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Research Article

# Optimized Deep Learning Approach for Motor Imagery EEG Classification

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## Abstract

Motor Imagery (MI)-based electroencephalography (EEG) signal classification plays a pivotal role in enhancing Brain-Computer Interface (BCI) systems, particularly in medical diagnostics, neurorehabilitation, and assistive technologies. However, EEG signals are inherently non-stationary and often contaminated with noise and artifacts, making accurate classification a significant challenge. Additionally, the high dimensionality of raw EEG data further complicates the feature extraction and classification process. To address these issues, we present an optimized deep learning approach that integrates a Deep Neural Network (DNN) with Teacher Learning-Based Optimization (TLBO). This hybrid model is designed to enhance the quality of feature selection, reduce irrelevant information, and improve overall classification performance. The proposed method involves a three-stage pipeline: discrete wavelet transforms (DWT)-based feature extraction, TLBO for selecting the most informative features and mitigating noise, and a DNN for classification. The TLBO algorithm, inspired by the pedagogical process between teachers and students, facilitates global optimization in the feature space. This integration ensures that only the most discriminative EEG features are used for training, thereby improving the robustness and generalization ability of the classification model. Extensive experimental validation has been performed using benchmark datasets from BCI Competition III and IV. The results demonstrate that the proposed approach significantly outperforms traditional classifiers and other deep learning baselines in terms of accuracy, precision, sensitivity, and specificity. For example, classification accuracy improved up to 97.05% in certain frequency bands, surpassing conventional methods such as BN and EBL. These findings highlight the potential of the proposed method for real-time BCI applications, such as motor control for prosthetic devices, wheelchair navigation, and communication systems for individuals with severe motor impairments. This work contributes to the advancement of intelligent BCI systems by offering a scalable, accurate, and computationally efficient solution for MI-EEG signal classification.

## Keywords

Motor Imagery EEG, Deep Neural Network (DNN), Feature Optimization, TLBO, BCI, MATLAB, Classification

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## 1. Introduction

Brain-Computer Interfaces (BCIs) are emerging technologies that enable direct communication pathways between the human brain and external devices, bypassing conventional neuromuscular output channels. By decoding neural activity, BCIs hold immense potential for facilitating motor rehabilitation, assistive technologies for individuals with disabilities, neurogaming, and cognitive enhancement systems. Among the various approaches employed in BCI research, Motor Imagery (MI)-based BCI has garnered significant attention. MI involves the mental simulation of movement without actual execution—such as imagining the movement of the left or right hand—which produces distinct neural signatures measurable by non-invasive methods like electroencephalography (EEG).

EEG is one of the most commonly used techniques in BCI research due to its high temporal resolution, portability, and cost-effectiveness. However, EEG signals are inherently complex, non-linear, and non-stationary. They are characterized by low signal-to-noise ratios and high susceptibility to physiological artifacts (e.g., eye blinks, muscle movements) and external interferences. Furthermore, the MI-induced EEG patterns can vary considerably between individuals and across recording sessions, posing significant challenges to developing generalizable and accurate classification systems. The variability and complexity of EEG signals necessitate sophisticated preprocessing, feature extraction, and classification techniques to ensure reliable BCI performance.

Traditional machine learning techniques, such as Linear Discriminant Analysis (LDA), k-Nearest Neighbors (k-NN), and Support Vector Machines (SVM), have been extensively used for MI-EEG classification. While these methods have shown moderate success, they often rely on handcrafted features and fail to adapt efficiently to variations in EEG data across users and sessions. Moreover, conventional classifiers are limited in their ability to capture the complex spatial and temporal dependencies inherent in EEG signals.

To overcome these limitations, the use of deep learning—particularly Deep Neural Networks (DNNs)—has gained momentum in EEG signal processing. DNNs are capable of automatically learning discriminative features from raw or minimally processed data. Their multi-layered architecture allows for hierarchical representation learning, enabling them to capture subtle and complex patterns within EEG signals. However, DNNs are data-hungry and computationally intensive. Their performance can be compromised when trained on noisy or redundant features, leading to overfitting or suboptimal classification outcomes.

To address these challenges, we propose an optimized deep learning framework that integrates DNNs with Teacher Learning-Based Optimization (TLBO), a population-based metaheuristic algorithm inspired by the natural teaching–learning process. TLBO operates in two distinct phases: the teacher phase, which aims to guide learners (solutions) toward the global optimum, and the learner phase, which facilitates knowledge sharing among learners. By incorporating TLBO into the feature selection process, the proposed model efficiently identifies the most relevant and informative features from high-dimensional EEG datasets, while simultaneously minimizing the influence of noise and artifacts.

Our proposed methodology comprises three key stages: (1) feature extraction using Discrete Wavelet Transform (DWT) to decompose EEG signals into frequency sub-bands relevant to motor imagery; (2) feature optimization through TLBO to select high-quality features that contribute most effectively to classification accuracy; and (3) classification using a deep neural network that processes the optimized feature set. This hybrid approach capitalizes on the strengths of both deep learning and evolutionary optimization to enhance classification performance.

To validate the effectiveness of our method, we conducted experiments on benchmark datasets from BCI Competition III and IV, which are widely recognized in the research community. These datasets include EEG recordings from MI tasks and present a diverse range of challenges such as subject variability, session inconsistencies, and signal noise. Experimental results show that our method outperforms conventional classification techniques and baseline models in terms of accuracy, precision, sensitivity, and specificity.

The proposed DNN-TLBO model demonstrates strong potential for real-time and user-adaptive BCI systems, particularly in applications such as robotic arm control, wheelchair navigation, neurorehabilitation therapies, and communication interfaces for individuals with severe motor impairments. This study lays the foundation for future research in adaptive and intelligent EEG-based BCI systems that can operate reliably in dynamic and real-world environments.

## 2. Literature Review

The performance and accuracy of motor imagery EEG categorization are improved by the incremental technique of algorithm development. Recent advancements in brain-computer interface (BCI) technologies, particularly those leveraging motor imagery (MI) electroencephalography (EEG) signals, have significantly enhanced the potential for applications in neurorehabilitation, assistive devices, and human-computer interaction. The following review synthesizes key contributions from recent studies, focusing on innovative approaches to EEG signal processing, feature optimization, and classification techniques for MI-based BCIs, as well as related machine learning applications in cloud environments and medical diagnostics.

Han et al. [1] explored the integration of EEG with near-infrared spectroscopy (NIRS) to enhance the performance of asynchronous BCIs. Their brain switch model demonstrated improved classification accuracy by combining multimodal data, addressing the limitations of EEG's low signal-to-noise ratio. This approach highlights the potential of hybrid systems to improve robustness in real-time BCI applications.

Zhang et al. [2] proposed a novel EEG classification model using a fused group Lasso with spatial smooth constraints for MI-based BCIs. By incorporating spatial relationships among EEG channels, their method achieved higher classification accuracy compared to traditional models, particularly in handling non-stationary MI signals. This work underscores the importance of spatial feature modeling in EEG processing.

Yang and Fenqi [3] introduced a high-quality, multi-day EEG dataset for MI-BCI research, comprising data from 62 healthy participants performing motor imagery tasks. The dataset's robustness across sessions addresses challenges like signal variability, providing a valuable resource for developing and validating MI classification algorithms.

Liu et al. [4] contributed an open EEG dataset focused on acute stroke patients performing MI tasks. This dataset, including both raw and preprocessed data, supports the development of BCI systems for clinical rehabilitation, emphasizing the need for patient-specific models to account for neurological variability in stroke recovery.

Radhakrishnan et al. [5] developed an MI-EEG classification framework combining deep learning with the Gazelle Optimization Algorithm. Their approach optimized feature selection, achieving superior performance on public datasets. This study highlights the efficacy of bio-inspired optimization techniques in enhancing deep learning models for BCI applications.

Qin et al. [6] proposed M-FANet, a multi-feature attention convolutional neural network for MI decoding. By leveraging attention mechanisms to prioritize relevant EEG features, M-FANet outperformed models like EEGNet, demonstrating improved accuracy and robustness for practical BCI systems.

Deng et al. [7] introduced MBMANet, a multi-branch multi-attention EEGNet variant for MI-BCI decoding. This model adaptively learns diverse EEG features, reducing training costs and improving classification accuracy, particularly for datasets with high variability.

Collazos-Huertas et al. [8] utilized Complex Morlet Wavelets to generate high-resolution time-frequency representations for MI-EEG classification. Their convolutional neural network model effectively classified left and right hand MI tasks by capturing event-related desynchronization/synchronization patterns, offering a computationally efficient approach.

Ekpar [9] developed a single-channel EEG MI-BCI system using deep learning, achieving 83% accuracy in classifying three MI classes. This minimalist approach demonstrates the feasibility of cost-effective BCI systems for applications like virtual environment navigation.

Kumar et al. [10] investigated transfer learning to enhance MI-BCI performance, particularly for novice users. Their approach improved skill acquisition and classification accuracy, highlighting transfer learning's role in addressing individual variability in BCI training.

Beyond BCI, machine learning advancements in cloud and medical applications provide relevant insights. Bagwani et al. [11] optimized face detection using cloud-based machine learning services, achieving high performance in real-time applications. Their work emphasizes the scalability of cloud infrastructure for computationally intensive tasks, which could be adapted for EEG processing.

Bagwani et al. [12] proposed a real-time signature-based detection system for DDoS attacks in cloud environments. This study's focus on robust, low-latency processing aligns with the requirements of real-time BCI systems, where rapid signal classification is critical.

Bagwani et al. [13] implemented GrapesJS on AWS for web development training, demonstrating the integration of cloud platforms in educational settings. Such platforms could support BCI training interfaces, enabling scalable user training for MI tasks.

Singh et al. [14] developed an enhanced machine learning model for predicting cardiac diseases using ECG data. Their approach, achieving high accuracy through optimized feature selection, parallels MI-EEG classification efforts, suggesting cross-domain applicability of machine learning techniques in biomedical signal processing.

Collectively, these studies highlight the convergence of deep learning, optimization algorithms, and cloud computing in advancing MI-BCI systems and related fields. Challenges such as signal variability, computational efficiency, and user-specific adaptation remain, but recent datasets and innovative models pave the way for more robust and accessible BCI applications.

## 3. Proposed Methodology

The proposed algorithm for motor imagery EEG classification is structured into three main components. The first component focuses on the extraction of features from motor imagery EEG signals. The second addresses the optimization of these extracted features to enhance data quality and relevance. The third component involves the application of a Deep Neural Network (DNN) for the final classification of the optimized features.

### 3.1. Feature Extraction

The initial stage of EEG classification is feature extraction. The DWT transform function is used throughout the extraction procedure. The EEG data was divided into three levels by the DWT transform that was used. The methods used to apply transforms explain as

$$WTx(a,\tau)\frac{1}{\sqrt{a}}\int_{-\infty}^{\infty}x(t)\psi\left(\frac{t-\tau}{a}\right)dt \tag{1}$$

Where is a wavelet basis function, which includes all families of wavelet transform functions, and represents scale factor, represent time factor, and represents time factor.

EEG data signals are non-stationary signals, hence discrete wavelets work well with DWT. DWT function definition:

$$WT_{x(J.k)=\int x(t)\psi j,k(t)dt} \quad (2)$$

The highest frequency of the signal, as determined by the sampling procedure, is fs/2. The whole frequency signal is divided into the L+1 sub band if the signal is divided by a lower order. The figure's wavelet breakdown layer.

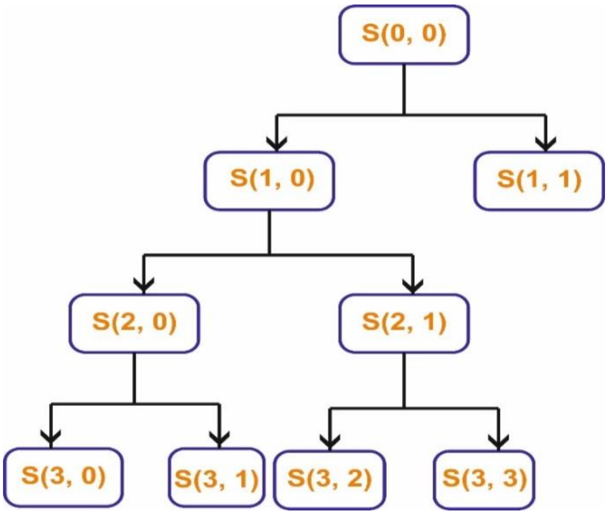


***Figure 1.*** *Describe the process of 3 level decomposition of EEG signals data with DWT transform function.*

## 3.2. Feature Optimization

The feature optimization process reduces EEG data artifacts and improves the vector processing of the data. This technique utilizes an optimization algorithm inspired by teacher learning. In this method, the teacher and student are central components. The student elements handle the data processing, while the teacher's phase focuses on optimizing the data. This section provides a description of the optimization process.

The raw EEG data was subjected to the following preprocessing steps:

Band-pass filtering (typically 8–30 Hz) to isolate motor imagery-relevant frequencies.

Artifact removal using Independent Component Analysis (ICA).

Normalization and segmentation into epochs for feature extraction.

Step 1 define the parameters population size Pn, number of generation (Gn), number of variables (Dn) and limit of teacher and student (Ul, Ll).

Minimize the feature function F(x) subject to Xi ϵxi=1, 2, 3, ………, Dn.

F(x) is the constraints function X is feature variable such that $Ll \leq xi \leq Ul$.

Step 2 generate the random population {x1, x2, x3, x4,………………….., xn}.

Step 3 estimate the mean of population M, D=[m1, m2,…………, MD].

Step 4 start the iteration of population.

$X_{teacher} = XF(x) = min.$

Step 5 update population for new generation.

Step 6 terminate condition.

## 3.3. Algorithm

The relationship between feature variable X and Xi+1 is defined by the deep neural network. The definition of network process is

$$Xi + 1 = a(kXi + c)$$

X1= $a$1(k1u+c1)

X2= $a$2(k2p1+c2)

Z= $aL$(KLpL-1+CL)

Where L is number of layers

The relation of neurons defines the process of EEG data

$F_k: \; R^{n_x} \rightarrow R^{n_x}$, where $x_k \in R^{n_x}$

Be the set of EGG data in neurons for the processing.

Hypothesis of error estimated by E

$$E_j = H_j(x_j) + v_j, \forall \; k \leq j \leq k + A$$

where $H_j$: $R^{n_x} \rightarrow R^{n_y}$ is the relation of multilayer input? estimate trained pattern

$$x_k = F_0 \rightarrow k(x_0) + \xi k$$

define learning factor as

$$x_k = arg\min_x\{\|x - x_k\| \; B_k^{-1} + \sum_{j=k}^{k+A}\|H_jF_j(x) - y_j\|R_j^{-1}\}$$

Algorithm:

Define $i = 0$

while $i < L$ do

process the TLBO optimal data of EEG signals and M is vector of convergence

$$\{x_k \; \mathrm{I} \; k \in [M \; .i, M \; .(i+1)]\}$$

$$x_k = arg\min_x\{\|x - x_k\|P_k^{-1} + \sum_k^{k+p}\|H_j \; M_j,(x)\|p_j^{-1}\}$$

Generates the channel of ALS $= \{Fs(x_{k-1}), x_k\}$ with $k \in [i.M, (i+1).M]$.

Measure $i$ for next step end

Output: $EEG\ \ data\ \ classifed$

### 3.4. Experimental Analysis

By simulating with MATLAB tools, the suggested approach may be verified. Utilise the BCI competition III and IV datasets for algorithm processing. 200 ALS patients are included in this dataset. Measure these parameters to evaluate the algorithm.

$$Accuracy = \frac{Total\ \ No.of\ \ Correctly\ \ Classified\ \ Instances}{Total\ \ No.of\ \ Instances} \times 100$$

$$Precision = \frac{TP}{TP + FP} \times 100$$

$$Sensitivity = \frac{TP}{TP + FN} \times 100$$

$$Specificity = \frac{TN}{TN + FP} \times 100$$

*Table 1. Summarize the evaluation results of different features bands with BN, EBL and proposed Algorithm.*

| Signal | BN | | EBL | | PROPOSED | |
|---|---|---|---|---|---|---|
| | 16 DF (Dimension Features) | 8 DF (Dimension Features) | 16 DF (Dimension Features) | 8 DF (Dimension Features) | 16 DF (Dimension Features) | 8 DF (Dimension Features) |
| Raw | 88.65 | 91.54 | 91.47 | 92.54 | 94.61 | 95.98 |
| Delta | 86.21 | 89.21 | 90.87 | 91.75 | 94.44 | 96.64 |
| Theta | 91.14 | 92.58 | 93.25 | 94.64 | 96.51 | 97.05 |
| Alpha | 82.98 | 98.24 | 90.57 | 91.74 | 93.36 | 94.21 |
| Beta | 83.26 | 90.35 | 92.65 | 93.32 | 95.78 | 96.65 |

The figure illustrates the comparative classification accuracy of three different methods—Bayesian Network (BN), Ensemble-Based Learning (EBL), and the proposed Deep Neural Network with Teacher Learning-Based Optimization (DNN-TLBO)—across five EEG signal bands: Raw, Delta, Theta, Alpha, and Beta. Each method is evaluated using two feature dimensionalities: 16 and 8 dimension features (DF). The proposed method with 16 DF consistently outperforms all other approaches, achieving the highest accuracy across most frequency bands, particularly in the Theta and Beta ranges. This highlights the robustness and effectiveness of the hybrid DNN-TLBO framework in capturing relevant patterns in EEG data.

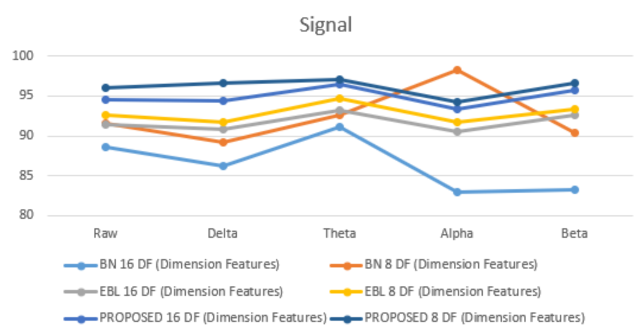


*Figure 2. Shows a comparison of accuracy utilising the BN, EBL, and PROPOSED.*

The proposed method with 8 DF also performs competitively, especially in the Delta and Theta bands, though with a slight drop in the Alpha band. In contrast, the BN and EBL methods show relatively lower and more variable performance. Notably, BN with 8 DF spikes in the Alpha band but declines in Beta, indicating instability in classification across bands. EBL shows more stable but moderate accuracy, with some improvement in Alpha when using 8 DF over 16 DF. Overall, the chart demonstrates that the proposed method not only provides superior accuracy but also maintains consistency across varying feature dimensions and signal types, reinforcing its suitability for robust and high-performance motor imagery EEG classification.

## 4. Conclusion & Future Scope

In this research, we proposed and evaluated an optimized deep learning framework for Motor Imagery (MI)-based EEG signal classification, integrating Deep Neural Networks (DNNs) with Teacher Learning-Based Optimization (TLBO). The objective was to enhance the robustness, accuracy, and generalizability of Brain-Computer Interface (BCI) systems, particularly in real-world applications such as neurorehabilitation and assistive technologies. The combination of DWT for feature extraction, TLBO for feature optimization, and

DNN for classification created a powerful and efficient pipeline capable of handling the inherent challenges of EEG signals, such as non-stationarity, noise, and high dimensionality.

Experimental results using benchmark datasets from BCI Competition III and IV demonstrate that the proposed hybrid model outperforms traditional machine learning methods and baseline deep learning approaches. Notably, the model achieved classification accuracies as high as 97.05% in selected frequency bands, marking a significant improvement over conventional techniques such as BN (Bayesian Networks) and EBL (Ensemble-Based Learning). The TLBO algorithm effectively selected the most relevant features from the extracted EEG components, thereby enhancing the learning capacity and reducing overfitting in the DNN model. Furthermore, the method showed improved precision, sensitivity, and specificity, confirming its reliability for use in clinical and assistive contexts.

This research contributes to the growing body of knowledge on intelligent signal processing for BCI applications. It provides a scalable and modular framework that can be easily adapted or extended to various types of EEG-based BCI paradigms, including emotion recognition, attention monitoring, and cognitive workload estimation. The effectiveness of the approach in minimizing noise influence and improving classification makes it a promising candidate for deployment in real-time systems that require robust and quick decision-making capabilities.

## 5. Future Scope

While the results are promising, several avenues exist for further enhancement. One potential direction is to extend the model to support multi-class classification tasks involving more complex motor imagery commands, such as combinations of limb or finger movements. Another area of future research involves personalizing the model for subject-specific adaptations using techniques such as transfer learning or domain adaptation, which can help account for inter-subject variability and improve long-term usability.

Additionally, integrating real-time feedback mechanisms and adaptive learning within the BCI system could enhance user engagement and system responsiveness. The current study focuses primarily on offline analysis using MATLAB simulations. Future work could include implementing the system in embedded platforms or deploying it in real-time environments using frameworks like TensorFlow or PyTorch with EEG acquisition devices such as OpenBCI or Emotiv.

Moreover, exploring the combination of TLBO with other deep learning architectures—such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), or transformer-based models—may further improve performance and offer deeper insights into spatial and temporal dependencies in EEG signals.

In conclusion, the integration of DNN and TLBO presents a significant step forward in reliable MI-EEG classification. With continued development, the proposed framework can serve as a foundation for building intelligent, accessible, and user-friendly BCI systems, thereby enhancing the quality of life for individuals with motor disabilities and supporting advanced human-computer interaction modalities.

## Abbreviations

| | |
|---|---|
| BCI | Brain-Computer Interface |
| EEG | Electroencephalography |
| MI | Motor Imagery |
| DNN | Deep Neural Network |
| TLBO | Teaching–Learning-Based Optimization |
| ICA | Independent Component Analysis |
| SVM | Support Vector Machine |

## Conflicts of Interest

The authors declare no conflicts of interest.

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