optimizing EEG signal features

Input: Feature matrix

Return: The optimized feature set with the highest accuracy rate of classification

1. Initialization:

- Set parameters for the (ES_FSDR) Strategy, including population size, chromosome length, mutation rate, and maximum generation numbers.

2. Generate Initial Population:

- Randomly generate the initial population of chromosomes; Integers representing the locations indicates.

3. Evaluate Population Function:

- Initial the chromosome for evaluation, based on the chromosome's genes, select a subset of features corresponding to the values of locations indicated in the original set of all features of trials.

- Dimensionality Reduction, as part of the evaluation method, Reduces the feature space to a lower-dimensional representation to improve classification performance by applying the (LDA) algorithm on the selected feature's subset,
- Splitting the data into Training and Testing sets, in our research as follows:
  - Within one day-Divide the reduced dataset into a 50% training set and a 50% testing set within the dataset from one day
  - Within two days- Divide the reduced dataset into a 50% training set all from the first day and a 50% testing set all from the second day.
- Training on the classifier, training the model by using (SVM) or (LDA) or (MLD) classifier on the training set.
- Calculate the fitness of each chromosome: the accuracy rate of classification on the testing set of EEG signal is the fitness value of the chromosome based on the Misclassification Rate

  Accuracy Rate=1−Misclassification Rate

  (The correctly classified instances out of the total instances),

  Fitness = 1 / (1 + Accuracy rate).
- Store the return fitness value for all chromosomes.

4. Selection Function:

- Calculate cumulative probabilities based on fitness values.
- Use a roulette-wheel selection mechanism to select chromosomes for the next generation.
- Return the selected population.

5. Mutation Function:

- Introduce random mutations to the selected chromosomes based on the mutation rate.
- Perform mutation on the current population and predicted mutated population.

6. New Population:

- Replace the old population with the new mutated population.

7. Strategy (ES_FSDR) Loop:

- Run the Strategy (ES_FSDR) for steps 3, 4, 5, and 6 until you reach the maximum of generation numbers.

In each generation:

- Evaluate the population.
- Calculate selection probabilities.
- Perform selection to create the selected population.
- Perform mutation on the selected population.
- Replace the old population with the new mutated population.
- Find the fitness values and the maximum fitness value for each generation.

The proposed Evolutionary Strategies (ES_FSDR) for Optimizing can be considered contributions to Hybridization feature selection with dimensionality reduction in machine learning techniques. Let's break down your contributions in more detail:

- Focused exploration: Mutation-only Evolutionary Strategies can facilitate a more focused and detailed search of the solution space by generating variations to solutions using only mutation operations, which is advantageous in scenarios where small incremental changes are more effective than large-scale recombination, especially when simply adjusting representing chromosomes as means of choosing the optimal features for EEG brain signals in our method with integer numbers and maintaining the strategic balance by excluding the crossover process, hence simplifying the traditional evolutionary strategies and reducing computational complexity, particularly in situations where crossover does not significantly contribute to exploring the solution space or when recombination is not beneficial in the problem domain.
- Integration dimension redaction methodology: This adds a new pretreatment stage in the traditional evolutionary strategy by hybridizing it as a dimensionality reduction technique before assessing classification accuracy for the chromosome that generates. The most discriminative information of features for EEG brain signals is preserved along the dimensionality of the feature set is reduced with the aid of the dimension reduction technique and tuning its parameters, which can enhance the effectiveness and performance of the classification model.
- Improved fitness evaluation: Improved fitness evaluation occurs when LDA diminishes the feature set before the fitness function-based classification accuracy is computed. The fitness function becomes stronger because LDA focuses on maximizing the separation between different classes, which can lead to better generalization and higher classification accuracy.
- Evaluate the classifiers of the distinguished dataset: - which consisted of five mental task scenarios mixed with dynamic and non-dynamic imagery tasks. This strategy was applied to data that had not been used frequently by previous studies. The dataset was divided into two distinct sets, on a single day to what extent is the classification stable in a day? And in two days How well does a model trained on the first day do on the second day's unseen data? This testing set's objective is to evaluate the performance of the using LDA, SVM, and MLP classifiers created by using the suggested evolutionary strategy in the process of finding the best features. Utilizing the best classifier on the testing dataset is the result.

All the above contributions passed significantly with the initial contribution, which was described in session 3-1 during the pre-processing stage for selecting the suitable channels for our activity shared all of these above contributions.

3.4.2 Linear Discriminant Analysis (LDA) for Dimension Reduction

It is crucial to realize that not every variable that may be collected through suitable measurements in a high-dimensional data set is used to analyze the underlying region of interest [40].

Reduced data dimensions can be achieved by distinguishing a collection of significant characteristics that are closely related to specific significant criteria. The influence of the lowered dimensions is essential in the classification process. The overall volume of trials is around 200(714810×30) samples for each patient in one day. Which becomes 200 trials * (30 pandas of frequencies * 30 EEG channels) each day for each participant a features matrix of instantaneous frequencies. For the EEG signals to be processed smoothly, it is therefore imperative that the data's dimensions be reduced.

For one day, each participant's trial matrix feature vectors with 200*900 features were reduced to 200*2 by using our (ES_FSDR) strategy to choose the features and reduce their dimensions.

One popular technique for lowering dimensionality is Linear Discriminant Analysis (LDA) [41]. It is discovered that there is an orientation P that condenses feature vectors from several or higher classes into a low-dimensional space. Thus, if the decrease in dimensionality is from a b-dimensional (Rb) space to a c-dimensional (Rc) space (where c < b), then supporting, then by maximizing the Fischer's criterion function Z (P), the orientation P's magnitude may be easily determined. Three crucial parameters are involved in determining the criteria function: the orientation P, the within-class scatter matrix (SP), and the between-class scatter matrix (SB).

It is essential to take into account a multiclass pattern recognition and classification problem with e-classes to determine the LDA specifically. The collection of "e" class labels is represented by Ω= {Pi: 1, 2… e}, where Pi stands for the i th class label. Fischer's criterion as a function of "P" in these circumstances can be expressed as follows [40].

$$Z(P)=\frac{|P^T S_B\, P|}{|P^T S_P\, P|} \tag{3}$$

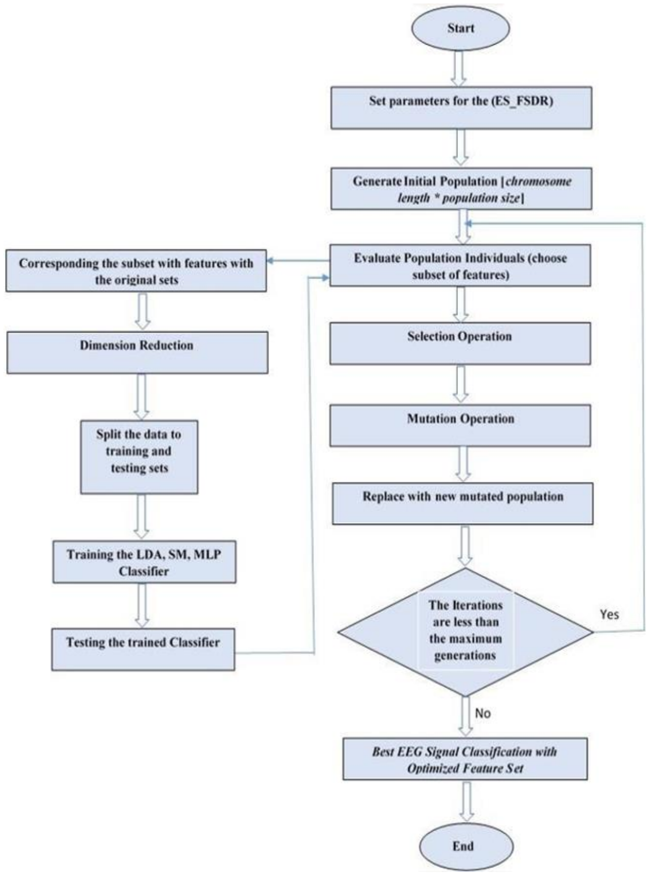

Figure 3. (ES_FSDR) strategy

3.5 Classification Employing SVM, MLP, and LDA

In this research, we classified and identified five distinct imagined objects that a person might conceive using, well-known and advanced machine learning-based classification methods. There are three prominent and sophisticated machine learning-based classification algorithms: LDA, SVM, and MLP. The objective is to determine and assess which can yield the best results.

Fisher's LDA classifier uses a linear hyper-plane classifier. LDA uses a line to represent high-dimensional data and thresholds the data to classify the projected one-dimensional space. The projection minimizes variance within each class while maximizing the distance between the means of the two classes. For further information about LDA, see the study [42].

Vapnik created the SVM, a relatively new classification technique. It has a strong mathematical basis in statistical learning theory and has demonstrated efficacy in a number of real-world scenarios. Especially those using BCI. It employs a nonlinear map to convert a higher-dimensional row of training data. It looks for the best linear division hyper plane, which is also referred to as a "choice border" that divides the tuples of one class from another inside this new dimension. Data from two classes can always be divided into an appropriately big dimension using a hyperplane and good nonlinear mapping.

With the help of support vectors, the SVM locates this hyperplane (the "essential" training tuples) and margins. These two approaches are described in detail in studies [43, 44, 49].

A well-liked machine learning algorithm, MLP is an effective tool for categorizing brain activity. Usually, characteristics taken from EEG or other neuroimaging data are fed into the MLP. After that, these features are sent through several tiers of networked nodes, each of which processes the input data using a mathematical process. The MLP's output layer represents the anticipated class label for the input data. Using methods like backpropagation, the MLP's weights are adjusted during training to reduce the discrepancy between the actual and anticipated results. But given the MLP architecture's size and complexity, as well as the relevance and quality of the input data, have a significant impact on their performance [45, 46]. The experiment's hidden layers have a size of twenty.

4. RESULTS AND DISCUSSION

Brain-computer interfaces (BCIs) based on EEG signals can utilize imaginations for different mental tasks. These devices facilitate direct communication between the brain and external devices without needing peripheral nerves and muscles. BCIs interpret brain activity patterns to translate user intentions into commands for device control, whether mental imagery focuses on motor activities like hand or foot movements or others on non-motor, like imagining objects or scenes for tasks such as menu selection or virtual environment control.

In this research, we examined how mental task pictures affected the multiclass classification performance of rarely utilized datasets combining dynamic (pictures refer to motor movements) and non-dynamic tasks in individuals using brain-brain interfaces who had CNS tissue damage, such as those who had suffered stroke or spinal cord injury (SCI).

Healthy persons typically attain a binary classification performance of about 75% when using a brain-brain interface. Generally speaking, users with CNS tissue injury do worse, and researchers in this field have previously performed binary classification on this dataset [32], seeking how mental tasks affected the binary classification performance of brain-brain interface users who achieved a binary classification score (65 to less than 85), concentrating on the traditional MI task pair (hand–feed) mental motor imagery effect from. As mentioned in Table 1, other methods in references were used for comparison with our Strategies (ES_FSDR).

Our proposed method for a performance with many classifications focused from the beginning on carefully selecting the most effective channels for mental tasks imagination , as well as focusing on effective degradation ranges for motor imagination channels, continuing to reduce dimensions when selecting good features by (ES_FSDR) strategy, since research that uses dimension reduction at the beginning and directly may lose good features that we need to enhance the classification and thus strengthen the model, as we noticed, this stage is necessary for our strategy, as shown in Figure 4. On the one hand, this was. However, by the strategy's chromosome representation to an integer representation and ensuring that it is compatible with hybridization through the use of the dimension reduction technique, the strategy's balance was maintained by being content with the mutation process without requiring the crossover process.

Table 1. A Proposed strategy (ES_FSDR) comparison with other methods

Ref.	Method	Sub. No.	Mental Tasks Imagery	Mean of Subject Accuracy
[30]	CSP+ SRCFS+ LDA	5	Mental tasks imagery includes “dynamic imagery,” 2 classes (left and right motor imagery)	Binary classifications 90.05% ± NR
[31]	WPD+ GWO+ KNN	2	Mental tasks imagery includes “dynamic imagery,” 3 classes (right hand, left hand, both feet)	92.86% for first Subject (a) and 91.5% for second Subject (b) 92.18% ± 0.96%
[18]	CNN+ GA	5	Mental tasks imagery includes “Non_dynamic imagery,” 3 classes (house, airplane, dog)	60.5% ± NR
[19]	CSP+ LDA	6	Mental tasks imagery includes “Non_dynamic imagery,” 4 classes (Hovering, Splitting, Dispersing, and Aggregating)	83% ± NR
[32]	CSP+ LDA	9	Mental tasks imagery (bnci-horizon) includes “dynamic imagery” and “non-dynamic imagery,” 5 classes (hand, feet, word, subtraction, and navigation)	Binary classification for 9 Subjects between 65% to 85% ≈75.0% ± 6.7%
Our proposed model includes a new strategy ES_FSDR	IF+ ES_FSDR+ LDA	9	Mental tasks imagery (bnci-horizon) includes "dynamic imagery" and "non-dynamic imagery," 5 classes (hand, feet, word, subtraction, and navigation)	Multi-classification for 9 Subjects: Within a day [98.8, 98.3, 99.0, 98.5, 97.5, 97.2, 98.4, 98.8, 98.3]. 98.31% ± 0.60%; Between two days [90, 98, 91, 96, 95, 93, 94, 97, 97]. 94.56% ± 2.79%

Note: Values are reported as mean ± standard deviation (SD) across subjects; a smaller SD indicates greater consistency/robustness. NR = not reported; (*) estimated from the reported range - e.g., our within-day SD = 0.60%, indicating excellent stability

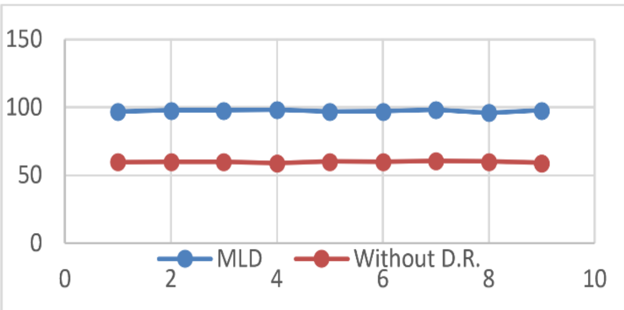

Figure 4. A proposed strategy with and without dimension reduction D.R

Figure 5. Accuracy rate in the day and between days

Figure 5 shows high results, reaching 98.31% within one day and about 95% within two days for categorization performance on five mental tasks using EEG data captured on nine individuals, each of whom completed 400 trials over two days.

Due to this, choosing the technique for reducing dimensions plays a crucial role in analyzing data with high dimensionality in our hybrid strategy, particularly in improving classification accuracy rates in mental imagery in brain signal data, where the challenge lies in handling multiple dimensions effectively. I can't deny LDA analysis's superiority in classification and dimensionality reduction. The accuracy rates for all participants in the three classification methods, LDA, SVM, and MLD, were 98.31 and about 97.5 for both SVM and MLD. Figure 6 illustrates how the classification results were divided by distinct results in LDA despite the excellent results we obtained from all classifications, with a slight difference between the three types of classification and the nine people who participated in obtaining the data. In addition to the coordinated formulation we have suggested, a plausible explanation might be that the EEG pattern's categorization becomes more dependable when a suitable blend of dynamic and non-dynamic mental tasks is included [32]; we were able to classify and identify five different imagined things that a person imagines, integrating imagination for dynamic and non-dynamic (sensory and cognitive not sensory) tasks, tasks, our results demonstrate the efficacy of the hybrid approach feature selection and dimension reduction in (ES_FSDR) strategy. This method offers a new communication conduit between the brain and the external environment.

And ultimately, recognizing that a limitation encountered pertained to the adjustment of parameters during the dimensionality reduction process within a chromosome, it necessitates that we align or correspond the length of the chromosome with the quantity of experiments conducted. Consequently, the dimensionality reduction process is rendered efficient and yields favorable outcomes in classifying brain signals.

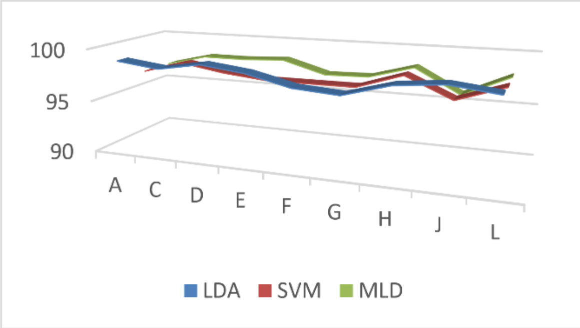

Figure 6. After proper processing in pre-processing and IF for feature extraction of the EEG signal from all classifications

5. CONCLUSIONS AND FUTURE WORK

To sum up, this research looked at how choosing a combined dynamic and non-dynamic mental activity affected the functionality of BCIs based on images in patients with impairment to their central nervous system. Previous studies did not frequently use this dataset.

According to the research's findings, the new strategy that made use of evolutionary computing was successful in both reducing dimensions at the chromosome level (as opposed to what is typically reported as occurring at the population level) within the features selection and in also strengthened the validity function of the final solution which was represented of elevated categorization efficacy across five cognitive tasks utilizing EEG data collected from nine subjects over two days, the stability of classification within a single day as well as the performance When applied to unknown data from another day, the results of a model learned on one day are crucial factors to consider.

Furthermore, end users with functional impairments are classified using various classification methods, such as LDA, SVM, and MLP, demonstrating the dominance of LDA in brain signal classification, its high-performance level, and its role in dimensionality reduction.

It is advisable to first model in real time by segmenting the incoming EEG stream into a specific time window, e.g., 2 s, then normalizing and applying a band-pass filter bank (8–32 Hz) and extracting the instantaneous frequency (IF) per channel–band to form a feature vector. The ES_FSDR-selected feature indices are then applied, followed by LDA projection and classification (SVM/MLP/LDA). Second, employ this strategy with a different dimension reduction technique and try tuning its parameters. And last try to apply this strategy to something other than brain signal classification.

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