

Feature-Based Classification of Motor Imagery Tasks using Electroencephalogram Recordings

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ABSTRACT

Stroke is recognized as a source of numerous impairments, encompassing deficits in physical, motor, and emotional functions in affected individuals. While the visible manifestations of a stroke are evident, the internal effects on the brain remain mostly enigmatic. Research has shown that utilizing motor imagery tasks via Electroencephalogram (EEG) bio signals achieves a 10% increase in accuracy relative to traditional techniques. This research work aims to employ feature extraction techniques on motor imaging tasks combining right- and left-hand grasping, utilizing motor imagery-based EEG data to extract the most pertinent features from two distinct datasets. One dataset comprises individuals with stroke, and the other consists of healthy individuals. Techniques such as the Common Spatial Filter (CSP) and the Filter Bank Common Spatial Filter (FBCSP) are employed to extract relevant features from the processed and filtered data. Three supervised machine learning algorithms, including Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), and Gaussian Naïve Bayes (GNB), have been employed for data classification. A comparative study has been conducted to understand the fundamental differences in the EEG signals between stroke patients and healthy individuals. The findings indicated that the FBCSP approach surpassed CSP in both categories of patients, with the SVM achieving an accuracy of up to 98.86% in classifying motor imagery tasks. This comparative study enhances our understanding of Brain-Computer Interface (BCI) systems and motor rehabilitation methods by elucidating critical differences between EEG data from stroke patients and healthy individuals.

Keywords-electroencephalogram; motor imagery; common spatial filter; filter bank common spatial filter; support vector machines; brain-computer interface

I. INTRODUCTION

Stroke is one of the most prevalent cerebrovascular diseases worldwide. It is a recognized life-threatening emergency that can lead to death or long-term motor disability [1, 2]. Upper-limb motor dysfunction significantly impacts an individual's independence in doing ordinary everyday tasks [3]. The seriousness of this ailment has been elucidated by studies examining stroke prevalence. It is estimated that 33 million individuals globally experienced their first stroke in 2010, representing a significant number [4]. Furthermore, northeast and southeast China have undertaken surveys revealing estimated stroke prevalence rates of 7.2% and 3.1%, respectively [5, 6]. These examples illustrate the substantial economic impacts of stroke on a global scale. The incidence of stroke is elevated among many demographic groups, particularly African Americans and individuals residing in the "Stroke Belt" region. Significant variations in stroke incidence were identified in a research study undertaken in Europe with notably elevated rates in the eastern and northern regions of the continent [7]. Collectively, these findings demonstrate that stroke continues to be a significant global healthcare concern, resulting in life-threatening and devastating consequences for individuals. Healthcare systems can allocate resources more efficiently and invest in preventative interventions to mitigate the effects of stroke on individuals and society by analyzing the incidence of stroke and its associated causes [8].

The majority of post-stroke patients select a standard rehabilitation program designed to restore motor function through Constraint-Induced Movement Therapy (CIMT) or physical therapy. Nevertheless, approximately 20-30% of post-stroke patients are either incompetent or too advanced in age to engage in traditional therapy; however, Brain-Computer Interfaces (BCIs) have proven effective and have been increasingly recognized as a viable method for restoring motor functions in post-stroke patients in recent years. Motor imagery entails the cognitive simulation of a physical movement without any concomitant muscle activation. The utilization of Electroencephalogram (EEG) using traditional procedures is less successful for post-stroke patients [9].

Motor imaging is a cognitive procedure in which an individual mentally rehearses or visualizes a specific movement or activity without executing it physically. It involves the cognitive simulation of motor actions without physical execution. This cognitive exercise is commonly known as mental rehearsal, mental practice, or mental visualization. In this exercise, the individual typically envisions activities such as grasping a ball, compressing a ball, elevating the legs, and various other movements that facilitate limb mobility. Motor imagery delineates its imagery mission by establishing connections between motor limbs, so creating a relationship among neural connections in the brain. Brain regions that exhibit concurrent activity during motor imagery tasks and true movements include the primary motor cortex and supplementary motor centers. The fact that motor imagining stimulates the same brain regions used in real-world activities advances our understanding of its possible therapeutic benefits [10].

Authors in [11] stated that the ability of the EEG to analyze the processes involved in recovery following a stroke has provided important new information on the brain's recovery process. It is an important tool for individualized treatment plans due to its capacity to offer post-stroke patients' prognostic value. According to authors in [12], mirror therapy is a well-known low-cost and user-friendly technique. Additionally, this therapy demonstrates that it can help patients, particularly those with diseases that cause regional discomfort, to feel pain-free. According to authors in [13], the camera-based mirror visual input method is a straightforward and affordable technique that may be used with stroke patients. Although camera-based mirror visual input may aid in the early recovery of motor skills through priming, further research is needed to properly understand how such input may affect functional results and long-term gains in motor skills.

Authors in [14] said that developing hemiplegic post-stroke patients' sensorimotor connections through physical activity connected to motor connectivity is a simple strategy that may be used. Further research is needed to determine the long-term effects of sensorimotor connection with neurofeedback on rehabilitation and standard life satisfaction for post-stroke individuals with hemiplegia. Based on the results in [15], it appears that the trained Symmetry Index over BSI_{theta} increased the observed variation using Fugl-Meyer scores from 61.5% to 68.1%. This suggests that the index may serve as a biomarker for top-limb motor dysfunction at six months. Nevertheless, when the Delta/Alpha Ratio (DAR) was applied to stroke patients between one and fourteen days following the stroke, no changes or increases in delta activity were seen. Authors in [16] demonstrated a notable enhancement in upper limb Fugl-Meyer assessment and Action Research Arm Test (ARAT) scores, which rose above the reference point by 3.92 ± 3.73 (72%) and 5.35 ± 4.62 (63%) points, respectively. In addition, kinematic measures revealed that most participants exhibited faster and more flexible movements.

According to authors in [17], many patients (81%) who received motor-imagery training were able to regain some range of motion in their wrists. As a bonus, 42.3% of patients were able to display a pattern of Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS), unique to the brain areas responsible for processing sensory information, reasoning, and motor control. Authors in [18] employed a 3D-based Convolutional Neural Network with Generative Adversarial Networks (3D-CNN-GAN) for EEG-based motor imagery classification that achieved an accuracy of 77.03% on the GigaDB dataset and 71.63% on the SUH dataset. Authors in [19] utilized a Convolutional Neural Network-Long-Short Term Memory (CNN-LSTM) model for motor imagery EEG signal classification and achieved 79.03% of accuracy on the MI dataset that consists of 29 subjects. Authors in [20] explored Empirical Mode Decomposition (EMD) and ensemble-EMD for motor imagery classification and achieved 96.83% on the BNCI Horizon dataset using a Narrow Neural Network (Narrow NN). The objective of this study is to improve the performance of motor imagery tasks via EEG using the Common Spatial Filter (CSP) and the Filter Bank Common Spatial Filter (FBCSP) feature extraction methods, and machine learning algorithms.

II. METHODOLOGY

Figure 1 illustrates the specific methods followed in this research. The proposed methodology encompasses several key steps. Firstly, two different types of feature extraction methods are employed to extract the features from an open-source dataset. To separate the frequency band pertinent to the EEG signals, a bandpass Chebyshev Type II filter is used in the signal processing, which includes 188 channels for channel selection and filtering. For feature extraction, the EEG data were processed using the CSP and FBCSP approaches to identify distinguishing elements for motor imagery tasks. Subsequently, three machine learning algorithms were used to classify the motor imagery tasks: Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), and Gaussian Naïve Bayes (GNB). Although various artificial intelligence techniques have been used in many other applications [21], this study focuses on comparing the performance of these three classifiers. This comprehensive methodology allowed for a detailed investigation and classification of motor imagery-based EEG signals in the context of stroke and healthy individuals.

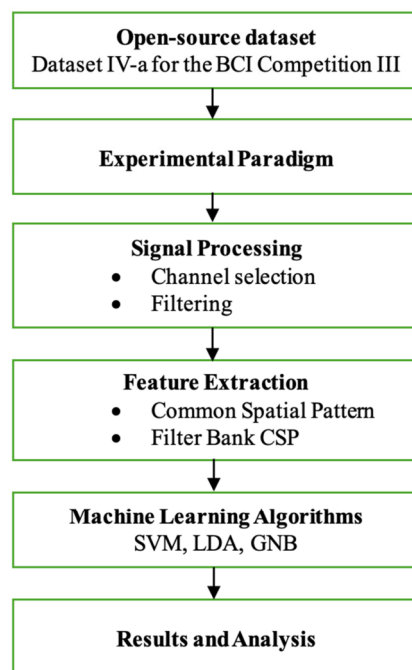


Fig. 1. Overview of the methodology used in this research.

A. Dataset Description

The dataset used in this study originates from the Charité - University Medicine Berlin's Campus Benjamin Franklin and is based on the dataset IVa for the BCI Competition III [22]. BrainAmp amplifiers with 128 EEG channels were used to record the electrical signals generated in the brain during a motor imagery activity, and 118 EEG channels were recorded at various places in the enlarged international 10-20 system. The configuration had a sampling frequency of 1000 Hz. Each motor imagery trial had a duration of 8 s, with 140 trials

conducted for each task, resulting in a total of 280 trials for two distinct tasks.

B. Signal Processing

1) Channel Selection

There are about 118 channels in the dataset. "FC2", "FC4", "FC6", "CFC2", "CFC4", "CFC6", "C2", "C4", "C6", "CCP2", "CCP4", "CCP6", "CP2", "CP4", "CP6", "FC5", "FC3", "FC1", "CFC5", "CFC3", "CFC1", "C5", "C3", "C1", "CCP5", "CCP3", "CCP1", "CP5", "CP3", and "CP1" are the 30 channels that have been extracted. By removing unnecessary channels, the classification system's resilience is enhanced [23].

2) Filtering

A bandpass Chebyshev Type II filter was used to identify the frequency band pertinent to the EEG signals of the dataset. The Chebyshev Type II filter was selected for its ability to create ripples in the stopband while providing a rapid roll-off and attenuation in the stopband. It is employed to create a bandpass filter ranging from 7 to 30 Hz, as the alpha and beta rhythm bands are situated within that frequency spectrum. These rhythm bands are known to correlate with motor imagery tasks. The beta frequency range (13 Hz to 30 Hz), indicative of sensorimotor region activity in the brain during actual movement execution, is especially pertinent for motor imaging tasks. Conversely, the alpha frequency range (8 Hz to 13 Hz) facilitates the attenuation of sensory input during motor imagery, hence enhancing the suppression of extraneous sensorimotor information and augmenting the focus and accuracy of motor imagery.

C. Feature Extraction

Feature extraction techniques are crucial for processing multi-channel EEG data for applications requiring two-class categorization. These methods seek to pinpoint distinct patterns associated with various cognitive tasks or emotions.

1) Common Spatial Pattern

The steps involved in the CSP filtering are as follows:

- Step 1: Segment the processed EEG data into epochs corresponding to the time window of interest, such as motor imagery periods.
- Step 2: Obtain the covariance matrix, relying on the segmented EEG, for each class (e.g., left- and right-hand motor imagery).
- Step 3: To acquire the eigenvectors and eigenvalues, compute the mean covariance matrix between the two classes.
- Step 4: Choose the eigenvectors that maximize the variance of a class while minimizing it for the other class.
- Step 5: Acquire the CSP-transformed features by multiplying the initial EEG data with the spatial filters.

2) Filter Bank Common Spatial Filter

The steps involved in the FBCSP filtering are as follows:

- Step 1: Divide the EEG data into several frequency sub-bands, such as delta, theta, alpha, beta, and gamma, using a filter bank.
- Step 2: Apply CSP independently to each frequency sub-band to create spatial filters that improve discriminative information.
- Step 3: Create a single feature vector by merging all the CSP-filtered features together.

After applying the main phases for each technique, the extracted features are fed into a classifier to categorize the data accordingly. In two-class categorization tasks, feature extraction methods like CSP and FBCSP are essential for analyzing multi-channel EEG data. They aid in the discovery of distinctive patterns connected to mental processes or emotional states, enhancing classification accuracy, and allowing useful BCI applications.

D. Machine Learning Algorithms

1) Support Vector Machines

Finding the ideal hyperplane that best distinguishes several classes in each dataset is the basic idea of the SVM classification technique. Support vectors are the data points that are nearest to a hyperplane and have the most effect on its location. These support vectors, which are the most important for generating a well-separated classification, are critical in identifying the decision boundary [24]. SVM can process linearly and non-linearly separable data. When dealing with linearly separable data, the data points can be correctly categorized using just one hyperplane.

2) Linear Discriminant Analysis

The goal of LDA classification duties is to allocate data points to specified classes based on their attributes. Projecting the data into a lower-dimensional region while maintaining the class-specific information is the main idea of LDA. The separation among the means of several classes is maximized, whereas the variation among each class is minimized to produce this lower-dimensional region. To create well-separated classes, the ideal projection will optimize the proportion of between-class variation to within-class variance [25].

3) Gaussian Naïve Bayes

GNB classification is based on the Bayesian theorem and the assumption of variable independence. It is a supervised learning method that works well with datasets that have continuous features. The fundamental premise of GNB is that, given the class label, every attribute is voluntarily independent. In a nutshell, whether a feature is present or not has no influence on whether other features are present or not. This assumption makes probability calculations easier and enables the algorithm to operate well even when dealing with datasets of a high dimensionality [26].

III. EXPERIMENTAL RESULTS

A. Signal Processing Results

After applying the preprocessing steps, the dataset exhibited a significant improvement in the quality of the EEG signals. The bandpass filtering technique effectively reduced noise and artifacts in the dataset, resulting in clearer and more focused EEG data. The filtering process aimed to target frequency components relevant to motor tasks performed by the subjects. The resulting refined EEG signals showcased smoother and more consistent oscillations, which could facilitate subsequent feature extraction algorithms, such as the CSP and FBCSP methods, used for motor imagery classification. The results obtained from the dataset for subject S2 are presented in Figure 2 and 3, both before and after data processing, respectively.

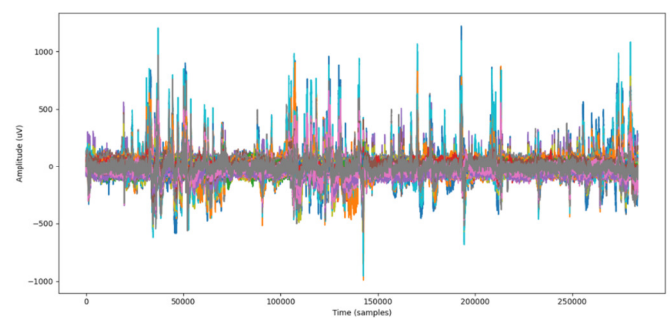


Fig. 2. EEG signal of subject S2 before processing.

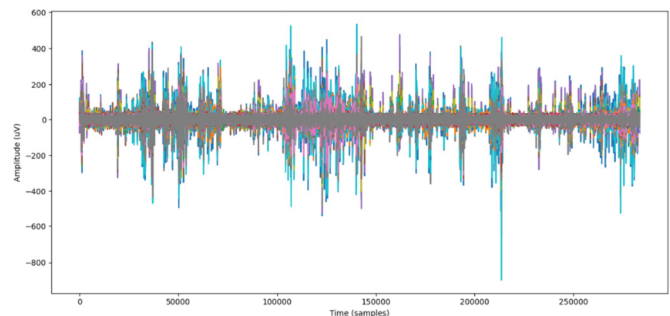


Fig. 3. EEG signal of subject S2 after processing.

The filtered EEG data laid the groundwork for further feature extraction and classification tasks, while also capturing the differences in neural activities between the two distinct subject populations. These observations highlight the importance of tailored preprocessing techniques for distinct datasets, considering the unique characteristics of each subject.

B. Feature Extraction and Classification Results

The classification of motor imagery necessitates the extraction of features from the alpha and beta frequency bands. Filtering these frequency components enhances the signal-to-noise ratio, enabling the detection of motor-related patterns with greater accuracy. The feature-extracted EEG signals serve as valuable inputs for subsequent analysis, where the algorithms like CSP and FBCSP are employed to distinguish between left-hand and right-hand motor imagery tasks. Three

distinct classification techniques, including SVM, LDA, and GNB, were used to categorize the motor imagery tasks based on the extracted features. The outcomes of the feature extraction and classification procedure demonstrate the extent to which the approach distinguishes between left- and right-hand motor imagery with accuracy.

1) Classification Performance

The performance of machine learning classifiers using CSP is illustrated in Figure 4. This figure presents the classification results for motor imagery EEG signals across five subjects (S1–S5), evaluated using three classifiers: SVM, LDA, and GNB. For each subject and classifier, the accuracy, precision, and recall metrics are presented. Among the classifiers, SVM continuously exhibits exceptional performance, attaining elevated accuracy of 96.43%, precision of 96.60%, and recall of 96.20% across most subjects, notably in S1, S2, S4, and S5. GNB demonstrates competitive outcomes, closely following SVM in multiple instances. Conversely, LDA demonstrates relatively poor performance, particularly in S1. Subject S3 exhibits the lowest classification metrics among all classifiers, suggesting potential individual variability or signal quality concerns. The chart demonstrates that the combination of CSP and SVM produces the most reliable outcomes for EEG-based motor imagery categorization, as evidenced by the closely aligned precision and recall values that signify consistent and balanced predictions.

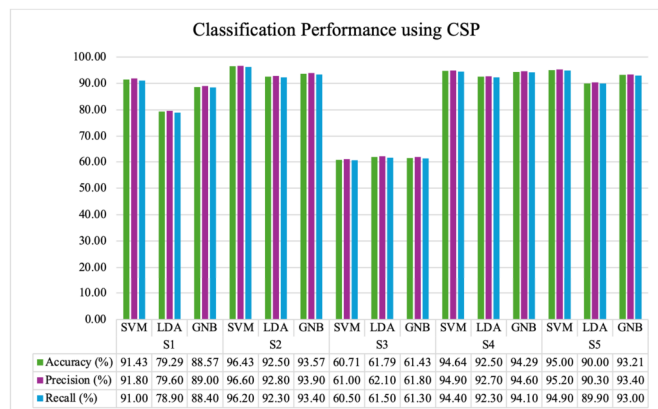


Fig. 4. Classification performance using CSP with SVM, LDA, and GNB classifiers.

The performance of machine learning classifiers using FBCSP is illustrated in Figure 5, which includes data from subjects S1 through S5. The findings indicate that SVM surpasses the other classifiers, achieving the best accuracy (98.86%), precision (99.00%), and recall (98.70%) for subject S2. Both LDA and GNB exhibit robust performance, especially for subjects S2 and S4, with precision and recall metrics exceeding 98%. Subject S3 consistently exhibits the lowest performance across all classifiers, with accuracy, precision, and recall around 70%, indicating potential subject-specific variability or signal inconsistencies. Overall, the three metrics exhibit strong alignment, signifying consistent performance. The figure demonstrates that FBCSP improves classification

outcomes, especially when paired with SVM, rendering it an effective method for EEG-based motor imagery classification.

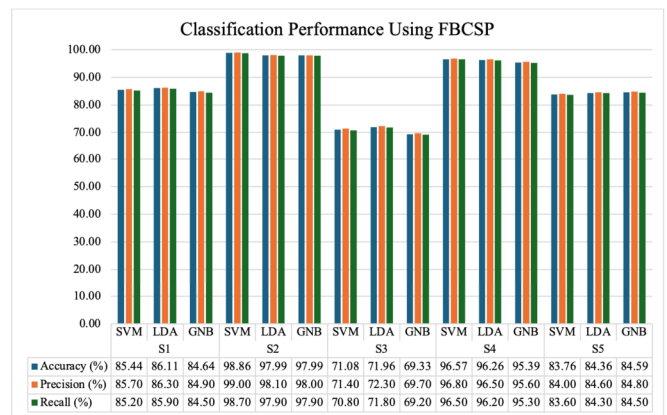


Fig. 5. Classification performance using FBCSP with SVM, LDA, and GNB classifiers.

Table I provides a comparative analysis of current works on EEG-based motor imagery classification. The enumerated works span from 2023 to 2025, utilizing diverse databases including GigaDB, SUH, MI, and Horizon. The reviewed methods incorporate Temporal-Frequency-Phase Feature (TFPF) [18], CNN variations [19], and ensemble-EMD [20] with sophisticated classifiers like 3D-CNN-GAN [18], CNN-LSTM [19], CNN-Transformer [19], and Narrow NN [20]. In contrast, the proposed method leverages the Dataset IVa from BCI Competition III, utilizes FBCSP for feature extraction, and applies SVM for classification, achieving an accuracy of 98.86%. The proposed method surpasses alternative methods, demonstrating the efficacy and promise of the suggested strategy for motor imagery-based BCI systems. This comparison highlights the novelty and enhancement provided by the suggested methodology.

TABLE I. PERFORMANCE COMPARISON OF THE PROPOSED METHOD WITH EXISTING WORKS

Reference, year	Dataset	Feature extraction	Classification algorithm	Acc. (%)
[18], 2024	GigaDB	TFPF	3D-CNN-GAN	77.03
[18], 2024	SUH	TFPF	3D-CNN-GAN	71.63
[19], 2025	MI	3-layer CNN	CNN-LSTM	79.03
[19], 2025	MI	3-layer CNN	CNN-Transformer	78.64
[20], 2023	Horizon	Ensemble-EMD	Narrow NN	96.83
Proposed method	Dataset IVa	FBCSP	SVM	98.86

IV. CONCLUSION AND FUTURE SCOPE

The research thoroughly investigated the application of two separate feature extraction methods, Common Spatial Pattern (CSP) and Filter Bank Common Spatial Patterns (FBCSP), alongside three machine learning algorithms—Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), and Gaussian Naive Bayes (GNB)—for the classification of EEG signals in motor imagery tasks. This study's primary innovation

is the comparative assessment of CSP and FBCSP for EEG-based motor imagery classification in both healthy and stroke-affected persons, a domain that has been insufficiently investigated in previous studies. Our findings underscore the exceptional efficacy of the FBCSP-SVM combination, with a classification accuracy of 98.86%, demonstrating its capability to distinguish between various subject groups effectively. This finding substantially advances the development of Brain-Computer Interface (BCI) technologies. While the findings are encouraging, it is crucial to account for individual variability and context-specific aspects when implementing these models. Future research may concentrate on refining the feature extraction and classification processes, as well as expanding the existing work using deep learning methodologies to improve accuracy and resilience.

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