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Multiclass Motor Imagery EEG Signal Classification using FBCSP-CNN

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ABSTRACT

Recently, brain-computer interfaces (BCIs) have gained more attention. One of the BCI tasks is to categorise EEG motor imagery (MI). A significant amount of work has been put into MI categorization. Even with significant breakthroughs, multimodal MI decoding remains unsatisfactory. The spatiotemporal-frequency properties of distinct MI were retrieved using a filter bank common spatial pattern (FBCSP) method. The MI EEG recognition model's performance is substantially influenced by the EEG's operational frequency band. Unfortunately, because they employed a vast frequency range, the majority of algorithms failed to successfully harness discrimination from many sub-bands. Consequently, extraction of discriminative features from EEG signals using convolutional neural networks (CNNs) with different frequency components might be a promising method for multi-subject EEG identification. In order to verify this suggested method, experiments were conducted using the BCI Competition III dataset III a, which is publicly available. The performance obtained (accuracy and kappa) was comparable to the best strategy across the comparisons. The findings showed that the FBCSP-CNN technique lowered computational complexity while maintaining a mean categorization accuracy of more than 84.52% and an average kappa value of 0.8. Thus, we can say this algorithm is suitable for MI-BCI systems with less data

Keywords: BCI, CNN, Electroencephalograph, FBCSP.

I. INTRODUCTION

The high temporal resolution of the electroencephalography (EEG) [1] signal makes it a key component in brain-computer interface (BCI) systems. One traditional approach in BCI systems, especially for individuals with brain damage, paralysis, or stroke, is motor imagery (MI)-based BCI [2], [3]. This method allows patients to communicate and potentially regain movement function without physically moving by imagining actions [4].

The process of feature extraction is essential to developing BCI systems. A popular technique for extracting spatial information is known as common spatial pattern (CSP) [5], [6], which efficiently creates an optimal spatial filter to differentiate between various MI classes. CSP considers temporal dynamics while seeking the optimal spatial filter. Typically, a bandpass filter is used before CSP to concentrate on a distinct frequency band, which significantly influences CSP's performance. Each subject's frequency band is selected to achieve peak performance. Filter bank common spatial pattern (FBCSP) [7] is an alternate method that takes traits from various frequency bands at the same time, collecting discriminative spatiotemporal data.

Recent advances in DL algorithms have accelerated the development of BCI systems based on EEG. CNNs have gained popularity in EEG-based MI classification due to their ability to extract both temporal and spatial features from EEG data.

Fiederer L.D et al. [8] proposed two CNN topologies, Shallow and Deep, for MI-based EEG recognition. These CNN models surpassed traditional techniques such as the FBCSP algorithm. Notably, the suggested models excel at

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utilising spectral power features across several frequency bands, as indicated by CNN visualisation findings. Additionally, Lawhern et al. introduced EEGNet [9], a small CNN design that performs consistently across a variety of BCI scenarios.

CNNs are the deep learning frameworks that work well for categorising MI tasks [10-14] because of their ability to capture hierarchical spatial patterns, exploit parameter sharing, achieve translation invariance, automatically learn discriminative features, and use transfer learning.

A typical CNN architecture [15-17] is as shown in fig.1 includes the following:

Input: EEG data is multi-channel time-series recordings from electrodes put on the head. Each channel represents a unique input dimension.

Convolutional layer captures temporal patterns throughout the time dimension of EEG signals. These layers learn local characteristics, including oscillations and event-related potentials.

Pooling layers reduce the computational cost of feature maps by downsampling them along the time dimension. Common pooling strategies include maximum pooling and average pooling.

A dense layer in which each neuron in the layer is linked to every neuron in the preceding layer. It serves an important role in learning complicated linkages between input data and output labels, which makes it an essential building block in neural network.

Classification Layer: The last layer in the network is a dense layer activated by softmax , which is responsible for providing predicted outcomes based on previously learned characteristics.

Fig. 1: Generalized model of convolution neural network

The following are the main contributions.

A) As seen in Figure 2, we provide an efficient filter bank to capture CSP features from different channels. CNN architecture gathers discriminative data from different FBCSP bands and classifies it.

B) Extensive experimental testing is carried out on the benchmark dataset BCI III IIIa [25] to demonstrate the effectiveness as well as the practicality of the proposed filter bank CNN framework.

Section 2: A comprehensive assessment of relevant prior work on the topic is offered. This includes a discussion of current methodologies and advancements in the area of MI categorization.

Section 3: This section describes the FBCSP- CNN approach for four-class MI classification. It explores CNN architecture.

Section 4: The suggested FBCSP-CNN method produces outcomes that are comparable to those of other researchers. The merits and cons of the suggested strategy are compared to comparable cutting-edge studies.

Section 5: In Section 5, the study summarises the important results and implications, followed by extensive analysis and future studies.

II. RELATED WORK

Gong Xiaoliang et al. [10] proposed a Temporal-Spatial CNN (FBSF-TSCNN) for decoding MI research. Unlike standard techniques that focused exclusively on energy aspects, FBSF-TSCNN incorporated both spatial and temporal details from EEG data. To address optimisation issues, a novel stage-wise training technique was proposed:

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feature extraction layers were trained using triplet loss optimisation, followed by classification layers trained using cross-entropy loss. Li et al. [11] proposed amplitude enhancement of perturbation data and employed the CPMixedNet architecture with raw electroencephalograph as input to increase decoding accuracy for MI tasks in BCI. The system is made up of three major blocks: a fundamental representation in space and time learning block, a convolutional block at mixed scale for effectively collecting mixed-scale time information, and a classification block for task categorization using extracted features. A new Filter-Bank Convolutional Network (FBCNet) developed by Mane et al. [20] used multi-view data representation and spatial filtering to extract spectro-spatially selective features for rapid training even with sparse data. A unique variance layer was presented to efficiently gather EEG time-domain information. The system has increased its robustness by integrating several data formats. Zhao X. et al. [21] designed a unique MI classification system with a multi-branch 3D CNN to take advantage of the spatial dispersion of EEG electrodes. The three-dimensional depiction is created by converting EEG signals into an assortment of 2D arrays that maintain the spatial distribution of sampling electrodes.

Meng F. et al. proposed [22] TS-SEFFNet, a new network of squeeze-and-excitation features based on time and frequency data. Initially, the deep-temporal convolution block extracted high-dimensional temporal representations from raw EEG data using the cascade architecture. Next, the multi-spectral convolution block is executed concurrently. The squeeze-and-excitation feature fusion block converted deep-temporal and multi-spectral data into complete fused maps of features, emphasising channel-wise feature responses by generating interdependencies among distinct domain features. Lu et al. [23] developed a frequential deep belief network (FDBN) based on restricted Boltzmann machines (RBMs) for MI classification. The FDBN provided considerable gains by using frequency domain representations derived from FFT and wavelet packet decomposition. The RBMs and softmax regression output layer are fine-tuned with conjugate gradient and backpropagation to improve results. Yang Huijuan et al. [24] proposed a parallel architecture based on CNN for energy-sensitive features with dropout normalization and a three-layered MLP for static features. Averaging combines the forecasts from the two networks. When comparing the structure to the support vector machine, its categorization accuracy improves dramatically.

Ricardo Aler et al. [26] suggested utilizing evolution strategies to simultaneously enhance spatial and frequency-selection filters. Functions may be optimized using evolution techniques without making significant assumptions about them. Rather than using surrogate metrics to assess class separability, this approach seeks to identify the optimal filters that maximize the algorithm's accuracy. Eltaf Abdalsalam Mohamed et al. [27] identified features from the EEG information utilizing wavelet coefficients, and the common pattern of left, right, and forward imagery was identified using the RBFN.

In [28], H. Wang presented a unique strategy for expanding CSP and local temporal CSP (LTCSP) to handle multi-class EEG classification. The method involved maximising the harmonic mean of all pairs of symmetric Kullback-Leibler (KL) divergences between filtered class-conditional densities. This technique enabled the optimisation of spatiotemporal filters for improved discrimination across several EEG classes. The technique gave a probabilistic interpretation for CSP and LTCSP by constructing a framework based on KL divergence.

In [29], the authors employed a single-channel convolutional neural network (CNN) for multi-classification tasks. The method used single-channel learning to get data independently from each channel, eliminating interference between adjacent channels. The research also introduced a data assessment approach and an auto-selection algorithm for regularisation parameters that used mutual knowledge to provide efficient spatial filters. The suggested technique, known as data evaluation-based auto-selected filter bank regularised common spatial pattern voting (D-ACSP-V) paired with a single-channel series CNN (SCS-CNN), is tested using tenfold cross-validation. In the BCI III 3a dataset, the suggested technique attains a mediocre level of accuracy of 83.70% and a kappa of 0.7827, up 9.54% from classical.

It is observed that most of the above methods are complex and require more time. Also these systems require GPU or higher end processors. To overcome these limitations to some extent we have used FBCSP method which is robust and can find spatio temporal features from noisy EEG information. The CNN is utilised to further refine the features and improve accuracy.

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III. EXPERIMENTAL SETUP

In this section we describe the BCI III III a dataset used in our experimentation. We give detail details regarding the FBCSP extraction process. A synopsis of our suggested FBCSP-CNN is given along with the parameters used for comparison.

A. BCI III III a Dataset

In this study we have used the above dataset [25] for multi class classification. The dataset consists of electroencephalography (EEG) recordings taken during motor imagery (MI) activities. Motor imagery challenges require participants to imagine motions without actually doing them. Three individuals' EEG data doing diverse motor imagery tasks was collected using 60 electrodes placed on the head in a typical EEG montage. The data was gathered using a 250 Hz sample rate and filtered via a 50 Hz low pass filter. Each individual completed 40 trials for the whole motor imagery task. Each trial tool has a total time of seven seconds. Figure 2 shows the time diagram for each activity.

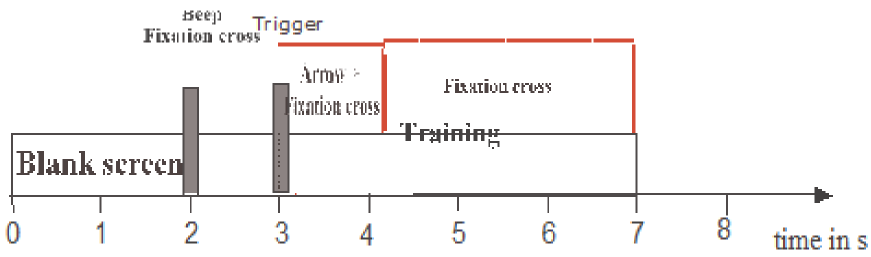

Fig. 2: Timing diagram of an event

B. FBCSP Extraction Method

The filter bank technique is used for dividing EEG signals into discrete bands of frequencies. This is helpful because different mental processes can elicit brain activity in various frequency ranges. Given EEG signal is passed through filter bank containing filters f_i, f_2.....,f_n and the EEG contents are filtered, generating a filtered signal:

$$EEG^{n}_{filtered} = f_k(EEG) \quad (1)$$

After filtering CSP algorithm [30] is applied. CSP is a spatial filtering approach that finds spatial filters that maximise the variance of one class while minimising the variance of another. The CSP approach computes covariance matrices for every data category based on filtered EEG signals from a frequency range. The eigenvectors related to the biggest and smallest eigenvalues serve as spatial filters. These filters transfer the EEG data to a new space in which the variation across classes is maximised. The CSP method generates spatial filters for every range of frequencies, which are then applied to filtered EEG data. To generate characteristics for each class, the predicted signals are squared and averaged across time.

$$f_i^n = \log\left(\frac{1}{T}\sum_{t=1}^{T}\left(x_i^T\left(EEG^n_{filtered}(t)\right)^2\right)\right) \quad (2)$$

Where n is frequency band index, x_i is a spatial filter, $f_i^n$is feature extracted using i[th] band of frequencies. The characteristics obtained from every frequency range and spatial filter are concatenated to create the feature vector for every EEG measurement.

C. Proposed FBCSP-CNN method

Eight filters with a 4Hz bandwidth are used to bandpass filter the dataset's input data. The obtained EEG data are first separated into multiple signals that correspond to different spectrums. Then CSP is applied to each filter bank output and FBCSP features are obtained. These features are given to a 2D convolution layer [31, 35] to extract more prominent features. Output of convolution layer is given to max-pooling layer to reduce total number of features. We have used two convolution and max-pooling layers.

The output is further given to flatten layer to get one dimensional output. A dense layer is one that connects every input neuron to every output neuron, resulting in a dense matrix of connections. A dropout layer is used to avoid overfitting. Softmax layer is used for multi class classification. The detailed model is described in table I.

TABLE I

Detailed CNN Model

Layer	Output shape	Parameters
Convolution 2D	(None,10558,1,16)	64
Max_pooling 2D	(None,5279,1,16	0
Convolution 2D	(None,52771,16)	1568
Max_pooling 2D	(None,2638,1,16	0
Flatten	(None,84416)	0
Dense	(None,128)	10805376
Dropout	(None.128)	0
Dense	(None,64)	8256
Dropout	(None,64)	0
Dense	(None,4)	260

The performance indicators that were employed to compare the classification performance are accuracy and Cohen kappa [32].

$$Accuracy = \frac{\text{total Right Predictions}}{total\ predicted\ outcomes} x100 \quad (3)$$

$$k = \frac{p_{obs} - p_{\exp}}{1 - p_{\exp}} \quad (4)$$

where P stands for the degree of agreement.

IV. RESULT AND DISCUSSION

This section gives the outcomes of proposed method on BCI III IIIa dataset. Data of each subject is divided such that 70% is utilised for training and 30% is utilised for testing. The batch sizes for experimentation is chosen to be 16 and number of epochs are 50. Two dropout layers are having dropout rate 0.5 and 0.3 respectively. To evaluate stability of proposed algorithm we have used subject dependent MI classification approach as chosen by many other authors.

Figure 3 shows the curves for training and validation accuracy for various subjects. The training curve shows that our algorithm has good capability of learning from training data and performing well on unseen data. Both trends' stabilization could suggest that the model has converged, and training may be terminated. A confusion matrix is a method for evaluating the efficacy of the classification model by contrasting actual labels alongside expected labels in a dataset. It summarises the model's prediction outcomes, demonstrating how effectively it distinguishes between classes. It can highlight biases in the model, such as if it favours one class over another, and help steer performance improvements. The confusion matrix [33] in the figure 4 demonstrates how effectively our model can differentiate between the different classes. Table II shows the comparison of our suggested method's accuracy with other methods used by different researchers.

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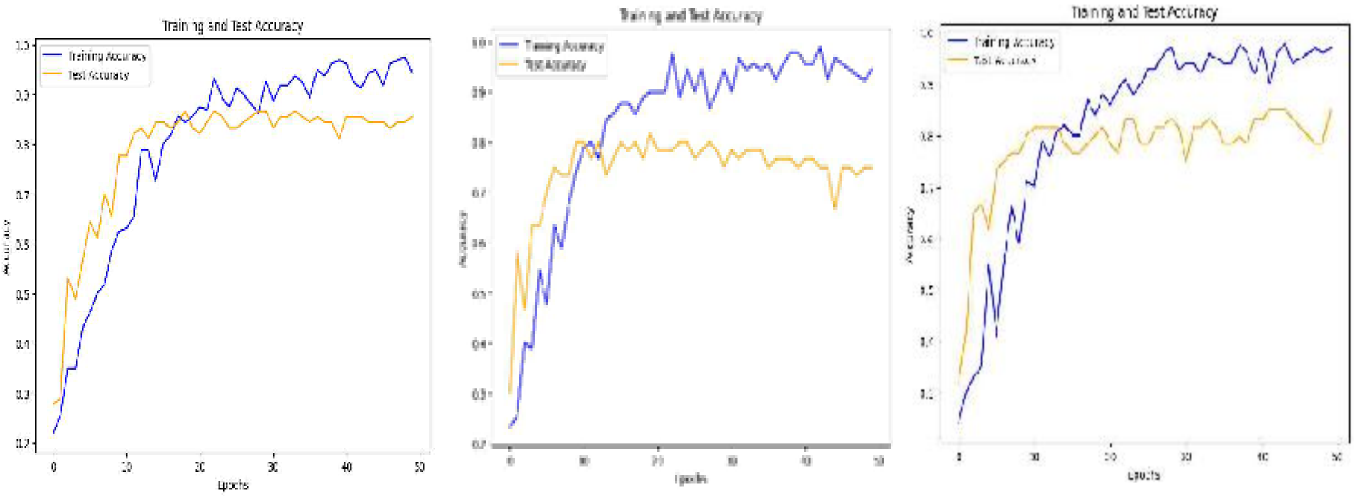
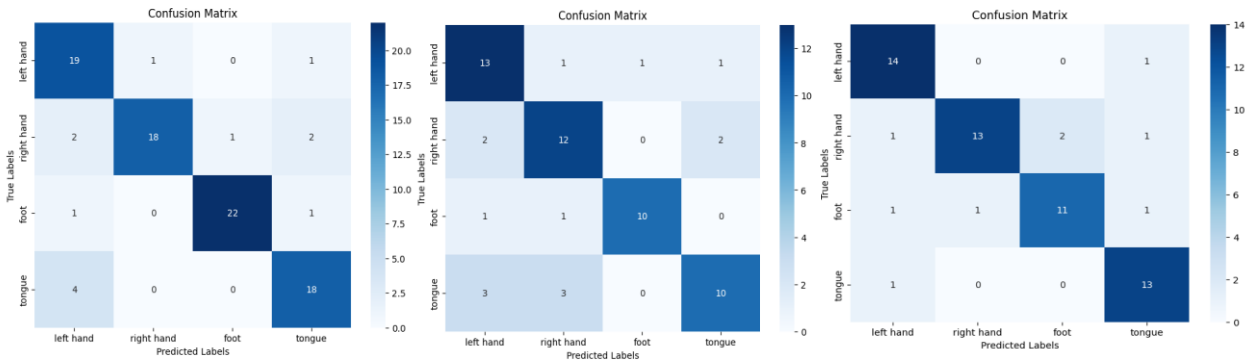


(a) (b) (c)

Fig. 3: Accuracy of training and validation curve of FBCSP-CNN model for BCI III IIIa dataset subjects (a) k3b, (b) k6b and (c) l1b.



(a) (b) (c)

Fig. 4: Confusion matrix for different subjects: (a) k3b, (b) k6b, (c) l1b

TABLE III

Comparison of accuracies of different methods

Method	% Accuracies of different subjects			
	k3b	k6b	l1b	Avg. accuracy
SVM with evolved filters[26]	77.95	71.35	56.75	68.68
RBFN [27]	80.02	84.98	82.9	82.63
LTCSP with KL[28]	84.32	62.12	65.62	70.35
SCS-CNN [29]	86.65	64.15	76.65	75.81
FBCSP-CNN	85.56	80	85	83.52

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Figure 5 gives the graph of classification accuracy of different methods.

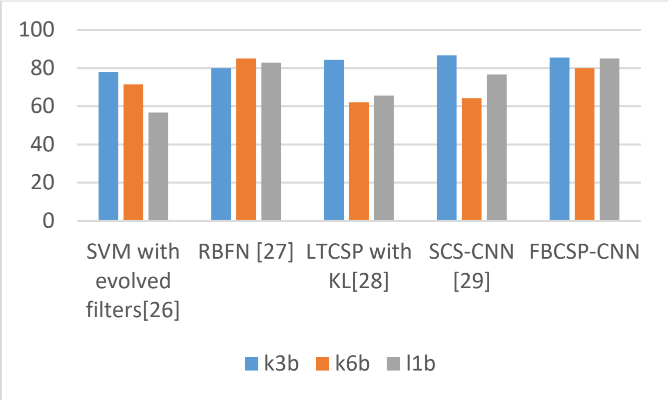

Fig.5 Classification accuracies of different methods.

Table III gives the Cohen kappa values for the three subjects.

TABLE IIII

Cohen Kappa

Subject	Cohen Kappa value
k3b	0.81
k6b	0.79
l1b	0.80

An elevated kappa score indicates that the model's predictions closely match actual results, giving confidence in its ability to perform consistently and reliably.

Ricardo Aler et al.'s [26] and Eltaf Abdalsalam Mohamed et al.'s [27] approaches may rely on certain frequency bands or wavelet coefficients [34], limiting their capacity to collect information over a wider frequency range, whereas the FBCSP-CNN method employs various frequency bands and spatial patterns, resulting in a more thorough method that takes into account a wider range of EEG signal properties.

H. Wang's [28] approach to KL divergence optimisation and other strategies may be difficult to develop and apply. It may require a considerable understanding of probabilistic interpretation and optimisation methods. The FBCSP-CNN, however, combines the benefits of classical signal processing with CNN's automated feature extraction capabilities, potentially simplifying the model creation process.

The method presented in [29] uses a single-channel CNN methodology, which may limit the capacity to fully use spatial information from several EEG channels. This can limit the model's capacity to capture inter-channel interactions, thereby lowering classification performance. FBCSP- CNN can interpret data from several channels, allowing it to detect intricate spatial correlations between them. Some approaches, such as the one in [29], may need thorough human adjustment and parameter selection (e.g., regularisation parameters) to get optimal performance. This can be time-consuming and involve substantial testing. FBCSP-CNN's end-to-end learning capacity allows it to automate most of the feature extraction and parameter adjustment, decreasing the need for operator involvement.

Overall, the FBCSP-CNN method, which combines filter bank processing with CNN's hierarchical learning capabilities, can provide a more comprehensive and successful method for classifying motor imagery problems than the other approaches discussed.

V. CONCLUSIONS

This study introduces the filter bank CSP combined with CNN architecture for multi-subject MI-BCI, which enables the CNN's model to learn spatio-temporal data from a various EEG frequency bands. To improve multiple-

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class MI classification's efficacy, a unique approach has been suggested that combines similar spatial patterns in filter banks with neural networks. The proposed technique is tested on BCI Competition III dataset IIIa. The findings of our research revealed that, in terms of classification accuracy, our approach is comparable to the best existing method. The results revealed that the proposed technique can be applied to MI classification using multiple classes. on other datasets too. In short, the FBCSP-CNN method's future promise lies in enhancing its effectiveness, interpretability, and adaptability across a variety of fields, thereby assisting in the development of more accessible and efficient BCI technologies.

The above algorithms show that the success rate of training a deep neural network remains unclear and that there is still a lot of potential for new algorithms and network topologies that may be used to build better systems.

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