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# Improving the Accuracy of Motor Imagery in BCI for the Movement of Artificial Prostheses used for Disabled People

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## Abstract
A brain-computer interface (BCI) allows users to communicate directly with an external device, such as a computer, using brain signals. These systems involve signal acquisition, temporal and spatial filtering, feature engineering, and classification before transmitting the control signal to an external device. Brain-computer interfaces based on motor imagery (MI-BCI) hold significant potential for applications in motor enhancement and rehabilitation. However, the control capabilities of MI-BCI can vary among individuals. In this article, we present a motor imagery model that leverages the power of deep learning for feature extraction and optimization methods for feature selection, based on individuals' electroencephalogram (EEG) signals. For this purpose, we employed the convolutional neural network (CNN), the golden eagle optimization (GEO) method, and three hybrid classification models to achieve high accuracy in classifying EEG signals. The innovative classification method presented in the third phase of the proposed method has high flexibility and significant accuracy, which is presented for the first time. This method can be used in all matters of prediction and detection of phenomena to increase accuracy and high scalability. The experimental results demonstrate that the proposed model significantly outperforms baseline approaches across all key performance indicators. In terms of precision, the method achieves an improvement of approximately 12–18% over standard CNN and nearly 20% compared to conventional classifiers. For recall, it yields 10–15% higher performance than CNN and 18–22% higher than classical machine learning methods. Finally, the F-measure results indicate a 12–15% improvement over CNN and about 20% over traditional classifiers. These consistent enhancements confirm the robustness and scalability of the proposed approach for motor imagery-based EEG classification and highlight its potential for practical applications in rehabilitation and prosthetic control systems.

**Keywords:** Brain-Computer Interface; Motor Imagery; CNN; GEO.

## 1- Introduction

An electroencephalogram (EEG) is a signal that records brain activity and provides a wealth of physiological information to physicians. The data extracted from the EEG signal is of significant importance in clinical research and medical care. One of the most effective and promising applications of the electroencephalogram is its use in brain-computer interface (BCI) technology, which has the potential to greatly contribute to technological advancement and shape the future. A brain-computer interface is a device that serves as an intermediary between the brain and another object, transmitting brain information to a computer and then to an external device. In essence, a BCI system comprises a set of sensors and a signal processing unit that forms a direct connection between the brain and an external interface, converting an individual's brain activity into a series of communication or control signals [1, 2].

In motor imagery-based BCI (MI-BCI), users can control or move virtual or real objects without physically touching a mouse, keyboard, or other objects, using only their mind in conjunction with the computer, which acts as the interface between the brain and the object. These interfaces come in various types and are used in different ways. To operate such a system, electrical activity and brain waves must first be recorded using brain wave recording devices. Electroencephalography is commonly chosen for this purpose due to its high accuracy, low cost,

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and ease of use [3]. Signal recording with an EEG device relies on a non-invasive method, which stands in contrast to other signal recording techniques that require implanting a chip or electrode inside the human brain. In the non-invasive approach, EEG electrodes are placed on the surface of the scalp to measure the electric field produced by neuronal activity. Subsequently, these waves are analyzed to extract relevant features, which can be used to infer the user's intended activity.

Although the speed and accuracy of these systems have not yet reached an optimal level, and BCI-related equipment requires further research, EEG signals are prone to errors due to various types of noise. One of the most common sources of artifacts is the electrocardiography (ECG) signal and noise from the power supply of the equipment. To achieve high accuracy in diagnosing and processing EEG signals, it is essential to generate signals that are free from noise and artifacts. Therefore, their removal is of great importance [4]. Motion imagery (MI) is a mental representation of motor behavior and a widely used paradigm in electroencephalogram-based brain-computer interface (BCI) systems. Currently, due to the extensive use of BCI systems that rely on movement perception to assist patients with physical disabilities, rehabilitate injured individuals, control virtual reality environments, play computer games, and more, enhancing the performance of these systems is crucial and necessary [5].

Various conditions can cause damage to the neuromuscular system, which enables the brain to communicate with and control the external environment. Diseases such as amyotrophic lateral sclerosis (ALS), stroke, brain and spinal cord injuries, cerebral palsy, muscular dystrophy, and multiple sclerosis are examples where the neural pathways for muscle control are impaired. In severe stages of these diseases, the affected individual may lose all voluntary movements. Even involuntary actions such as eye movements and breathing may become impossible. Patients experiencing this are referred to as having locked-in syndrome. In the absence of methods to physiologically repair the damage caused by these diseases, there are three approaches to restore normal function in patients:

1. Enhancing the capabilities of the remaining neuromuscular pathways
2. Restoring lost function by bypassing the damaged areas in the neural pathways
3. Providing a new, non-muscular communication route for the brain, through which it can directly send control signals and instructions to the external environment.

The feature that distinguishes these brain-computer interfaces from other communication methods is the elimination of the need for any overt bodily movement to transmit information. Ideally, a person should be able to sit still and convey their intentions by focusing on specific thoughts and generating appropriate brain waves [6]. The performance of motor imagery is easily compromised by noise and extraneous information present in multichannel EEG recordings. To address this issue, numerous channel selection methods based on temporal and spatial features have been developed. However, these temporal and spatial characteristics do not accurately capture changes in oscillatory EEG power.

Variations in electroencephalographic (EEG) patterns among individuals necessitate the collection of extensive amounts of labeled data for each person to train models, which lengthens the calibration process. Another significant challenge in enhancing brain-computer interface systems is reducing the number of features extracted from brain signals. Decreasing the number of features can diminish noisy data, lower the risk of overfitting, reduce the memory needed for data storage, enhance classifier performance, provide faster models, and decrease computational complexity [7], [8]. To achieve this objective, various feature selection methods have been employed, which involves addressing current challenges and devising solutions.

In this paper, we will introduce a method designed to improve the accuracy of EEG classification for amputees or individuals with physical disabilities using brain-computer interface systems. This method utilizes a feature extraction mechanism based on deep learning and optimization techniques. The proposed study introduces several methodological innovations that collectively enhance the accuracy, robustness, and practicality of motor imagery-based brain–computer interfaces (MI-BCIs) for prosthetic control in individuals with movement impairments.

- **Hybrid Entropy-Based Preprocessing for Outlier Reduction**: Unlike many previous works that primarily rely on raw EEG preprocessing, this study employs a dual entropy–variance strategy to identify and eliminate outlier EEG segments. This innovation reduces noise introduced by abnormal recordings or measurement errors, thereby improving the quality of training data and ensuring more reliable model convergence.
- **Intermediate Feature Extraction via CNN**: Instead of limiting CNNs to final classification tasks, this work leverages intermediate representations obtained from convolution and pooling layers. These features retain both temporal and spatial dependencies of EEG signals, reducing the reliance on handcrafted features. This approach combines the advantages of deep automatic feature learning with interpretability and flexibility in downstream classification.

- **Golden Eagle Optimization (GEO) for Feature Selection**: To address the challenges of high-dimensional and imbalanced EEG data, a novel application of the Golden Eagle Optimization algorithm is introduced. GEO enables efficient selection of discriminative features by balancing accuracy with feature set compactness. This not only reduces computational complexity but also ensures better generalization, outperforming conventional feature selection and evolutionary optimization techniques.
- **Multi-Classifier Fusion with Semi-Supervised Learning**: A unique three-branch classification framework is proposed:
    - Fuzzy Clustering-Based Semi-Supervised Model, which estimates class probabilities and mitigates uncertainty in EEG classification.
    - Hybrid Voting Classifier, combining Decision Tree, Naïve Bayes, and XGBoost to achieve a balance between interpretability, robustness, and high accuracy.
    - Instance-Based KNN Classifier, which complements the ensemble by capturing local feature similarities.

This study is guided by the overarching research question: "How can the integration of entropy-based preprocessing, CNN-driven intermediate feature extraction, optimization via the Golden Eagle Optimization (GEO) algorithm, and multi-classifier fusion improve the accuracy, robustness, and real-time applicability of motor imagery-based brain–computer interfaces (MI-BCIs) for prosthetic control in individuals with movement impairments?" To address this question, the following hypotheses are formulated:

- H1: Entropy- and entropy variance–based preprocessing will reduce the impact of noisy and outlier EEG segments, thereby improving the quality of input data and enhancing classification stability.
- H2: Intermediate feature extraction using convolutional neural networks will capture spatio-temporal dependencies in EEG signals more effectively than handcrafted features, leading to superior discriminative power.
- H3: The application of the Golden Eagle Optimization (GEO) algorithm for feature selection will outperform conventional feature selection methods by achieving higher accuracy with a reduced feature set, while also lowering computational complexity.
- H4: A multi-classifier fusion framework—combining fuzzy clustering-based semi-supervised classification, a hybrid ensemble of Decision Tree, Naïve Bayes, and XGBoost, and an instance-based KNN classifier—will achieve higher accuracy and robustness compared to any single classifier.

The remainder of the paper is organized as follows: Section 2 discusses related work, Section 3 outlines a proposed strategy to enhance the accuracy of BCI systems based on motor imagery, Section 4 presents an analysis, and Section 5 offers conclusions.

## 2- Related Works

Arpaia et al. [9] have developed a technique for enhancing the selection of EEG signals in brain-computer interfaces that utilize motion imagery. This advancement aims to improve the real-time functionality and adaptability of BCI systems, while also increasing user comfort. The study further seeks to diminish the variability and interference commonly encountered in MI-BCI due to the extensive array of EEG channels. In another study [10], efforts were made to construct a robust classifier with a high generalization capacity for BCIs that are based on motor imagery (MI). This study introduced a framework known as cluster decomposition-based ensemble learning (CDECL) specifically for classifying MI-based BCIs. Ensemble learning was approached as a multi-objective optimization challenge, leading to the development of a fruit fly-inspired multi-objective binary optimization algorithm utilizing stochastic fractal search to address the problem.

In research presented by [11], a novel methodology termed Knowledge-Based Support Matrix Machine (KL-SMM) is described. This method aims to enhance classification accuracy when dealing with a limited quantity of labeled EEG data in the target domain. The strength of KL-SMM lies in its matrix learning machine capability, which directly processes the structural data from EEGs in matrix form. Furthermore, KL-SMM efficiently leverages the minimal labeled EEG data from the target domain while incorporating pre-existing model knowledge from the source domain during its learning phase. Bispectral analysis is an established approach for extracting complex, non-linear, and non-Gaussian information from signals of similar nature. In light of this, Jin et al. [12] put forward a bispectral channel selection (BCS) strategy tailored for BCIs based on motion perception. Their proposed technique employs sum of logarithmic amplitudes (SLA) and first-order spectral moment (FOSM) derived from bispectral analysis to pinpoint relevant EEG channels without relying on supplementary data.

In an exploration detailed in [13], researchers scrutinized the performance of pianists interacting with an MI-based BCI system, contrasting it with that of a non-pianist control group. To process the EEG signals, various machine learning techniques such as common spatial patterns (CSP) and linear discriminant analysis (LDA) were utilized for feature extraction and classification. The findings indicated that pianists exhibited superior BCI control through movement imagination, achieving a higher score in the final test (74.69%) compared to the control group (63.13%).

Idowu et al. [14] investigated the efficiency of nature-inspired algorithms including Ant Colony Optimization (ACO), Genetic Algorithm (GA), Cuckoo Search Algorithm (CSA), and Modified Particle Swarm Optimization (M-PSO) in analyzing EEG and ECoG datasets. Their findings demonstrated that M-PSO, particularly with a minimal set of selected features (SF), displayed impressive efficiency and converged rapidly within a low number of iterations.

The Common Spatial Pattern (CSP) and its extension into a filter bank have been demonstrated to be effective in extracting spatial and spectral features from EEG signals that are associated with the perception of movement. To enhance the specificity of CSP-derived features, Liu et al. [15] introduced a framework known as the Distinct Spatial-Spectral Feature Learning Neural Network (DSSFLNN) tailored for brain-computer interfaces that are based on motion perception. The initial phase within this framework involves the extraction of Filter Bank Common Spatial Pattern (FBCSP) features from the raw EEG data. Subsequently, modules for pressure and excitation are employed to refine the CSP attributes. Following this, a parallel convolutional neural network module is utilized to discern and learn unique spatio-spectral characteristics. These features are then processed through a fully connected layer for the purpose of classification.

In research carried out by Dhiman [16], a feature generation approach for EEG signals in Motor Imagery-based Brain-Computer Interface (MI-BCI) systems employs wavelet packet decomposition (WPD) and Approximate Entropy (ApEn). Due to the presence of redundant features within the extracted EEG signal data, a feature selection process is implemented using an enhanced version of binary gray wolf optimization, termed modified binary gray wolf optimization (MBGWO). Classification is subsequently conducted using the K-nearest Neighbors (KNN) algorithm. The findings indicate that this proposed methodology significantly enhances classification accuracy, particularly in BCI applications designed to detect MI activities in individuals with physical impairments.

Signal Decomposition (SD) serves as a fundamental technique for isolating components or intrinsic mode functions from EEG signals, which is crucial for the advancement of brain-computer interface systems. Yu et al. [17] have applied Empirical Fourier Decomposition (EFD) along with its refined iteration, Improved EFD (IEFD), to process EEG signals for mental and motor imagery (MeI). This approach incorporates multiscale principal component analysis (MSPCA) to reduce noise in EEG data. During the classification stage, features from both time and frequency domains are extracted and categorized using a feed-forward neural network (FFNN).

In the context of controlling robotic arms via brain-computer interfaces, Ak et al. [18] have put forth a novel classification strategy for EEG signals that align with motor imagery (MI) tasks in BCI frameworks. This technique involves transforming EEG data into spectrographic images which are then processed through deep learning techniques, feeding 400 images per task into GoogLeNet. After training the model, the system's efficacy was evaluated based on its ability to accurately execute imagined movements such as up, down, left, and right, to control a robotic arm. The outcomes demonstrated that the robotic arm was able to perform these movements with a high degree of precision, reaching an accuracy rate of 90%.

Khademi et al. [19] introduced a trio of composite models for categorizing EEG signals within MI-oriented BCI systems. These composite models integrate convolutional neural networks (CNNs) with long short-term memory (LSTM) networks. To address the challenge of small data sets, these models employ a transfer learning approach and data augmentation techniques, utilizing two robust pre-trained CNNs, namely ResNet-50 and Inception-v3. MI-BCIs rely on ML algorithms that necessitate comprehensive signal processing and feature engineering to identify variations in sensorimotor rhythms (SMR). Recent studies have focused on deep learning (DL) approaches for EEG classification due to their ability to autonomously extract spatio-temporal features from the signals. The disparity in BCI effectiveness among various user groups, particularly those who are less efficient, is problematic; this refers to some users' difficulties in producing the requisite SMR patterns for the BCI classifier to recognize.

Tibrewal et al. [20] examined the capacity of DL models to discern MI features in users who struggle with efficiency. Within the ML framework, Common Spatial Patterns were utilized for feature extraction, followed by the application of a Linear Diagnostic Analysis (LDA) model for binary classification. For the DL-based method, a CNN model was directly applied to raw EEG data. Meng et al [21] introduced an algorithm for classifying motion imagery using a recurrent graph convolutional neural network. Initially, EEG signals are processed to enhance signal strength during the test phase. Subsequently, features from both time and frequency domains are extracted to form the regression graph's feature pattern. A neural network is then constructed for precise detection of left and right movements.

Cherloo et al. [22] developed an advanced technique named Ensemble Regularized Joint Spatial-Spectral Pattern (Ensemble RCSSP), which diminishes the likelihood of overfitting in the Joint Spatial Pattern algorithm. Wang et al. [23] proposed an unsupervised deep transfer learning method to navigate the prevailing constraints of BCI systems, leveraging transfer learning concepts for classifying EEG signals related to motor imagery. This method incorporates a Euclidean space data balancing technique to equalize the covariance matrices of EEG data from both source and target domains within Euclidean space. Thereafter, Common Spatial Pattern is employed for feature extraction from the aligned data matrix, and a Deep Convolutional Neural Network is used for classifying EEG signals. Li et al. [24], introduced a feature fusion algorithm based on neural networks that merges a CNN with an LSTM network. In this design, CNN and LSTM operate in parallel—CNN is responsible for spatial feature extraction while LSTM handles temporal feature extraction. A flattening layer follows the middle layer's feature extraction by the convolutional layers. Subsequently, all features converge in a fully connected layer to heighten classification precision.

Despite notable advancements in motor imagery-based brain–computer interfaces (MI-BCIs), current systems still face substantial challenges that restrict their applicability in the real-world control of prosthetic devices. Although sophisticated feature extraction and optimization methods—such as bispectral analysis, wavelet packet decomposition, and swarm-inspired algorithms—have improved performance in controlled experimental environments, their generalization capacity across heterogeneous users remains limited. A particularly critical issue is the disparity in BCI efficiency, as many users, especially individuals with motor impairments, are unable to consistently generate distinct sensorimotor rhythms. This variability undermines the reliability of MI-BCIs, thereby limiting their practicality in clinical and assistive scenarios.

Another persistent gap lies in the dependence on large volumes of labeled EEG data, which are costly and time-intensive to obtain. While recent methods, including knowledge-based classifiers and unsupervised transfer learning strategies, attempt to mitigate this constraint, their effectiveness remains hampered by inter-subject variability, non-stationarity of EEG signals, and the risk of domain mismatch. Furthermore, deep learning architectures such as CNN–LSTM hybrids and graph convolutional networks have shown promise in spatio-temporal feature extraction but require extensive computational resources and often struggle with overfitting when applied to limited or imbalanced datasets.

Motivated by these limitations, this study seeks to advance MI-BCI research by developing a robust and adaptive framework that combines optimized feature selection, domain adaptation strategies, and lightweight deep learning architectures. The proposed work aims to enhance classification accuracy and ensure real-time responsiveness. Ultimately, this research aspires to contribute toward reliable, user-friendly brain-controlled prostheses that can significantly improve the independence and quality of life of individuals with motor disabilities.

## 3- Proposed Method

The use of neural networks to process biological signals such as electroencephalogram has been used many times in various researches [25,26]. In this study, we aim to acquire valuable insights into motor imagery for individuals with movement impairments by analyzing existing data. To this end, we have recorded brainwave activity using an EEG device from 30 participants with disabilities, encompassing both male and female genders, ranging in age from 20 to 50 years. We have identified seven distinct movements, labeled Q1 to Q7, which are:

1. Move up
2. Move down
3. Move left
4. Move right
5. Stop movement
6. Grasp
7. Release

Electroencephalographic data is gathered using 21 electrodes placed on the scalp. Participants are instructed to watch a video that depicts a series of movements and pauses, and to imagine themselves performing the movements shown. Subsequently, during a specific time frame, we record the EEG signal values of each participant as they visualize the movement. Feature selection is a powerful technique for addressing classification challenges in datasets with imbalanced classes. It can be approached as a multi-objective optimization problem with the goal of identifying a small subset of features that yields high classification accuracy. Traditional methods tend to focus on extracting an optimal solution without considering the variability within the solution space. In our proposed approach, we plan to address issues such as outlier data, high computational complexity, and the necessity for precise prediction accuracy by employing a novel method.

### 3-1- Data preparation

In the first phase of this project, to generate fundamental features from EEG data, individual signal records are analyzed using two methods: entropy and entropy variance. A lower entropy value indicates that there is a degree of regularity in the brain signal data, whereas a higher value suggests disorder. By identifying and addressing these measures, we can minimize the error introduced by outlier data, which may result from measurement errors, the subject's abnormal condition during signal recording, or other unexpected factors. Eliminating such data from the brain signal records enables the model to be trained on more precise data.

## 3-2- Feature extraction using convolutional neural network

In the second phase of analyzing people's movement perception, we will employ a convolutional neural network (CNN) to extract intermediate features and account for the temporal aspects of users' brain signals, which involves considering two-dimensional data. At this stage, the EEG data from each individual's previous time periods will be inputted as a matrix into the CNN-based architecture. The CNN represents a pivotal point between feature extraction and classification. Utilizing a CNN eliminates the need to design feature descriptors manually. This type of neural network has recently demonstrated impressive performance in deep learning tasks. The rationale for choosing CNNs in our proposed method is their reduced need for pre-processing compared to other techniques. This implies that the network learns to identify patterns that previously required manual intervention in earlier methods. This independence from prior knowledge and human intervention is a significant advantage of CNNs. The CNN designed for feature learning comprises three convolutional layers and three pooling layers, with the convolution and pooling layers arranged in an alternating sequence (repeating three times with one convolution layer followed by one pooling layer).

## 3-3- Features Selection using the golden eagle optimization

Another innovation is that we extract the intermediate features obtained after the convolution and pooling layers. Following optimization with the Golden Eagle Optimization (GEO) method, we input these features into several different classifiers to achieve accurate and semi-supervised classification performed on the optimized intermediate features. Since selecting relevant and effective features to increase the accuracy of motion imagery is a time-consuming and complex process, we will employ the GEO in the third phase of our current plan.

The Golden Eagle Optimization (GEO) algorithm provides a distinctive advantage over many traditional metaheuristic methods due to its ability to effectively balance global exploration and local exploitation. Unlike algorithms such as Genetic Algorithms or Particle Swarm Optimization, which often suffer from premature convergence or require complex parameter tuning, GEO dynamically alternates between spiral movements for wide search and direct chasing for intensification around promising solutions. This dual mechanism not only prevents the algorithm from being trapped in local optima but also accelerates convergence, making it more suitable for complex tasks such as EEG feature selection in motor imagery–based BCI systems.

Another important strength of GEO lies in its structural simplicity and low dependency on parameter adjustments, which ensures greater robustness across different datasets and applications. In the context of MI-BCI, where the data are high-dimensional and often noisy, GEO enables the selection of a more compact and discriminative subset of features. This leads to improved classification accuracy while simultaneously reducing computational complexity. Consequently, GEO is a particularly effective optimization strategy for real-time BCI applications, where both accuracy and efficiency are critical for reliable prosthetic control.

Figure 1 illustrates an example of the vector of selected features, representing a problem solution within the general scheme of the optimization method.

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| solution | 6 | 1 | 12 | 18 | 9 | 34 | 5 | 46 | 19 |

Fig. 1. The structure of a sample solution in the proposed scheme

The concept of GEO is inspired by the intelligent hunting behavior of golden eagles, particularly their ability to adjust their speed during different phases of the hunt. Initially, golden eagles search for prey, and as they near the end of the hunt, they prepare to attack. A golden eagle finely tunes these two phases to efficiently capture the best prey in a given area within the shortest time frame. This behavior has been mathematically modeled to enhance the processes of exploration (searching for prey) and exploitation (capturing prey) within a global optimization method [25]. Each golden eagle starts its hunt by soaring high above its territory, making large circles as it looks for prey. Upon spotting potential prey, the eagle begins to spiral inward, moving from the perimeter towards the center above the prey. While the eagle remembers the prey's location, it continues to circle, gradually decreasing its altitude. As it gets closer to the prey, the radius of the imaginary circle it makes becomes smaller. Concurrently, the eagle scouts the surrounding area for better opportunities. Sometimes, they even share information about the best prey they have found with other eagles.

If an eagle does not find a more suitable target or location, it will continue to circle above the current prey, with the circles' radius decreasing until it finally attacks. However, if a better option is found, the eagle will start circling around this new target and disregard the previous one [27]. It is important to note that the final attack is executed in a straight line. Figure 2 illustrates the cruise and attack vectors in a two-dimensional space. If a new location

determined by these vectors is superior to the one in the eagle's memory, the memory is updated accordingly. During each iteration, every golden eagle (denoted as 'i') randomly selects a target from another golden eagle (denoted as 'f') and circles around the best location that eagle 'f' has encountered. Additionally, Golden Eagle 'i' may also circle around a location it has previously memorized.
The attack vector for golden eagle i is calculated as the following equation:

$$\overrightarrow{A_i} = \overrightarrow{X_f} - \overrightarrow{X_i} \quad (1)$$

Where $A_i$ is the attack vector of eagle i. and $X_f$ is the best location (prey) ever seen by eagle f and $X_i$ is the current position of eagle i.

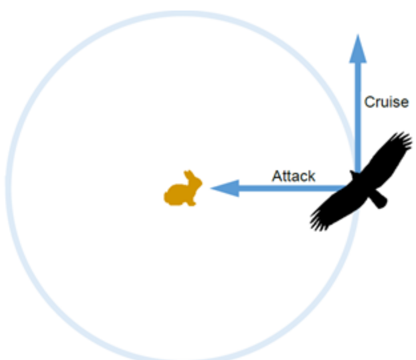


Fig. 2. Spiral movements of the golden eagle [27]

The exploration vector is calculated based on the attack vector. In fact, the exploration vector is a vector that is tangent to the sphere and perpendicular to the attack vector. "Cruise" can also be described as the linear speed of the golden eagle relative to its prey. The cruise vector in n-dimensional space lies within the hyperplane that is tangent to the sphere. The movement of golden eagles, including both attack and exploration phases, for golden eagle i in the t-th iteration, is represented by the following relationship:

$$\Delta x_i = r_1 p_a \frac{\overrightarrow{A_i}}{\|\overrightarrow{A_i}\|} + r_2 p_c \frac{\overrightarrow{C_i}}{\|\overrightarrow{C_i}\|} \quad (2)$$

Where $p_a$ is the attack coefficient and $p_c$ is the cruise coefficient in each repetition t and it regulates how golden eagles are affected by attack and cruise. The vectors $r_1$ and $r_2$ are random vectors whose elements are in the range of [0,1]. $\|\overrightarrow{A_i}\|$ and $\|\overrightarrow{C_i}\|$ are soft Euclidean attack and cruise vectors which are calculated using the following equations.

$$\|\overrightarrow{A_i}\| = \sqrt{\sum_{j=1}^{n} a_j^2} \quad (3)$$

$$\|\overrightarrow{C_i}\| = \sqrt{\sum_{j=1}^{n} c_j^2} \quad (4)$$

The position of the golden eagles at iteration t + 1 is easily calculated by adding the displacement vector to the current position at iteration t:

$$x^{t+1} = x^t + \Delta x_i^t \quad (5)$$

If the fitness of the new position for the golden eagle is better than the position in its memory, the memory of this golden eagle is updated with the new position. Otherwise, the memory remains unchanged, and the eagle settles into the new position. In the next iteration, each golden eagle randomly selects another golden eagle from the group to follow and circles around the best location it has visited. To evaluate each solution, a fitness function (objective) is used during the optimization process. Our goal in the current design is to ensure that the final model has high accuracy in fraud detection. Therefore, the fitness function for each solution is based on the model's recognition accuracy and the size of the selected feature set.

$$fitness(sol_i) = \frac{Accuracy(sol_i)}{|sol_i|} \quad (6)$$

## 3-4- Presenting a hybrid classification model for motion imagery

In the fourth phase, the collected data are fed into three distinct classification models simultaneously. In the first model (the initiative classification model), the extracted features are grouped into K clusters using the fuzzy clustering method, which is a type of unsupervised learning algorithm. Initially, we set the number of clusters to k=4. However, as we increase the number of clusters in the fuzzy clustering method, the selection of samples based on feature similarity becomes more precise, potentially leading to improved accuracy in the model. This grouping is determined by the similarity in feature patterns of the samples, without regard to whether they are related. Following the application of fuzzy clustering, the characteristics of the cluster centers can serve as indicators for the members within those clusters. Now, by examining the status of each example from the brain signal profile in this training dataset, we calculate the cluster index value for each cluster (which reflects the density of the seven motion samples in each cluster).

$$m_{ik} = \frac{tv_{ik}}{n_i} \tag{7}$$

Where, $n_i$ is the number of samples in cluster k and $tv_{ik}$ is the number of samples i in this cluster. Then, in the evaluation phase, for each profile of brain signals such as l, we calculate the distance from these cluster centers under the title of alk. In other words, we want to find out how far the features of each transaction l are from the status of features in each cluster k, for this we have used the Euclidean distance.

$$a_{lk} = \varepsilon + \sum_{f=1}^{\#feature} \|center(k,f) - sample(l,f)\|^2 \tag{8}$$

Where $center(k,f)$ is the value of feature f in the center of cluster k and $sample(l,f)$ is the value of feature f in sample signal l. Now, using the formula of the membership value in the second type of fuzzy, the probability of the occurrence of a signal of type i (seven samples of movement) in profile l is calculated as follows:

$$P_{li} = \sum_{k=1}^{\#cluster} \frac{m_{ik}}{a_{lk}} \tag{9}$$

Now, having the values of $P_{li}$ (as an indicator of the probability of a move occurring in user profile x), we will rank the probability values and choose the largest probability. In this way, the nature of a brain signal can be semi-supervisedly evaluated using the flexibility of fuzzy logic and as a probability number.

In the second classifier, we aim to harness the strengths of three renowned classifiers: Decision Tree (DT), Naive Bayes (NB), and the XGBoost method to create a voting-based hybrid classifier. Concurrently, the feature set is introduced to the third classifier, which utilizes the K-nearest neighbor (KNN) method. This classification algorithm is instance-based, involves an observer, and falls under the category of lazy learning algorithms. It determines the similarity of a new sample to those in the training dataset by comparing their proximity. To ascertain the similarity between two samples, we employ a distance metric. Various methods exist for calculating the distance between two samples within the problem's search space, including Euclidean distance, Minkowski distance, and Manhattan distance. In the KNN classifier, a set of S similar samples is selected from the nearest cluster based on their resemblance to the brain signal pattern and the extracted features. Ultimately, the final decision is made through a voting mechanism that integrates the outcomes of the three classification models.

## 4- Results and Discussion

Xie et al. [28] have proposed a hybrid data augmentation method in the time-frequency domain. The approach involves a parallel CNN that processes both raw EEG signals and images transformed by the continuous wavelet transform (CWT). We will utilize this paper to benchmark the performance of our proposed approach against other classification models, including CART, C4.5, and Bayesian classifiers. The effectiveness of a classification method for binary data is characterized by metrics such as true positives (TP), false negatives (FN), true negatives (TN), and false positives (FP). These allow us to define four key performance parameters: accuracy, precision, recall, and the F-Measure.

To compute classification accuracy for multi-class data, one must first construct a confusion matrix. Within this matrix, correct classifications by the method are recorded along the main diagonal. The sum of the entries in each column corresponds to the total number of samples labeled as class X, while the sum of the entries in each row pertains to the number of samples predicted to be class X. By comparing the predictions of the proposed model with the actual data, we can calculate two metrics—accuracy and recall—for each class separately. Ultimately, to compare the efficacy of our model with other methods in classifying new samples, we typically average these performance metrics across all classes.

$$Precision(label\ X) = \frac{TP(x)}{Total\_Predicted(x)} \tag{10}$$

$$Recall(label\ X) = \frac{TP(x)}{Total\_Label(x)} \tag{11}$$

$$\text{F} - \text{Measure} = 2.\frac{Precision.Recall}{Precision + Recall} \tag{12}$$

statistically significant, an appropriate statistical test for classifier performance comparison was employed. Depending on the evaluation protocol, the comparison was conducted based on the scores obtained from repeated runs and cross-validation folds. The results were reported as mean ± standard deviation, and the statistical significance level was set at 0.05. In addition, p-values were calculated and reported for the comparisons between the proposed model and the reference methods in order to assess whether the observed performance differences were statistically significant.

The Matlab software is utilized for simulations. In the proposed method, we aim to detect individuals' perception of movement, encompassing seven actions: up, down, left, right, stop, grab, and release, using training examples. The simulation encompasses two distinct scenarios. Initially, we assess performance based on the number of test samples. Subsequently, we calculate and display the average accuracy for each method. As illustrated in Figures 3 and 4, the accuracy and comprehensiveness of motor imagery have been enhanced across all states related to the number of test samples for most classes. Moreover, the proposed model accurately predicts an individual's decision to execute a hand movement based on the training data. The confusion matrix presents the classification results compared to the actual data. Figure 6 illustrates the confusion matrix for proposed method.

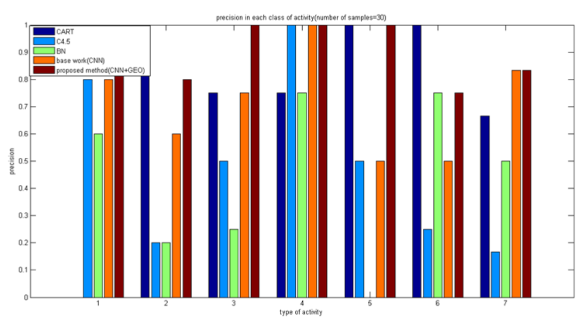


Fig. 3. Precision Analysis of Classification Methods for Different Activity Types

Figure 3 illustrates the precision values obtained from different classification models. As observed, the proposed method integrating CNN-based deep feature extraction, Golden Eagle Optimization for feature selection, and the novel hybrid classification strategy achieves the highest precision compared to conventional approaches. This indicates its superior capability in reducing false positives, which is crucial in motor imagery-based BCI systems. The consistent improvement in precision demonstrates the robustness and generalization ability of the proposed approach, making it a reliable solution for real-world EEG-based applications such as prosthetic control and rehabilitation systems

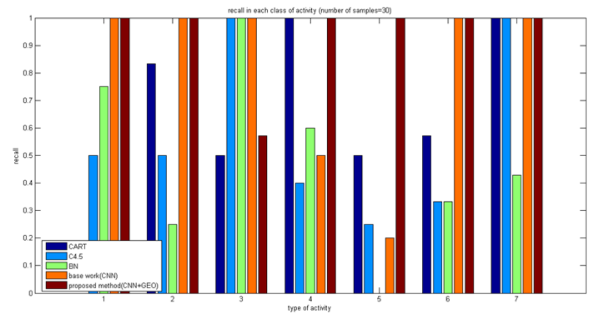


Fig. 4. Comparison of Recall Scores for Different Activity Types

Figure 4 presents the recall performance of the proposed method compared to conventional classifiers. The results demonstrate that the CNN-GEO-hybrid classifier significantly outperforms baseline approaches, achieving an approximate 10–15% improvement over standard CNN and nearly 20% enhancement compared to traditional machine learning classifiers such as SVM. This substantial gain highlights the ability of the proposed approach to reduce false negatives and reliably capture motor imagery signals, which is particularly important in practical BCI applications where missing relevant brain activities could hinder device control accuracy.

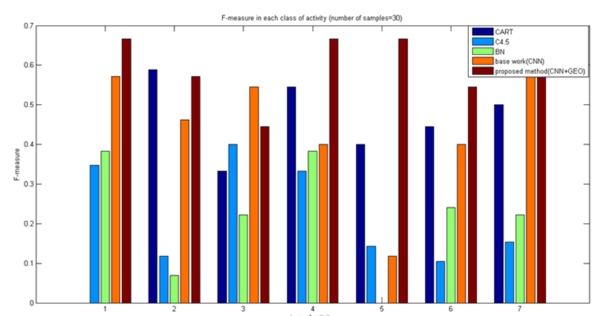


Fig. 5. F-measure Performance Across Different Activity Classes

Figure 5 illustrates the F-measure comparison among the proposed approach and baseline methods. The proposed CNN-GEO-hybrid model demonstrates a remarkable improvement, achieving approximately 12–15% higher F-measure than the baseline CNN and nearly 20% higher than traditional classifiers such as SVM and KNN. Since F-measure is a balanced metric reflecting both precision and recall, this superior performance highlights the effectiveness and robustness of the proposed method in real-world EEG classification tasks. The improvements confirm that the method not only reduces false positives and false negatives but also ensures overall reliability for motor imagery-based BCI applications.

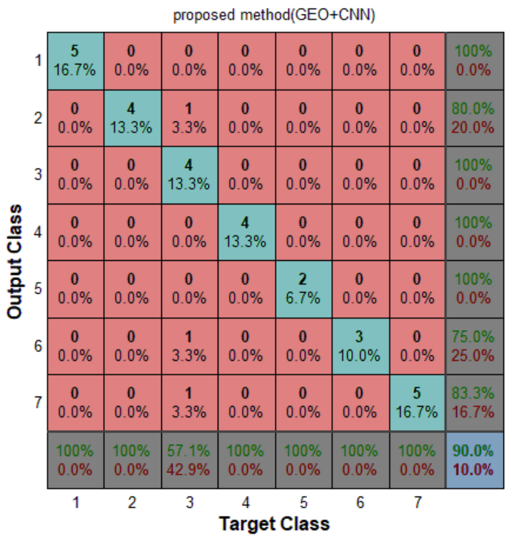


Fig. 6. Confusion matrix of proposed methods for motor imagery

We then evaluated the F-measure, which is the harmonic mean of precision and recall. According to the results depicted in Figure 5, the value of this metric is consistently higher for the proposed method than for the basic methods. To further demonstrate that the proposed method represents an overall improvement across all classes compared to the basic methods, we examined the average accuracy and recall. The outcomes of this analysis are presented in Figures 7 through 9. For this purpose, we conducted simulations with varying numbers of test samples. As illustrated in these figures, the proposed method shows a significant enhancement over the other four methods.

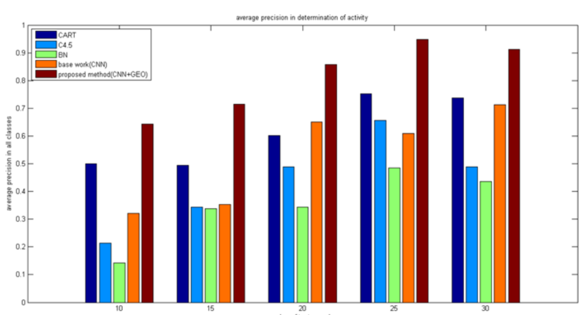


Fig. 7. Average Precision of the Proposed Method

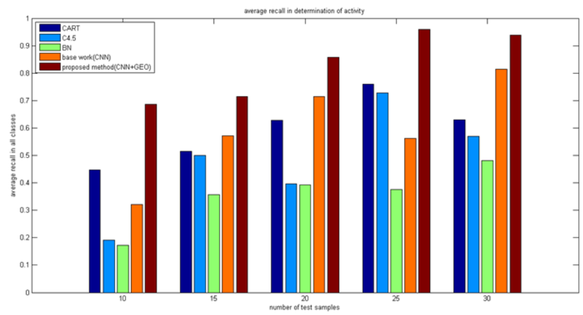


Fig. 8. Average Recall of the Proposed Method

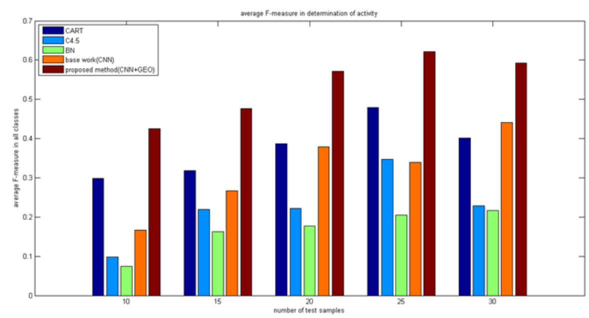


Fig. 9. Average F-measure of the Proposed Method

The comparative results showed that the proposed method outperformed the baseline methods in terms of precision, recall, and F-measure. To verify that these improvements were not caused by random variation, a statistical significance test was conducted on the obtained results. T-test was employed based on the results obtained from repeated runs. The comparisons showed that the proposed method achieved statistically significant improvements at the 0.05 level, over CNN in terms of precision, recall and F-measure, with p-values of 0.23, 0.18, and 0.2, respectively.

## 5- Conclusions

In summary, the novelty of this work lies in the synergy of entropy-based data refinement, intermediate CNN feature utilization, optimization-driven feature selection with GEO, and a multi-classifier fusion framework. Together, these contributions bridge the gap between experimental MI-BCI research and real-world deployment, offering a reliable pathway toward user-friendly and accurate brain-controlled prostheses.

In this paper, we presented an architecture based on a convolutional neural network (CNN) that allows for automatic feature learning in the intermediate layers of the network, thereby eliminating the need for manual extraction of statistical features from the training dataset.

This approach leverages the power of deep learning for feature extraction. Additionally, optimization methods were employed to select features in order to reduce the computational burden of the design while simultaneously enhancing accuracy. Specifically, the Golden Eagle Optimization (GEO) method was utilized. Furthermore, both supervised and semi-supervised classification models were applied to categorize electroencephalogram (EEG) signals.

The comparative analysis of the proposed CNN-GEO-hybrid classifier against baseline approaches across three key performance indicators—precision, recall, and F-measure—demonstrates its significant superiority. In terms of precision, the proposed method reduces false positives more effectively, achieving approximately 12–18% improvement over baseline CNN and nearly 20% over traditional classifiers. Regarding recall, it also outperforms existing methods by 10–15% compared to CNN and 18–22% compared to classical machine learning models, thereby reducing false negatives and ensuring more reliable detection of motor imagery signals. Finally, in terms of F-measure, which reflects the balance between precision and recall, the proposed model achieves 12–15% higher performance than CNN and almost 20% higher than conventional classifiers.

These consistent improvements across all three metrics confirm that the integration of deep feature extraction, golden eagle optimization for feature selection, and hybrid classification provides a robust and scalable solution for EEG-based motor imagery tasks. Such balanced and reliable performance is crucial for real-world brain-computer interface applications, particularly in rehabilitation and prosthetic control, where both accuracy and consistency are essential.

In future research, we aim to select an optimal subset of features with high descriptive power by extracting new features. This may involve applying wavelet and contourlet transforms to the data and examining the correlation between features and class labels within each sample group. The goal is to attain greater accuracy in detecting the perception of human movement in individuals with disabilities. To this end, we may explore other meta-heuristic methods such as the Arithmetic Optimization Algorithm (AOA) [29] and the African Vulture Optimization Algorithm (AVOA) [30].

## References

[1] H. Wang, P. Chen, M. Zhang, J. Zhang, X. Sun, M. Li, and Z. Gao, "EEG-Based Motor Imagery Recognition Framework via Multisubject Dynamic Transfer and Iterative Self-training," IEEE Trans Neural Netw Learn Syst., vol. 35, no. 8, pp. 10698-10712, Aug. 2024. DOI: 10.1109/TNNLS.2023.3243339.

[2] H. ALTAHERI, et al. "Deep learning techniques for classification of electroencephalogram (EEG) motor imagery (MI) signals: A review," Neural Comput Appl, vol. 35, no 20, pp. 14681-14722, Jul. 2023. DOI: 10.1007/s00521-021-06352-5

[3] J. RAHUL, D. SHARMA, L. D. SHARMA, U. Nanda, and A. K. Sarkar, "A systematic review of EEG based automated schizophrenia classification through machine learning and deep learning," Front Hum Neurosci, vol. 18, p. 1347082, Feb. 2024. DOI: 10.3389/fnhum.2024.1347082.

[4] A. Nandhini and J. Sangeetha, "A Review on Deep Learning Approaches for Motor Imagery EEG Signal Classification for Brain–Computer Interface Systems," in Proc. Computational Vision and Bio-Inspired Computing. Advances in Intelligent Systems and Computing, Singapore, vol. 1439, pp. 353-365, Apr. 2023. DOI: 10.1007/978-981-19-9819-5_27.

[5] I. Raoof, and M. K. Gupta, "Domain-independent short-term calibration-based hybrid approach for motor imagery electroencephalograph classification: a comprehensive review," Multimed Tools Appl, vol. 83, no 3, pp. 9181-9226, Jan. 2024. DOI: 10.1007/s11042-023-15900-1.

[6] I. ABDULLAH FAYE, and M. R. ISLAM, "EEG channel selection techniques in motor imagery applications: a review and new perspectives," Bioengineering, vol. 9, no 12, p. 726. Nov. 2022. DOI: 10.3390/bioengineering9120726.

[7] V. S. KARDAM, S. TARAN and A. PANDEY, "Motor imagery tasks-based electroencephalogram signals classification using data-driven features," Neurosci Inform, vol. 3, no 2, p. 100128, Jun. 2023. DOI: 10.1016/j.neuri.2023.100128.

[8] D. JAIPRIYA and K. C. SRIHARIPRIYA, "Brain computer interface-based signal processing techniques for feature extraction and classification of motor imagery using EEG: A literature review," Biomed Mater Devices, vol. 2, no 2, pp. 601-613, Sep. 2024. DOI: 10.1007/s44174-023-00082-z.

[9] P. ARPAIA, F. DONNARUMMA, A. ESPOSITO and M Parvis, "Channel selection for optimal EEG measurement in motor imagery-based brain-computer interfaces," Int J Neural Syst, vol. 31, no 03, p. 2150003, 2021. DOI: 10.1142/S0129065721500039.

[10] C. Zuo, et al, "Cluster decomposing and multi-objective optimization based-ensemble learning framework for motor imagery-based brain–computer interfaces," J Neural Eng, vol. 18, no. 2, p. 026018, 2021. DOI: 10.1088/1741-2552/abe20f.

[11] Y. Chen, et al. "A novel transfer support matrix machine for motor imagery-based brain computer interface," Front Neurosci, vol. 14, p. 606949, Nov. 2020. DOI: 10.3389/fnins.2020.606949.

[12] J. Jin, et al. "Bispectrum-based channel selection for motor imagery based brain-computer interfacing," in Proc. IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 28, no. 10, pp. 2153-2163, Oct. 2020. DOI: 10.1109/TNSRE.2020.3020975.

[13] J. V. Riquelme-Ros, G. Rodríguez-Bermúdez, I. Rodríguez-Rodríguez, J. V. Rodríguez and J. M. Molina-García-Pardo, "On the better performance of pianists with motor imagery-based brain-computer interface systems," Sensors, vol.20, no. 16, p. 4452, Aug 2020. DOI: 10.3390/s20164452.

[14] O. P. Idowu, P. Fang and G. Li, "Bio-inspired algorithms for optimal feature selection in motor imagery-based brain-computer interface," in Proc. 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology

Society (EMBC), Montreal, QC, Canada, pp. 519-522, Jul. 2020, DOI: 10.1109/EMBC44109.2020.9176244.

[15] C. Liu, et al. "Distinguishable spatial-spectral feature learning neural network framework for motor imagery-based brain–computer interface," J Neural Eng, vol. 18, no. 4, p. 0460e4, Aug. 2021. DOI: 10.1088/1741-2552/ac1d36.

[16] R. Dhiman, "Motor imagery signal classification using Wavelet packet decomposition and modified binary grey wolf optimization," Measurement: Sensors, vol. 24, p. 100553, Dec 2022. DOI: 10.1016/j.measen.2022.100553.

[17] X. Yu, M. Z. Aziz, M.T. Sadiq, Z. Fan and G. Xiao, "A new framework for automatic detection of motor and mental imagery EEG signals for robust BCI systems," IEEE Trans Instrum Meas, vol. 70, pp. 1-12, 2021. DOI: 10.1109/TIM.2021.3069026.

[18] A. Ak, V. Topuz and I. Midi, "Motor imagery EEG signal classification using image processing technique over GoogLeNet deep learning algorithm for controlling the robot manipulator," Biomed Signal Process Control, vol. 72, p. 103295, Feb. 2022. DOI: 10.1016/j.bspc.2021.103295.

[19] Z. Khademi, F. Ebrahimi and H. M. Kordy, "A transfer learning-based CNN and LSTM hybrid deep learning model to classify motor imagery EEG signals," Comput Biol Med, vol. 143, p. 105288, Apr. 2022. DOI: 10.1016/j.compbiomed.2022.105288.

[20] N. Tibrewal, N. Leeuwis and M. Alimardani, "Classification of motor imagery EEG using deep learning increases performance in inefficient BCI users," Plos one, vol. 17, no. 7, p. e0268880, Jul. 2022. DOI: 10.1371/journal.pone.0268880.

[21] X. Meng, S. Qiu, S. Wan, K. Cheng and L. Cui, "A motor imagery EEG signal classification algorithm based on recurrence plot convolution neural network," Pattern Recognit Lett, vol. 146, pp. 134-141, Jun. 2021. DOI: 10.1016/j.patrec.2021.03.023.

[22] M. N. Cherloo, H. K. Amiri and M. R. Daliri, "Ensemble regularized common spatio-spectral pattern (ensemble RCSSP) model for motor imagery-based EEG signal classification," Comput Biol Med, vol. 135, p. 104546, Aug. 2021. DOI: 10.1016/j.compbiomed.2021.104546.

[23] X. Wang, R. Yang and M. Huang, "An unsupervised deep-transfer-learning-based motor imagery EEG classification scheme for brain–computer interface," Sensors, vol. 22, no. 6, p. 2241, Feb. 2022. DOI: 10.3390/s22062241.

[24] H. Li, M. Ding, R. Zhang and C. Xiu, "Motor imagery EEG classification algorithm based on CNN-LSTM feature fusion network," Biomed Signal Process Control, vol. 72, p. 103342, Feb. 2022. DOI: 10.1016/j.bspc.2021.103342.

[25] J. Uddin, "An Autoencoder based Emotional Stress State Detection Approach by using Electroencephalography Signals", Journal of Information Systems and Telecommunication (JIST) RICEST, vol. 11, no. 41, pp. 24-30, Jun. 2023. DOI: 10.52547/jist.32267.11.41.24.

[26] S. Motamed and E. Askari, "Recognition of Attention Deficit/Hyperactivity Disorder (ADHD) Based on Electroencephalographic Signals Using Convolutional Neural Networks (CNNs)," Journal of Information Systems and Telecommunication (JIST). Vol. 10, No. 39, pp. 222-228, Aug. 2022. DOI: 10.52547/jist.16399.10.39.222.

[27] A. Mohammadi-Balani, M. D. Nayeri, A. Azar and M. Taghizadeh-Yazdi, "Golden eagle optimizer: A nature-inspired metaheuristic algorithm," Comput Ind Eng, vol. 152, p. 107050, Feb. 2021. DOI: 10.1016/j.cie.2020.107050.

[28] Y. Xie and S. Oniga, "Classification of Motor Imagery EEG Signals Based on Data Augmentation and Convolutional Neural Networks," Sensors, vol. 23, no. 4, p. 1932, Feb. 2023. DOI: doi.org/10.3390/s23041932.

[29] L. Abualigah, A. Diabat, S. Mirjalili, M. Abd Elaziz and A. H. Gandomi, "The Arithmetic Optimization Algorithm," Comput Methods Appl Mech Eng, vol. 376, p. 113609, Apr. 2021. DOI: 10.1016/j.cma.2020.113609.

[30] B. Abdollahzadeh, F. S. Gharehchopogh and S. Mirjalili, "African vultures optimization algorithm: A new nature-inspired metaheuristic algorithm for global optimization problems," Comput Ind Eng, vol. 158, p. 107408, Aug. 2021. DOI: 10.1016/j.cie.2021.107408.