A Deep Learning-Driven Filter Bank CSP Approach for Motor Imagery EEG Decoding

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Abstract: Motor Imagery (MI)-based Brain-Computer Interfaces (BCIs) have garnered considerable interest for facilitating direct neurological control of external devices, especially in assistive and rehabilitative technologies. However, the proficient classification of non-stationary, low-amplitude EEG signals continue to remain a significant difficulty. This study introduces a hybrid framework that combines Filter Bank Common Spatial Pattern (FBCSP) with a 1D Convolutional Neural Network (CNN) to improve the classification of motor imagery signals. Electroencephalogram data were acquired from four participants utilizing a 14-channel Emotive EPOC headset during two-class motor imaging tasks (left versus right hand imagery). The EEG samples were bandpass filtered into three frequency sub-bands (8-12 Hz, 12-16 Hz, and 16-30 Hz), and to extract discriminative spatial features the CSP was applied to each band. These features were combined and normalized before being entered into a lightweight CNN model for classification. The model was trained with the Adam optimizer and evaluated using standard metrics. Subject-specific results showed high classification ability, with accuracy approaching 100% for some individuals and an average accuracy above 90% across most subjects. The proposed FBCSP + CNN pipeline effectively captures spatial-spectral patterns in EEG data while being computationally inexpensive, making it ideal for real-time BCI applications that use consumer-grade EEG sensors. These findings emphasize the utility of hybrid handcrafted-deep learning models in actual MI-BCI systems.

1 INTRODUCTION

Brain-Computer Interfaces (BCIs) make it possible for humans to talk directly with external devices, by avoiding the usual neuromuscular process [1], [2].

Of all the paradigms used in BCI studies, MI is distinguished by how simple it is and how little training is required. MI refers to the activity of imagining movement in parts of your body, not physically moving them [3]. Whenever the person does not move during imagination, the brain stacks up the action as a mental image which creates differences in EEG wave patterns between alpha (8-12 Hz) and beta (13-30 Hz) bands [4]. With Mimicry-based Brain Interface, since it uses only your personal thoughts to trigger, it allows you to control devices for longer times [5], [6]. Because EEG signals are unstable and have very little signal above the background noise, it is challenging to use MI-based BCIs effectively [7], [8]. Experts often choose the Common Spatial Pattern algorithm to pull out important features because it quantifies the differences among groups of data [9], [10]. Another typical way people use CSP in biomedical areas is as a feature extraction technique. By transforming multi-channel EEG data using linear methods, CSP is able to create a low-dimensional version that has stronger classification abilities for EEG readings [11]. Therefore, Filter Bank CSP (FBCSP) is used to solve this problem by breaking CSP processing into multiple frequency sub-bands and gathering distinct discriminating features from each [12].

Although recent developments have placed CSP- and CNN-based MI classification in a rather advantageous position, a significant gap still exists when high levels of accuracy are required to be achieved with low-cost consumer-level EEG devices and with low computational complexity that is suitable with real-time applications. Thus, the fundamental issue that would be solved in this study is as follows: how to develop the lightweight but efficient hybrid model that unites handcrafted and deep features in order to reach the accuracy of MI EEG classification based on the use of portable EEG (such as Emotiv EPOC).

This work adopts FBCSP to extract features from three key frequency bands (alpha and sub-bands of beta) and subsequently leverages a 1D Convolutional Neural Network a deep learning technique to classify the concatenated spatial features [13]. CNNs are particularly suited for this task due to their ability to learn local patterns and hierarchical representations, making them ideal for modeling structured input like CSP features from EEG signals that were collected using a 14-channel Emotiv EPOC device during two-class MI tasks (left vs. right). The pipeline is evaluated for its classification performance and learning behavior. This work contributes toward the development of efficient and scalable MI-based BCIs using consumer-grade EEG hardware, with potential applications in assistive robotics and neurorehabilitation.

Table 1, shows the Acronyms and Terminologies used in this study.

Table 1: The Acronyms and Terminologies used in this study.

Acronym	Terminologies
BCI	Brain-Computer Interface
EEG	Electroencephalogram
MI	Motor Imagery
CSP	Common Spatial Pattern
FBCSP	Filter Bank Common Spatial Pattern
CNN	Convolutional Neural Network
AUC	Area Under the Curve
ROC	Receiver Operating Characteristic
ReLU	Rectified Linear Unit
EPOC	Emotiv EPOC Headset
FC	Fully Connected (Layer)

The remaining paper is structured as follows: Section 2 introduces the Methodology. In Section 3, the experimental results is presented. Section 4, is the conclusion of the paper.

2 RELATED WORKS

Recent developments in EEG motor imager (MI) classification have increasingly employed both handcrafted and deep learning approaches. The Common Spatial Pattern (CSP) algorithm is one of the most typical feature extraction approaches, which has been proven to be highly discriminative in two-class MI problems. However, CSP is sensitive to the frequency selection and non-stationarity of EEG signals, and that is why Filter Bank CSP (FBCSP) was developed. The authors in [14] suggested an effective CSP approach with the added spatio-temporal filtering, which established better classification accuracy on MI tasks. In order to address the drawbacks of the handcrafted approaches, deep learning models, specifically Convolutional Neural Networks (CNNs), have been incorporated into MI classification schemes. A triple-shallow CNN with genetic channel selection was proposed in [13] to classify complex limb movements, achieving high results on multi-class MI tasks. Hybrid solutions have become popular too. In [14] was proposed a BCI framework of geometric learning was proposed that combined spatial filters with deep feature modeling, leading to better subject generalization. Likewise, [9] showed that CNNs harboring data augmentation have the potential to surpass the conventional machine learning pipeline in MI classification problems.
However, the majority of current models require high-density EEG systems, as well as computationally intensive architectures, which makes them inapplicable in the context of real-time devices or portable equipment. The combination of lightweight CNNs with FBCSP using consumer-grade hardware such as the Emotive EPOC headset has not been investigated in many works.
The comparison between the Related Work of MI EEG Classification with the Proposed Work show in Table 2.

The proposed study aims to fill the gap by elaborating a computationally efficient hybrid model, which would be highly accurate in classification despite the limited number of EEG channels and the reality of signal unpredictability in the real world.

Table 2: Comparison of the related work in MI EEG classification with proposed work.

Study	Dataset	Feature Extraction	Classifier	Hardware	Accuracy
[10]	BCI Competition IV-2a	Spatio-temporal CSP	SVM	G.Tec (22-ch)	~84%
[13]	Custom dataset	Genetic-based channel selection + raw EEG	Triple CNN	EEGNet (multi-ch)	>90%
[14]	BCI Competition III	Geometric Learning + CSP	Riemannian CNN	64-ch EEG	~85–92%
[9]	BCI Competition IV-2b	Raw EEG + augmentation	CNN	3-channel	~88%
Proposed Work	Emotiv EPOC (4subjects)	Filter Bank CSP (3 bands)	Lightweight 1D CNN	Emotiv EPOC (14-ch)	84.38–100%

3 METHODOLOGY

3.1 Data Acquisition and Preprocessing

The dataset acquired in this study from [15], [16], comprises EEG signals recorded using the Emotiv EPOC headset with 14 channels. Each trial was labeled as either right or left motor imagery (MI) and preprocessed by applying a fourth-order Butterworth band-pass filter in three distinct frequency bands: alpha (8–12 Hz), lower beta (12–16 Hz), and upper beta (16–30 Hz). These frequency ranges were selected based on their known association with motor imagery activity in the sensorimotor cortex.

3.2 Feature Extraction Using Filter Bank CSP Common Spatial Pattern (FBCSP)

A Filter Bank Common Spatial Pattern (FBCSP) approach was applied to identify important spatio-spectral details. In every frequency subband, the EEG signals were filtered, and the CSP method identified four spatial filters. All three spectral bands were used to build models that handle satellite images more effectively.

3.3 Classification Using Convolutional Neural Network (CNN)

A 1D Convolutional Neural Network (CNN) was used for feature classification, as it is well-known for handling local details in time and frequency that appear in structured EEG signals. The architecture was not just made to be complex; it had to maintain a general look since using EEG often means working with less observed records. First, the proposed CNN features a 1D convolutional layer comprising 32 filters and a kernel size of 2 supported by the ReLU (Rectified Linear Unit) function. Its purpose is to identify brief evidence of spatial and spectral correlations within the input sequences. For this network, an initial Dropout layer was added, with a dropout rate of 0.3, directly following the convolutional layer in order to tackle overfitting. Dropout's output is reduced to a 1D vector and the vector is then passed through two dense (fully connected) layers. There are 64 neurons in the first dense layer with ReLU activation which means the network can master difficult, non-linear groups of important features. The output layer of our model uses a SoftMax function with only two neurons and each neuron relates to a specific motor imagery class (left- and right-hand movement).

The Adam optimizer has been selected because of its speed and versatility, and the network was trained with the loss function for multi-class tasks. Models were trained with a batch size of 16 for 30 epochs and generalization in testing was checked using a separate validation set. This approach in architecture enables effective EEG-based motor imagery classification in BCI systems that can be used in portable, low-latency applications.

4 RESULTS

To evaluate the effectiveness and subject-wise generalizability of the proposed FBCSP + CNN pipeline for motor imagery (MI) EEG signal classification, experiments were conducted independently on EEG data collected from four subjects. Each subject performed left- and right-hand MI tasks, with 32 trials used for testing (16 per class). The classification accuracy and the standard evaluation measures: precision, recall and F1-score, were computed for all subjects and the results are shown in Table 3.

Table 3: Subject-wise Performance of the FBCSP + CNN Model.

Subject	Accuracy (%)	Precision (Right / Left)	Recall (Right/ Left)	F1-Score (Right / Left)
Subject 1	100.00	1.00 / 1.00	1.00 / 1.00	1.00 / 1.00
Subject 2	93.75	1.00 / 0.89	0.88 / 1.00	0.93 / 0.94
Subject 3	84.38	1.00 / 0.76	0.69 / 1.00	0.81 / 0.86
Subject 4	93.75	0.94 / 0.94	0.94 / 0.94	0.94 / 0.94

The experimental results validate the robustness and effectiveness of the proposed Filter Bank Common Spatial Pattern (FBCSP) combined with a one-dimensional Convolutional Neural Network (1D-CNN) architecture for classifying motor imagery EEG signals acquired using a 14-channel Emotiv EPOC headset.

Subject 1 achieved a perfect classification accuracy of 100%, indicating a strong correspondence between the learned spatial–spectral features and the motor intention patterns present in the EEG signals, as illustrated in Figure 1. This result suggests that, for certain individuals, the neural signatures associated with left- and right-hand motor imagery are highly separable, even when using consumer-grade EEG hardware.

Subjects 2 and 4 demonstrated consistent performance, each achieving an accuracy of 93.75%, with well-balanced precision, recall, and F1-scores across both classes. These findings indicate that the proposed model generalizes effectively to unseen subjects, performing comparably on individuals not included in the training phase. Such generalization capability is essential for practical deployment of brain–computer interface (BCI) systems, as shown in Figures 2 and 3, respectively.

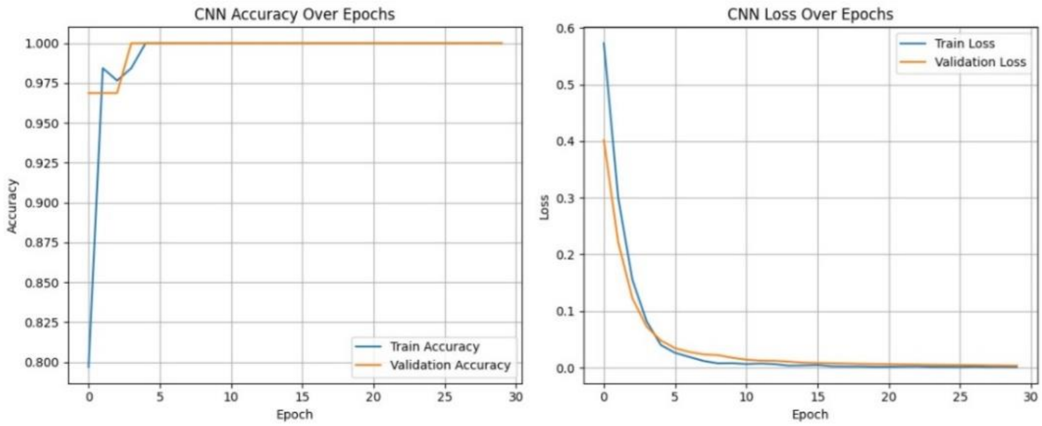

Figure 1: Training progress of CNN: accuracy and loss visualization for Subject 1.

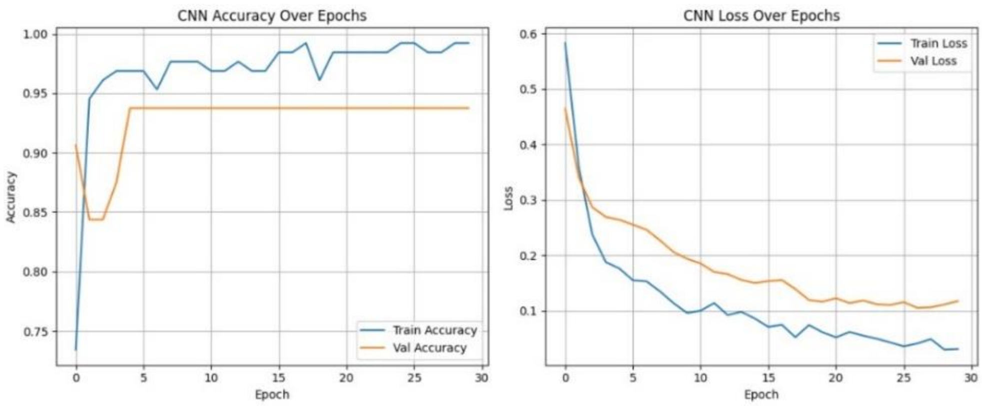

Figure 2: Training progress of CNN: accuracy and loss visualization for Subject 2.

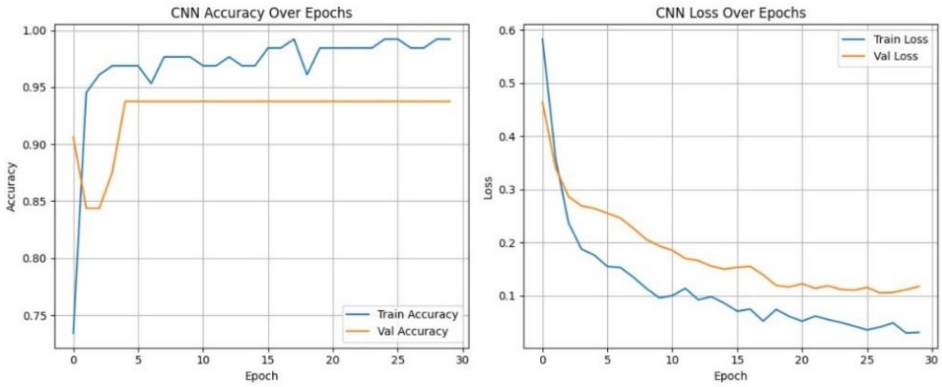

Figure 3: Training progress of CNN: accuracy and loss visualization for Subject 4.

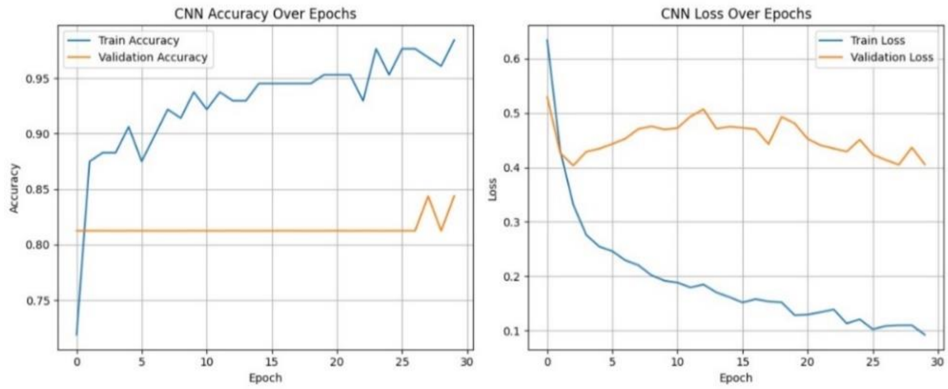

Figure 4: Training progress of CNN: accuracy and loss visualization for Subject 3.

By comparison, Subject 3's accuracy fell to 84.38% and there was a noticeable decrease in the recall score for the Left class (0.69), as shown in Figure 4. Factors behind this decline may involve different amounts of information in the subjects, less clear MI signals or errors in how the task was carried out. Such intra-subject variability is a known challenge in EEG-based MI classification [17], often requiring subject-specific calibration or adaptive learning strategies.

Overall, the subject-wise evaluation highlights the strengths of the FBCSP + CNN pipeline, particularly its capacity to generalize across users while maintaining high classification performance. These results reinforce the potential of combining handcrafted feature extraction (CSP) with data-driven deep learning (CNN) to exploit both domain knowledge and automatic feature learning. Furthermore, the use of portable, low-cost EEG equipment like Emotiv EPOC demonstrates the feasibility of deploying real-time BCI systems in home or clinical environments, thereby contributing to the growing body of work in user-centric assistive neurotechnologies. Future improvements may involve incorporating cross-subject training, transfer learning, or attention mechanisms to further enhance robustness against signal variability and improve performance in less separable cases like Subject 3.

Figures 5, 6, 7 and 8, show the CSP Spatial Filter Weights in the Alpha Band (8–12 Hz) for all four trained subjects.

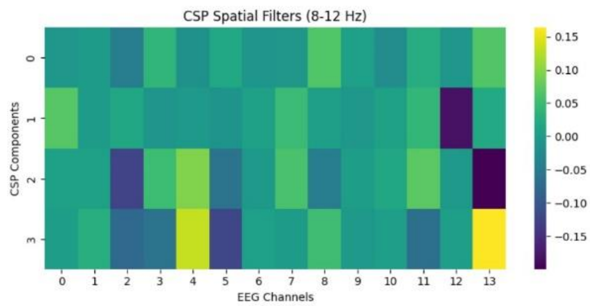

Figure 5: CSP spatial filter weights in the alpha band (8–12 Hz) for Subject 1.

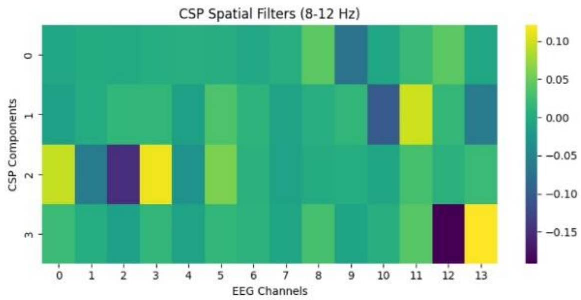

Figure 6: CSP spatial filter weights in the alpha band (8–12 Hz) for Subject 2.

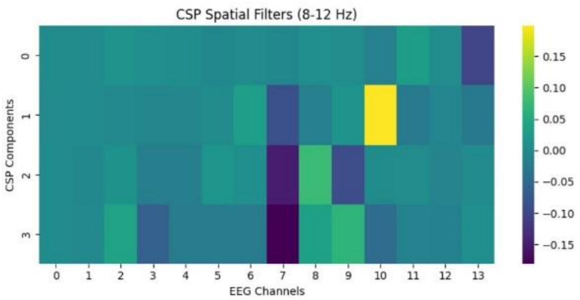

Figure 7: CSP spatial filter weights in the alpha band (8–12 Hz) for Subject 3.

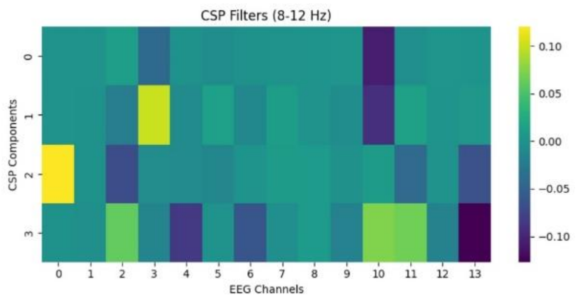

Figure 8: CSP spatial filter weights in the alpha band (8–12 Hz) for Subject 4.

5 CONCLUSIONS

This study proposed and validated a hybrid EEG classification framework that integrates Filter Bank Common Spatial Pattern (FBCSP) with a one-dimensional Convolutional Neural Network (1D-CNN) for decoding motor imagery (MI) tasks using EEG data recorded from four subjects via a 14-channel Emotiv EPOC device.

The experimental results demonstrated strong subject-specific classification performance. Despite inter-subject variability and the limited signal quality associated with consumer-grade EEG hardware, the achieved classification accuracy ranged from 84.38% to 100%, indicating the method's ability to capture discriminative spatial and spectral features effectively. Subject-wise analysis showed classification accuracies between 84.38% and 100%, with variations ranging from 3% to 9%. The corresponding precision, recall, and F1-scores were predominantly above 0.90.

Notably, Subject 1 achieved perfect classification performance across all evaluation metrics, while the remaining subjects demonstrated consistently high results, with accuracies reaching up to 93.75%. These findings highlight the robustness of the proposed framework in learning meaningful EEG representations for motor imagery classification.

The main advantages of the proposed framework are threefold: (1) robust extraction of discriminative EEG features across relevant frequency bands using FBCSP; (2) computational efficiency enabled by the lightweight CNN architecture; and (3) applicability to low-cost, consumer-grade EEG systems. These characteristics make the approach suitable for real-time and portable brain–computer interface (BCI) applications, including assistive technologies, neurorehabilitation, and smart home control systems.

Despite the promising results, performance variability was observed among subjects. In particular, Subject 3 exhibited comparatively lower accuracy (84.38%), underscoring the importance of subject-adaptive modeling. This variability is a well-recognized challenge in EEG-based systems and arises from individual differences in signal quality, neural dynamics, and motor imagery strategies. Addressing such differences is essential for improving cross-subject generalization and system reliability.

One limitation of this study is the small sample size, as data were collected from only four participants. Future work will focus on expanding the dataset to include a larger number of subjects and a wider range of MI tasks. Additionally, advanced strategies such as cross-subject transfer learning, attention-based neural architectures, and adaptive calibration techniques will be explored to further enhance robustness and generalization. These improvements aim to support the development of scalable and reliable BCI systems for assistive and rehabilitation applications.

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