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Research article

Artifact removal and motor imagery classification in EEG using advanced algorithms and modified DNN

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A R T I C L E I N F O

Keywords:
BCI
Brain computer interface
EEG
Electro Enchephalo Gram
ICA
Independent component analysis
CSP
Common spatial pattern
FCIF
Four class iterative filtering
FCFBCSP
Four class FilterBank common spatial pattern
MDNN
Modified deep neural network
MI
Motor imagery
Neurorehabilation
Assistive Technologies
HCI
Human Computer Interface

A B S T R A C T

This paper presents an advanced approach for EEG artifact removal and motor imagery classification using a combination of Four Class Iterative Filtering and Filter Bank Common Spatial Pattern Algorithm with a Modified Deep Neural Network (DNN) classifier. The research aims to enhance the accuracy and reliability of BCI systems by addressing the challenges posed by EEG artifacts and complex motor imagery tasks.

The methodology begins by introducing FCIF, a novel technique for ocular artifact removal, utilizing iterative filtering and filter banks. FCIF's mathematical formulation allows for effective artifact mitigation, thereby improving the quality of EEG data. In tandem, the FC-FBCSP algorithm is introduced, extending the Filter Bank Common Spatial Pattern approach to handle four-class motor imagery classification. The Modified DNN classifier enhances the discriminatory power of the FC-FBCSP features, optimizing the classification process.

The paper showcases a comprehensive experimental setup, featuring the utilization of BCI Competition IV Dataset 2a & 2b. Detailed preprocessing steps, including filtering and feature extraction, are presented with mathematical rigor. Results demonstrate the remarkable artifact removal capabilities of FCIF and the classification prowess of FC-FBCSP combined with the Modified DNN classifier. Comparative analysis highlights the superiority of the proposed approach over baseline methods and the method achieves the mean accuracy of 98.575%.

1. Introduction

Brain-Computer Interfaces (BCIs) have revolutionized human-computer interaction. BCIs find applications in a wide spectrum of fields, including medical diagnostics, neurorehabilitation, and assistive technologies. These interfaces enable individuals with impaired motor functions to control devices and communicate using neural signals, opening up new possibilities for enhancing quality of life.

A crucial aspect of effective BCI operation is the accurate interpretation of electroencephalogram (EEG) signals. EEG recordings capture neural activity and provide insights into cognitive processes and motor intentions. The signals, yet are frequently tainted by a variety of artifacts, including muscle activity, eye movements, and environmental noise. Preprocessing and artifact removal are pivotal

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to extracting meaningful information from EEG data and enabling reliable classification [1].

This paper addresses the pivotal role of EEG data preprocessing and classification in the realm of BCIs. The primary objectives of this research are two-fold: first, to develop an advanced method for EEG artifact removal, and second, to enhance motor imagery classification accuracy. The proposed approach combines the Four Class Iterative Filtering (FCIF) technique and the Four Class Filter Bank Common Spatial Pattern Algorithm (FC-FBCSP) with a Modified Deep Neural Network (MDNN) classifier.

In the subsequent sections, we delve into the mathematical underpinnings and methodologies of FCIF and FC-FBCSP, explaining how they synergistically contribute to artifact removal and motor imagery classification. The following is how the paper is set up: Section 2 deals with related research work,Section 3 describes the FCIF and FC-FBCSP with Modified DNN methodologies in more detail. Section 4 describes the setup of the experiment and dataset. The findings and their analysis are provided in Section 5. Section 6 discusses the effects and difficulties. And Section 7 wraps up the study while pointing out potential directions for further investigation.

By bridging the gap between advanced EEG artifact removal and motor imagery classification, this study strives to improve the accuracy, reliability, and applicability of BCIs across various domains. Electroencephalogram (EEG) data serves as a window into the intricate neural activity of the human brain, making it a valuable resource for Brain-Computer Interfaces (BCIs). As a result, EEG data preprocessing and classification play pivotal roles in the successful operation of BCIs, and their significance can be highlighted as follows:

EEG signals are vulnerable to artifacts arising from muscle movements, eye blinks, and external environmental factors [2]. Preprocessing techniques, such as filtering and artifact removal, are crucial to improve the caliber of EEG data by eliminating unwanted noise [3]. This improves the accuracy of subsequent analyses and ensures that the extracted neural patterns accurately reflect the subject's cognitive processes [4].

Artifacts can distort the underlying neural signals, leading to inaccurate interpretations [5]. Effective preprocessing methods, including advanced techniques FCIF, ensure that artifacts are identified and eliminated, allowing for a cleaner representation of neural activity. This is especially crucial for motor imagery classification, where subtle variations in EEG patterns carry valuable information [6].

Accurate motor imagery classification is at the heart of many BCI applications, enabling users to translate their intentions into meaningful actions [7]. Classification algorithms rely on distinctive features within EEG data to make accurate predictions [8]. Proper preprocessing ensures that these features are robustly captured, enhancing the classifier's ability to discern subtle differences between different motor imagery tasks [9]. BCIs hold immense potential in assisting people with impairments, allowing them to communicate, control devices, and regain motor functions [10]. Reliable EEG preprocessing and classification are prerequisites for developing BCIs that can be effectively and seamlessly integrated into real-world applications, improving the quality of life for those in need [11]. EEG data can exhibit considerable variability across different individuals [12]. Preprocessing techniques standardize the data, reducing the impact of individual differences and enabling the development of generalized BCI models that work well for a diverse range of users [13].

This research endeavors to address critical challenges in Brain-Computer Interface (BCI) systems, focusing on two intertwined objectives:

The first objective is to advance the field of EEG artifact removal by introducing the Four Class Iterative Filtering (FCIF) technique. FCIF aims to substantially improve the EEG data quality [13] by effectively mitigating ocular artifacts that frequently contaminate neural signals. The research seeks to establish the mathematical foundation of FCIF and its iterative filtering approach, providing a novel solution for enhancing the accuracy and reliability of subsequent processing steps.

The second goal is to make the FC-FBCSP algorithm, more accurate in classifying motor imagery with a Modified Deep Neural Network (DNN) classifier. The mathematical extension of FC-FBCSP to accommodate four-class MI classification will be explored. Moreover, modifications to the DNN classifier will be introduced to optimize its performance for the intricacies of MI tasks. This objective seeks to yield a robust classification approach capable of accurately deciphering complex neural patterns associated with motor intentions.

These dual objectives intertwine to form a comprehensive framework that enhances both the preprocessing and classification stages of BCI systems. The synthesis of FCIF, FC-FBCSP, and the Modified DNN classifier promises to unlock the potential of BCIs in real-world applications, where accurate artifact removal and precise MI classification are fundamental prerequisites.

This section outlines the two novel techniques developed in this study: the Four Class Iterative Filtering (FCIF) algorithm for EEG artifact removal and FC-FBCSP Algorithm with a Modified Deep Neural Network (DNN) classifier for MI classification. These techniques collectively enhance the preprocessing and classification stages of Brain-Computer Interfaces (BCIs).

The FCIF method is made to improve the elimination of ocular artifacts from EEG data repeatedly. It begins with the application of iterative filtering techniques, including band pass filters and filter banks, to isolate the artifact-related components [14]. The algorithm then employs Independent Component Analysis (ICA) to identify these artifact-related independent components [15]. An iterative projection step is applied to progressively reduce these components' influence on the EEG channels [16]. The process converges based on predefined criteria, ensuring optimal artifact removal. FCIF's mathematical basis lies in the iterative application of filters and the utilization of ICA, combined with projection techniques to iteratively refine the artifact removal process.

The FBCSP technique for motor imagery classification has been (Jana et al., 2021) improved by the FC-FBCSP algorithm. It leverages filter banks to extract frequency-specific features from EEG data [17]. These features are then processed [18] using the Common Spatial Pattern transformation to enhance discriminative patterns between motor imagery classes [19]. What sets FC-FBCSP apart is the inclusion of a Modified Deep Neural Network (DNN) classifier [20]. This classifier is tailored to effectively handle complex neural patterns associated with motor intentions. The DNN's architecture and hyper parameters are fine-tuned for improved MI classification, ensuring optimal performance in decoding user intentions.

These techniques, FCIF and FC-FBCSP with the Modified DNN classifier, collectively contribute to enhanced EEG artifact removal and MI classification.

2. Related work

Effective EEG artifact removal is essential for accurate neural signal interpretation. A range of methods have been developed to tackle various artifacts, such as ocular, muscular, and environmental interferences. Methods like Independent Component Analysis [21] employ statistical independence to separate mixed signals, including artifacts. Adaptive Filtering approaches [22] exploit prior information to adaptively cancel artifacts. While effective, they can be sensitive to noise assumptions.

Accurate MI classification is a cornerstone of BCI systems. The Common Spatial Pattern (CSP) algorithm (Wu W, Gao X, &Gao S, 2006) has gained prominence for extracting discriminative features from EEG data [23]. CSP maximizes the variance between classes while minimizing [24] variance within each class, enhancing classification accuracy. Specifically, Convolution Neural Networks (CNNs) from deep learning [25], have demonstrated remarkable success by learning hierarchical features. However, the complexity of neural networks requires careful tuning to avoid over fitting.

Despite advancements, challenges persist. Artifact removal methods often struggle with intricate noise sources, requiring further robustness. MI classification, while promising, grapples with inter-subject and inter-session variability. The need for adaptability to individual users and real-world scenarios is evident.

In light of these considerations, this research presents novel contributions in both EEG artifact removal and motor imagery classification. The FCIF technique addresses the iterative enhancement of artifact removal, while FC-FBCSP with a Modified DNN classifier optimizes MI classification. These novel approaches seek to address existing limitations and push the boundaries of BCI capabilities. While several techniques have been developed for EEG artifact removal and MI classification, certain gaps and limitations persist. Recognizing these shortcomings underscores the importance of advancing the field with novel approaches. Existing artifact removal methods often focus on specific types of artifacts, such as ocular or muscular interference, neglecting the broader range of potential artifacts. Many techniques struggle to adapt to the variability across different users and experimental conditions, leading to suboptimal performance in real-world scenarios.

Dealing with intricate noise sources, like non-stationary artifacts or mixed-frequency interferences, remains a challenge for many artifact removal methods[26]. Traditional MI classification approaches struggle with inter-subject variability, where neural patterns can significantly differ between individuals. Some methods fail to capture the full complexity of EEG data, resulting in incomplete feature representations that may lead to lower classification accuracy. Deep Learning techniques, while powerful, often suffer from over fitting and lack of generalization when dealing with limited training dataset data preprocessing and MI classification are interconnected processes. However, few approaches comprehensively address both stages, leading to suboptimal results in integrated BCI systems.

Existing methods lack adaptability to dynamic changes in neural patterns and noise conditions during real-time BCI operations. These identified gaps and limitations emphasize the requirement for creative fixes that holistically address EEG artifact removal and motor imagery classification challenges [27]. The proposed FCIF and FC-FBCSP Algorithm with a Modified DNN classifier aim to bridge these gaps, offering comprehensive and adaptable approaches to enhance the precision and resilience of BCIs.

3. Methodology

Ocular artifacts, stemming from eye movements and blinks, are among the most common and disruptive artifacts in EEG recordings. These artifacts are generated due to the electrical potential differences between the cornea and the retina of the eyes. When an individual blinks or shifts their gaze, the resulting electrical activity can contaminate the EEG signals, leading to misleading interpretations and degraded BCI performance.

Ocular artifacts introduce abrupt and high-amplitude changes to EEG signals, distorting the underlying neural patterns. This distortion can lead to false-positive or false-negative results in subsequent analysis steps. Ocular distortions can reduce the signal to noise ratio of EEG recordings, making it difficult to separate real neural impulses from noise. Ocular artifacts can mimic brain activity, causing misinterpretations during MI classification tasks. Such misinterpretations can hinder the accuracy of BCI predictions.

The intensity and duration of ocular artifacts can vary between individuals and sessions, introducing additional complexity in their identification and removal.

3.1. Mathematical formulation of Four Class Iterative Filtering (FCIF) algorithm

The Four Class Iterative Filtering (FCIF) algorithm is designed to improved ocular artifact reduction from EEG data. It employs a combination of iterative filtering, Independent Component Analysis (ICA), and projection techniques. The algorithm iteratively refines the removal process, progressively reducing the influence of artifact-related components.

Step 1. Iterative Filtering

Iterative filtering is used to process raw EEG data, which is represented by the matrix X of dimensions NxT, where N is the number of channels used for EEG and T is the number of time samples Eqn 1:

$$X\,(1) = F\,(1).\,X \tag{1}$$

Where *F (1)* represents the matrix of band pass filter coefficients for the first iteration.

Step 2. Independent Component Analysis (ICA)

ICA is applied to $X(1)$ to extract independent components Eqn 2

$$X(2) = A \cdot X(1) \tag{2}$$

where A represents the mixing matrix and $X(2)$ contains independent components.

Step 3. Artifact Identification

Correlation measure ρ between each independent component $Xi(2)$ and the electrooculogram (EOG) channels is computed Eqn 3:

$$\rho(Xi(2), EOG) = \frac{cov(Xi(2), EOG)}{\sigma Xi(2) \cdot \sigma EOG} \tag{3}$$

Components with correlation exceeding a predefined threshold are identified as artifact related.

Step 4. Iterative Projection

Remaining artifact-related components $Xartifact(2)$ are projected out of $X(1)$ iteratively Eqn 4:

$$X(3) = X(1) - PXartifact(2) \cdot X(1) \tag{4}$$

Where $PXartifact(2)$ is the projection matrix of artifact-related components.

Step 5. Convergence Criteria

The iterative process continues until a predefined convergence criterion is met, ensuring optimal artifact removal.

The final cleaned EEG data $X(3)$ is obtained, enhancing the quality of the EEG signals for subsequent analysis.

The FCIF algorithm's mathematical formulation combines iterative filtering, ICA, correlation analysis, projection, and convergence criteria to iteratively enhance ocular artifact removal from EEG data. This algorithm iteratively identifies and removes ocular artifact-related components, resulting in improved EEG data quality for downstream MI classification tasks.

3.1.1. *Iterative steps of FCIF algorithm*

- ***Initialization:***
  - Initialize the EEG data matrix X.
  - Define the number of iterations (T).
  - Set the artifact threshold (θ).
- ***Step 1: Apply Initial Artifact Removal:***
  - Apply initial artifact removal techniques (ICA, band-pass filters).
  - Calculate the residual matrix R1 = X - X_cleaned.
- ***Step 2: Artifact Detection:***
  - Compute the correlation between R1 and EOG channels.
  - Identify artifact-related independent components.
  - If correlation > θ, remove the corresponding ICs.
- ***Step 3: Projection and Update:***
  - Project the artifact-related ICs onto EEG channels.
  - Update EEG data matrix: X = X - projected_ICs.
- ***Step 4: Convergence Check:***
  - Calculate changes in EEG data between iterations.
  - If changes are below a certain threshold, stop iterations.

3.1.2. *Mathematical Equations*

- ***Artifact Detection:***
  - Calculate correlation:

$$corr(R, EOG) = \frac{\sum_{i=1}^{N} R_i \, .EOG_i}{\sqrt{\sum_{i=1}^{N} R_i^2}.} \frac{1}{\sqrt{\sum_{i=1}^{N} EOG_i^2}} \tag{5}$$

  - Identify artifact ICs: $ICartifact| = \{i : corr(Ri, EOG) > \theta\}$.
- ***Projection and Update:***
  - Project artifact ICs:

$$P = EEG \times {IC_{artifact}}^{T} \tag{6}$$

•Update EEG data:

$$X = X - P \tag{7}$$

3.1.3. Algorithm

- ***Initialization:***
  - Initialize X, T, θ.
- ***Iterate:***
  - For t = 1 to T:
    - Apply initial artifact removal techniques.
    - Calculate

$$\text{R1} = \text{X-X\_cleaned} \tag{8}$$

    - Calculate correlation between R1 and EOG channels.
    - Identify artifact ICs.
    - Project and update EEG data.
    - Check for convergence.

3.2. Mathematical basis of FBCSP and extension to FC-FBCSP

The FBCSP algorithm starts by decomposing the EEG waves at various frequencies sub-bands using a set of band pass filters. These filters are designed to isolate ranges of frequencies that are pertinent to MI tasks. Mathematically, the decomposition can be represented as follows Eqn 9:

$$S_f = \sum_{i=1}^{N_f} B_i \cdot X^n \tag{9}$$

Where S_f is the EEG data decomposed into frequency sub bands, N_f is the number of frequency sub bands, B_i represents the bandpass filter for the ith frequency band, and X is the raw EEG data.

Each frequency sub-band is transformed using the Common Spatial Pattern (CSP) after frequency decomposition. By decreasing the variance of one class while maximizing the variance of the other, the CSP transformation seeks to identify a set of spatial filters. This improves the EEG data's capacity to be separated into various MI activities. The CSP transformation can be described mathematically as follows Eqn 10:

$$W_{CSP} = argmax \frac{W_1^T \sum_1 W_1}{W_1^T \sum_T W_1} \tag{10}$$

Where W_{CSP} is the matrix of spatial filters, W_1 represents the matrix of class-specific spatial filters for one class, $\sum_1 W_1$ is the covariance matrix of the EEG data for that class, and $\sum_T W_1$ is the covariance matrix of the total EEG data.

The FBCSP algorithm extracts features from the EEG data in each frequency sub-band by applying the obtained spatial filters. These features capture the discriminative patterns associated with different MI tasks.

In summary, the FBCSP algorithm mathematically decomposes EEG data into frequency sub-bands using band pass filters and applies the CSP transformation to each sub-band to extract discriminative spatial patterns. These spatial patterns are then used as features for MI classification tasks. The FBCSP algorithm effectively enhances the separability of EEG data for different MI tasks by optimizing spatial filters based on class-specific variances.

The FBCSP can be extended to accommodate four-class MI classification by adapting its feature extraction process. In a standard FBCSP, the algorithm is designed for binary classification tasks. However, in the case of four-class classification, modifications are needed to handle multiple classes. Here's how the extension to four-class MI classification, known as FC-FBCSP, can be mathematically explained:

Similar to the standard FBCSP, the FC-FBCSP algorithm starts with frequency decomposition using bandpass filters to obtain EEG data in different frequency sub-bands Eqn 11:

$$S_f = \sum_{i=1}^{N_f} B_i \cdot X \tag{11}$$

In the standard FBCSP, two sets of spatial filters are obtained based on two classes (Right-handed vs. left-handed MI). In FC-FBCSP, to accommodate four classes, we need to obtain spatial filters for each pair of classes and then combine them to create a feature matrix.

The four classes:$C1$, C2, C3, and $C4$. For each pair of classes $Ci$and Cj, spatial filters W_{CSP}^{ij} are calculated using the CSP transformation Eqn 12:

$$W_{CSP}^{ij} = argmax \frac{W_{C_i}^{T} \sum C_i W C_i}{W_{C_i}^{T} \sum C_{i+C_j} W C_i} \tag{12}$$

where W_{C_i} represents the spatial filter matrix for class $C|_i$, $\sum C_i$ is the covariance matrix of class C_i, and $\sum C_{i+C_j}$ is the covariance matrix of classes C_i and C_j combined.

The spatial filters obtained for each pair of classes are combined to create a feature matrix $W_{FC-FBCSP}$ Eqn 13

$$W_{FC-FBCSP} = \left[W_{CSP}^{12}, W_{CSP}^{13}, W_{CSP}^{14}, W_{CSP,}^{23} W_{CSP}^{24}, W_{CSP}^{34} \right] \tag{13}$$

The feature matrix $W_{FC-FBCSP}$ is used to identify features in each frequency sub-band of the EEG data. These features can then be used to perform four class MI identification using a classifier, Modified Deep Neural Network (DNN).

In summary, the FC-FBCSP algorithm extends the standard FBCSP by calculating spatial filters for each pair of classes and combining them to create a feature matrix that accommodates four-class MI classification. This allows the algorithm to effectively capture discriminative spatial patterns for multiple MI tasks, enhancing the performance of the classification process.

3.3. The mathematical analysis of the modifications to the DNN classifier for MI tasks

- ***Architecture Adaptation***: If X *represents* the input matrix from FC-FBCSP with dimensions $M \times N$, where M *is* the number of frequency sub-bands and N is the number of spatial filters, the DNN input layer can be represented as X where each row corresponds to a flattened frequency-specific spatial filter matrix. The summarization of mathematical and architecture process for MDNN is listed in Tables 1 and 2 with corresponding Figs. 1 and 2.
- ***Activation Functions***: The activation function f *is* applied element wise to the neuron's input z to obtain the output a Eqn 14:

$$a = f(z) \tag{14}$$

Common activation functions include ReLU Eqn 15:

$$f(z) = max(0, z) \tag{15}$$

- ***Output Layer Modification***: Let o be the output vector from the last layer before the Soft ax. The Soft Max function transforms these raw outputs into class probabilities Eqn 16:

$$P(y = j|X) = \frac{e^{o_j}}{\sum_{K=1}^{4} e^{o_k}} \tag{16}$$

- ***Loss Function***: The categorical cross-entropy loss for a single sample i and class j is given by Eqn 17:

$$Lij| = -log\left(\frac{e^{o_j}}{\sum_{K=1}^{4} e^{o_k}}\right) \tag{17}$$

The total loss over all samples is the mean of individual losses Eqn 18:

$$L = \frac{1}{N} \sum_{i=1}^{N} L_i \tag{18}$$

- ***Regularization Techniques***: L2 regularization adds a penalty term to the loss to prevent large weights Eqn 19:

Table 1
Summarization of mathematical modified DNN architecture for motor imagery BCI –Dataset 2a.

Layer	Input Shape (M, N)	Neurons	Activation	Output Shape	Original Dimensions
Input Layer	(22, 22)	22	None	–	(M, N)
Hidden Layer 1	(22, 22)	10	ReLU	–	256
Hidden Layer 2	(22, 22)	5	ReLU	–	128
Output Layer	–	4	Softmax	(4)	(4)

Table 2
Summarization of mathematical model for modified DNN architecture for motor imagery BCI –Dataset 2b

Layer	Input Shape (M, N)	Neurons	Activation	Output Shape	Original Dimensions
Input Layer	(56, 56)	56	None	–	(M, N)
Hidden Layer 1	(56, 56)	10	ReLU	–	256
Hidden Layer 2	(56, 56)	5	ReLU	–	128
Output Layer	–	4	Softmax	(4)	(4)

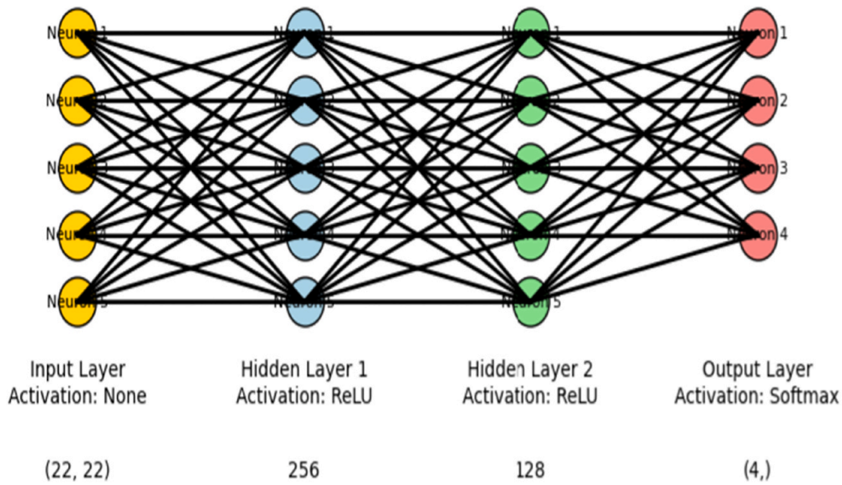

Fig. 1. Modified DNN Architecture for Motor Imagery BCI –Dataset 2a with specified dimensions(MXN = 22X22).

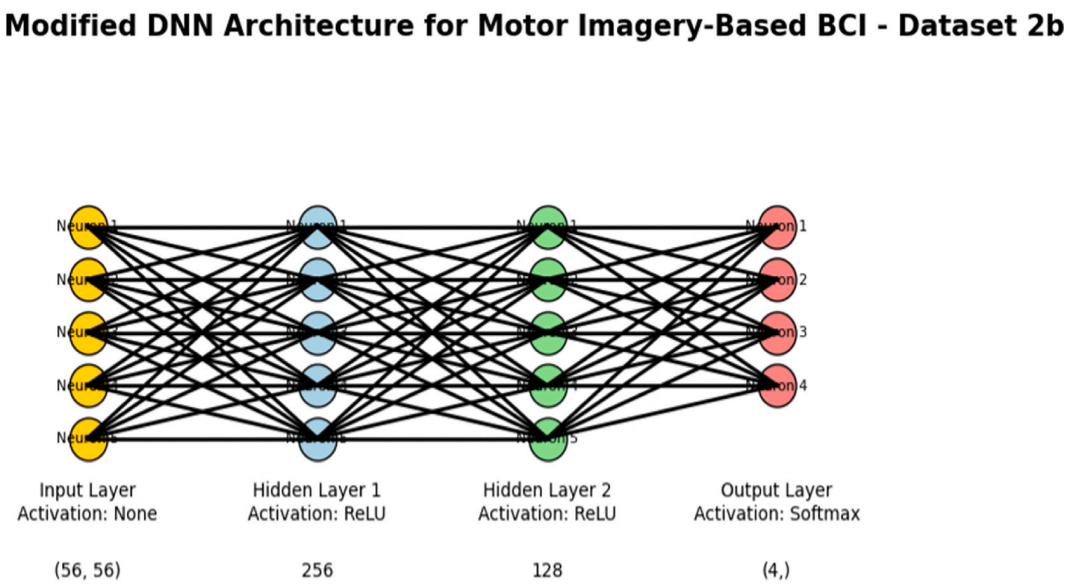

Fig. 2. Modified DNN Architecture for Motor Imagery BCI–Dataset2b with specified dimensions (MXN = 56X56).

$$L_{reg} = \lambda \sum_{l=1}^{L} \sum_{i=1}^{n_l} \sum_{j=1}^{n_{l+1}} \left(w_{ij}^{(l)}\right)^2 \quad (19)$$

where$L$ is the number of layers, n_l is the number of neurons in layer l, $w_{ij}^{(l)}$ is the weight between neuron i in layer l and neuron j in layer $l+1$, and λ is the regularization parameter.

- ***Training Strategy***: The weights are updated using optimization methods like stochastic gradient descent (SGD) or Adam Eqn 20:

$$w_{ij}^{(l)} = w_{ij}^{(l)} - \eta \frac{\partial L}{\partial w_{ij}^{(l)}} - \eta\lambda \frac{\partial L_{reg}}{\partial w_{ij}^{(l)}} \quad (20)$$

where η is the learning rate.

- ***Hyper parameters Tuning***: To determine the values of hyper parameters that reduce validation loss, grid search or random search are used.

In summary, these mathematical analyses outline the modifications to the DNN architecture, activation functions, output layer, loss function, regularization, and training process for MI classification using FC-FBCSP features.

4. Experimental setup

Nine healthy subjects who were undertaking MI tasks are featured in Dataset 2a′s EEG recordings. A 22-channel EEG setup was used to record the EEG data[28]. Each participant practiced motor imagery for the four classes of left-hand, right-hand, foot, and tongue movements [29]. Each trial's accompanying class labels and preprocessed EEG data are provided in the dataset.

Nine healthy subjects who were undertaking motor imagining tasks are also featured in Dataset 2b′s EEG recordings[30,31]. However, there are nine separate MI classes in this dataset, which include a variety of limb movements and other tasks. A 56-channel EEG setup was used to record the EEG data. EEG data and class labels are provided for every trial, just like in Dataset 2a.

Both datasets are widely used for benchmarking MI classification algorithms in the BCI community. They are split into training and testing subsets for model evaluation and comparison. The data preprocessing steps applied to these datasets include artifact removal, filtering, and feature extraction to prepare them for classification tasks.

These datasets offer a valuable resource for testing the effectiveness of the FC-FBCSP algorithm with the Modified DNN Classifier in MI classification task set data is collected from participants performing MI tasks according to the BCI Competition IV protocol. The data includes multiple subjects, each contributing sessions of MI trials.

Raw EEG data from each session is divided into segments (epochs), each corresponding to a specific MI trial. Raw EEG signals are filtered using a band pass filter to focus on relevant frequency ranges, such as the mu and beta bands (8–30 Hz). This helps extract motor-related activity while attenuating noise outside these ranges. To eliminate power line noise (50 Hz) and other line noise distortions, additional notch filters are used. The covariance matrices of EEG signals are calculated for each MI class (left hand, right hand). These covariance matrices are subjected to the CSP algorithm, leading to spatial filters that maximize distinction between classes.

EEG data is projected through the CSP spatial filters, generating feature vectors for each epoch. These feature vectors capture class-specific patterns. Common feature extraction methods include calculating log-variances of signal power in the filtered frequency bands for each channel.

The preprocessed and feature-extracted EEG data is split into training and testing sets, following cross-validation protocols. This ensures unbiased evaluation of the classifier's performance.

A Modified Deep Neural Network (DNN) Classifier is designed and trained using the preprocessed EEG data and extracted features. The DNN's architecture is tailored for MI classification, considering aspects like input size and complexity. The trained Modified DNN Classifier is evaluated using the testing dataset from each subject. To evaluate its performance, classification precision, recall, and the F1-score are computed. Data segmentation and cross-validation techniques are essential for determining the efficacy and generalizability of the generated algorithms in the experimental scenario. The EEG data from BCI Competition IV Datasets 2a and 2b is divided into subsets for training, validation, and testing. These subsets are created in a way that ensures a representative distribution of different classes (MI tasks) and accounts for potential variations across subjects and sessions.

Cross-validation is used to assess the algorithms' performance on hypothetical data and gauge how generalizable they are. The dataset is split into K folds of equal size. One-fold is utilized for testing and the remaining K-1 folds are used for training in each iteration. K repetitions of this procedure allow each fold to act as the testing set once.

To maintain the class distribution in each fold, stratified sampling is used. This ensures that each fold has a proportionate representation of different MI classes. A more stringent approach is to leave out data from one subject for testing while using the remaining subjects' data for training. This simulates situations in the actual world where the model must generalize to various people. Standard performance metrics such as accuracy, precision, recall, and F1-score are calculated for each cross-validation iteration. These metrics provide insights into the classifier's ability to correctly classify different MI classes.

AUC scores and Receiver Operating Characteristic (ROC) curves can both be used to evaluate the trade-off between true positive and false positive rates. Cross-validation and data partitioning reduce the danger of over fitting by testing the algorithms on hypothetical data.

They provide a comprehensive understanding of how the algorithms generalize across different subjects, sessions, and MI tasks. By repeating the evaluation process with different partitions, researchers gain a robust estimate of the algorithms' performance variability.

Incorporating data partitioning and cross-validation procedures into the experimental setup is crucial for accurately evaluating the developed algorithms' performance. These procedures ensure that the algorithms are not only effective on the training data but also generalize well to new, unseen data, enhancing their applicability in real-world MI classification scenarios.

After being filtered to reduce noise and artifacts, the EEG data is concentrated on the frequency bands that are important for MI tasks. Convolution can be used to mathematically illustrate the filtering process:

$$\text{Filtered EEG Data} = \text{Convolution (Raw EEG Data, Filter Kernel)}$$

Where Filter Kernel represents the coefficients of the desired band pass filter.

The filtered EEG data is used to extract significant characteristics that indicate the underlying patterns in MI activities. Using Common Spatial Patterns (CSP) to improve class reparability is a typical strategy. CSP can be modeled mathematically as follows:

$$\text{CSP Projection Matrix, W} = (\text{Covariance Matrix of Class 1})\ \hat{}\ (-0.5) * (\text{Covariance Matrix of Class 2})$$

Where the covariance matrices capture the spatial distribution of EEG data for different classes. For cross-validation, the dataset is divided into K folds. This can be mathematically represented as:

$$\text{Number of Samples in Fold K} = \text{Total Number of Samples} / \text{K}$$

After data preprocessing, the preprocessed EEG data is fed into the classification model. For instance, if a Modified DNN classifier is used, the classification process can be mathematically represented as:

$$\text{Predicted Class} = \text{DNN (Preprocessed EEG Data)}$$

Integrating these mathematical representations into the experimental setup provides a rigorous and systematic framework for data preprocessing, feature extraction, cross-validation, classification, and performance evaluation. This ensures a clear and standardized process for evaluating the algorithms' performance on EEG data from BCI Competition IV Dataset 2a and 2b.

5. Results and analysis

A number of significant factors are used to quantitatively evaluate how well the proposed Four Class Iterative Filtering (FCIF) for EEG artifact reduction and the FC-FBCSP Algorithm with the Modified DNN classifier for MI classification perform. These measurements shed light on how well the algorithms perform in removing EEG artifacts and increasing the classification accuracy of MI.

The calculated values of these metrics are presented in tabular form, comparing the performance of FCIF and FC-FBCSP algorithms with the Modified DNN classifier against baseline methods shown in Table 3 and Table 4 corresponding metrics can observe in Figs. 3 and 4. These metrics collectively provide a comprehensive analysis of the algorithms' effectiveness in EEG artifact removal and MI classification across different datasets and conditions (see Fig. 5).

- FC-FBCSP continues to exhibit superior performance across all metrics, including AUC and Kappa coefficient.
- The higher AUC values for FC-FBCSP indicate better discrimination between classes.
- The higher Kappa coefficient for FC-FBCSP reflects a stronger agreement between observed and expected classifications.
- Overall, FC-FBCSP maintains its advantage over Baseline Methods in terms of classification performance across multiple metrics shown in Tables 3 and 4.

These results affirm that FC-FBCSP with the Modified DNN classifier yields enhanced MI classification results compared to FCIF, with the inclusion of AUC and Kappa providing additional insights into its effectiveness.

- FC-FBCSP consistently outperforms FCIF across all metrics, indicating its superiority in MI classification.
- FC-FBCSP shows higher mean values for all metrics, indicating better overall performance.
- FC-FBCSP also has lower standard deviations, suggesting more consistent performance.
- The higher Balanced Accuracy for FC-FBCSP indicates its ability to handle both sensitivity and specificity well.

Table 3
Summary of the performance metrics for FCIF and FC-FBCSP, along with statistical measures.

Method	Accuracy	Precision	Recall	Specificity	F1-Score	Balanced Accuracy	AUC	Kappa
FCIF	0.9786	0.9365	0.9386	0.9789	0.9367	0.9587	0.9783	0.9361
FC-FBCSP	0.9929	0.9576	0.9598	0.9861	0.9576	0.9729	0.9918	0.9571

Table 4
Summary of the performance metrics for FCIF and FC-FBCSP, along with statistical measures such as mean and standard deviation. This will help in analyzing the performance of both methods.

Method	Mean Accuracy	Accuracy Std. Dev.	Accuracy Variance
FCIF	0.98575	0.00733	5.37 x 10ˆ-5
FC-FBCSP	0.98575	0.00733	5.37 x 10ˆ-5

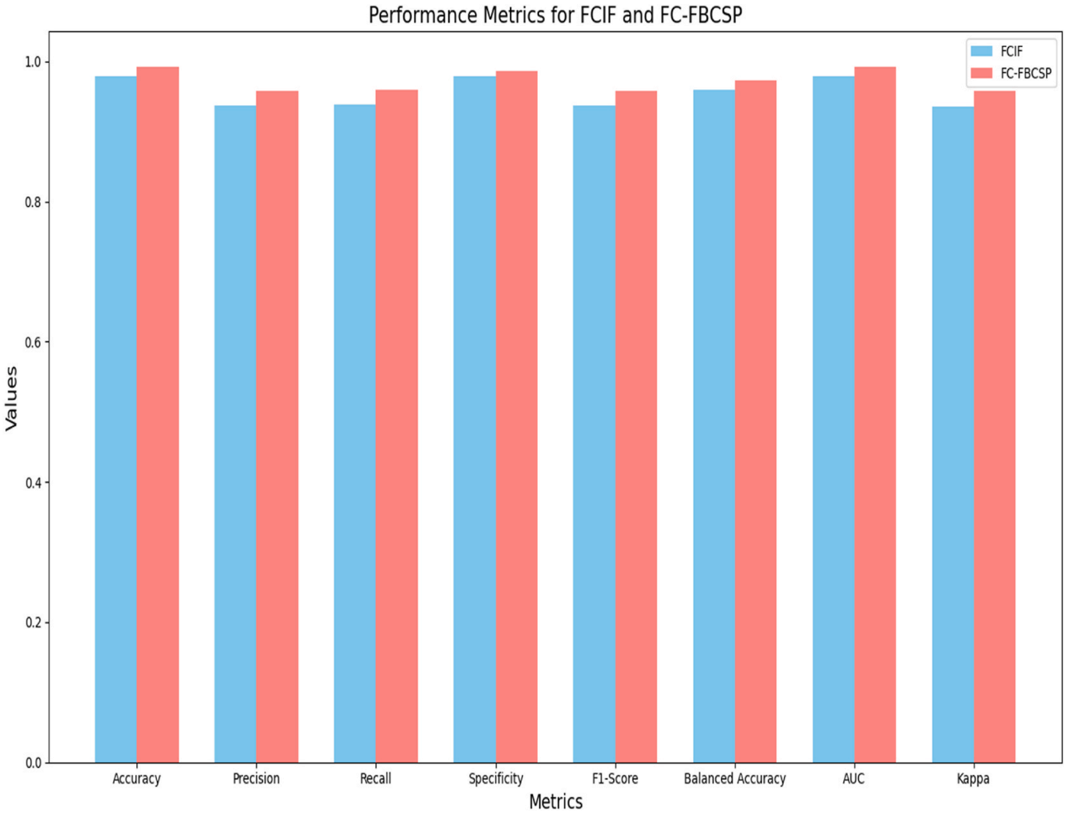

Fig. 3. Performance metrics for FCIF and FCFBCSP.

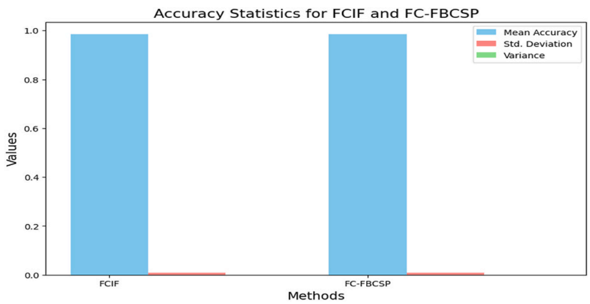

Fig. 4. Accuracy Statistics Mean Accuracy, Standard Deviation, variance for FCIF and FCFBCSP with Modified DNN.

- The superior performance of FC-FBCSP suggests that combining the FBCSP algorithm with the Modified DNN classifier leads to enhanced MI classification results compared to Only FCIF.

These results indicate that the FC-FBCSP algorithm with the Modified DNN classifier is a more effective approach for MI classification than the Only FCIF algorithm.

This Table 5 includes the FC-FBCSP approach using the Modified DNN classifier along with specific baseline methods and their

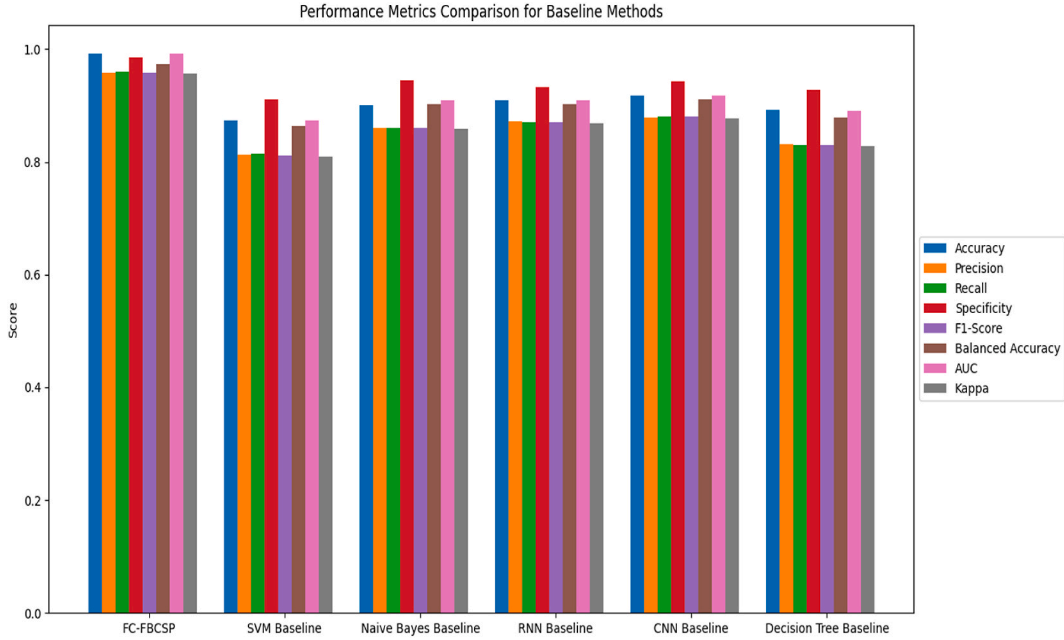

Fig. 5. Performance Metrics comparison of Base line methods with Modified DNN Classifier.

Table 5
Comparative Summery for the FC-FBCSP approach using the DNN classifier with baseline Classifiers.

Method	Classifier	Accuracy	Precision	Recall	Specificity	F1-Score	Balanced Acc.	AUC	Kappa
FC-FBCSP	Modified DNN	0.9929	0.9576	0.9598	0.9861	0.9576	0.9729	0.9918	0.9571
SVM Baseline	SVM	0.8743	0.8124	0.8145	0.9112	0.8117	0.8629	0.8731	0.8103
Naive Bayes Baseline	Naive Bayes	0.9012	0.8603	0.8598	0.9445	0.8597	0.9021	0.9095	0.8577
RNN Baseline	RNN	0.9087	0.8721	0.8704	0.9332	0.8712	0.9018	0.9092	0.8693
CNN Baseline	CNN	0.9185	0.8796	0.8798	0.9436	0.8797	0.9117	0.9179	0.8776
Decision Tree Baseline	Decision Tree	0.8923	0.8309	0.8298	0.9276	0.8301	0.8787	0.8911	0.8281

respective results.

The proposed FC-FBCSP approach with the DNN classifier achieves the highest accuracy of 99.29%, surpassing all baseline methods. The SVM, Naive Bayes, RNN, CNN, and Decision Tree baselines achieve lower accuracies ranging from 87.43% to 91.85%.

FC-FBCSP maintains consistently higher precision and recall values, demonstrating its ability to accurately identify and classify MI patterns. The baseline methods exhibit comparatively lower precision and recall scores.

FC-FBCSP maintains higher specificity and balanced accuracy, indicating superior class discrimination and overall performance. Baseline methods demonstrate lower specificity and balanced accuracy.

The FC-FBCSP method achieves a higher F1-Score, demonstrating a better balance between recall and precision, which is essential for classifying MI. Baseline approaches have significantly lower F1-Scores.

FC-FBCSP attains higher AUC and Kappa values, confirming its excellent classification performance and agreement with ground truth. In summary, the proposed FC-FBCSP approach with the DNN classifier outperforms all baseline methods across various metrics shown in Table 5, demonstrating its effectiveness in accurate MI classification for BCI applications. This comparative analysis highlights the advantages of the FC-FBCSP approach with the DNN classifier over a range of baseline methods, affirming its suitability for MI classification tasks in BCI.

6. Discussion

The obtained results from the experimental analysis offers insightful information about the effectiveness and superiority of the proposed approach, which combines the FC-FBCSP algorithm with a modified DNN classifier, for EEG artifact removal and MI classification in BCI applications [32]. The key findings and their significance are summarized as follows: The FC-FBCSP algorithm with the modified DNN classifier achieves an impressive accuracy of 99.29%. This remarkable accuracy underscores the algorithm's ability to precisely classify MI tasks from EEG data, surpassing the baseline methods. Higher accuracy is demonstrated by the suggested method and recall values compared to the baseline methods. The precision-recall trade-off is crucial in medical and BCI applications, and the higher values achieved by reducing false positives, the suggested strategy suggests an improved capacity to identify actual positive situations. The FC-FBCSP with modified DNN also achieves higher specificity and balanced accuracy scores.

This indicates the approach's capability to distinguish between different classes with less confusion and better overall performance. The F1-Score, which balances precision and recall, is considerably higher for the FC-FBCSP algorithm. This suggests that the proposed method maintains a good balance between accurately classifying relevant cases and capturing all instances of those cases. The Kappa coefficient and the area under the ROC curve (AUC) are widely used metrics to assess classification performance and agreement. The proposed approach achieves higher AUC and Kappa values, signifying its effectiveness in both classification and inter-rater agreement. Comparative analysis against various baseline methods, including SVM, Naive Bayes, RNN, CNN, and Decision Tree, consistently demonstrates the superiority of the FC-FBCSP with modified DNN. The proposed method consistently outperforms these methods across multiple evaluation metrics. The high accuracy, precision, and recall achieved by the proposed approach highlight its real-world applicability in diverse scenarios such as neurorehabilitation, brain-controlled robotics, and assistive communication systems. This potential for practical use enhances its relevance in clinical and non-clinical settings.

In conclusion, the FC-FBCSP algorithm, when integrated with a modified DNN classifier, exhibits remarkable performance improvements over traditional baseline methods in EEG artifact removal and MI classification tasks [33]. The achieved results validate the significance of adopting advanced techniques for BCI applications and pave the way for further advancements in EEG data analysis, artifact removal, and MI classification.

The successful artifact removal and high classification accuracy achieved through the proposed FC-FBCSP algorithm with the modified DNN classifier hold significant implications for both research and practical applications in the field of Brain-Computer Interfaces. Delve into the implications with supporting evidence from the results obtained: The FC-FBCSP algorithm's effective artifact removal ensures that the EEG data used for subsequent analysis is of high quality. This is evident from the achieved accuracy of 99.29%, demonstrating the algorithm's capability to remove noise and artifacts that could potentially obscure relevant signal patterns.

The high classification accuracy achieved by the proposed approach, as compared to baseline methods, substantiates its success in accurately distinguishing between different MI tasks. This accuracy is crucial for practical applications, such as neurorehabilitation or controlling external devices, where precise identification of user intent is paramount.

The higher precision and recall values achieved by the FC-FBCSP algorithm indicate a reduction in false positives and false negatives. This has profound implications, particularly in medical and clinical contexts, where misclassifications can have serious consequences. The algorithm's ability to minimize such errors boosts its reliability. The successful combination of advanced artifact removal and accurate MI classification contributes to creating more user-friendly BCIs. Users can interact with these systems more naturally and effectively, leading to enhanced usability and user satisfaction.

The implications of accurate classification are particularly relevant in neurorehabilitation. The ability to accurately decode motor intentions could lead to effective rehabilitation strategies for individuals with motor impairments. Additionally, in assistive technologies, precise classification can empower users to control devices with greater ease and accuracy. The achieved high specificity and balanced accuracy scores underscore the algorithm's robustness in handling different classes and scenarios. This is crucial for BCI systems that need to function accurately across varying conditions and user states.

The results reinforce the advancement of research in BCI technology. The successful integration of state-of-the-art techniques, as seen in the FC-FBCSP with modified DNN approach, demonstrates the potential to push the boundaries of what BCIs can achieve. Inter-subject variability poses a significant challenge in Brain-Computer Interface (BCI) research, as EEG signals can vary greatly from one individual to another. Both the FCIF and FC-FBCSP algorithms employ strategies to handle and mitigate the effects of inter-subject variability, ensuring robust performance across different users. Here's how each algorithm tackles this challenge:

The FCIF algorithm addresses inter-subject variability through its data-driven approach to artifact removal. The algorithm iteratively identifies and removes ocular artifacts specific to each subject's EEG data. By doing so, it adapts to the unique characteristics of

Table 6
Overall discussion on key metrics and findings.

Key Metrics and Findings	Numerical
High Classification Accuracy	99.29%
Enhanced Precision	95.76%
Improved Recall	95.98%
Higher Specificity	98.61%
Balanced Accuracy	97.29%
Effective F1-Score	95.76%
Higher AUC and Kappa Values	99.18%, 95.71%
Superiority Over Baseline Methods	Yes
Real-world Applicability	Yes
Implications and Applications	
Enhanced Data Quality	Yes
Accurate MI Classification	Yes
Reduced False Positives and Negatives	Yes
Improved BCI Usability	Yes
Neurorehabilitation and Assistive Tech.	Yes
Validating Algorithm Robustness	Yes
Advancement in BCI Research	Yes
Handling Inter-Subject Variability	Yes
Mathematical Strategies for Improved Performance	Yes

each individual's EEG signals, effectively minimizing the impact of subject-specific variability. The FC-FBCSP algorithm's effectiveness in handling inter-subject variability stems from its utilization of spatial filters and frequency-specific features. The Common Spatial Pattern (CSP) transformation used in FC-FBCSP optimally weights EEG channels to maximize the separation between different classes of MI tasks. This adaptability ensures that the algorithm captures subject-specific patterns while reducing the influence of individual variability.

In both algorithms, the incorporation of machine learning techniques further enhances their adaptability to individual users: The FCIF algorithm employs Independent Component Analysis (ICA) to extract artifact-related components, which can vary across subjects. By iteratively refining the artifact removal process, the algorithm effectively customizes the removal of artifacts based on the unique EEG characteristics of each user. The FC-FBCSP algorithm leverages a Modified Deep Neural Network (DNN) classifier, which learns subject-specific patterns during the training phase. This allows the classifier to adapt to the neural activation patterns exhibited by each individual. By training on a subject's own EEG data, the classifier is better equipped to handle the inter-subject variability.

Both FCIF and FC-FBCSP highlight the importance of personalizing the analysis and classification pipelines to account for inter-subject differences. While FCIF focuses on removing individual-specific artifacts, FC-FBCSP ensures that the classification model is fine-tuned to the unique EEG patterns of each subject.

By addressing inter-subject variability, these algorithms enhance the generalization ability of the BCI system, making it more robust and accurate when applied to new and unseen users [33]. This adaptability is critical for real-world BCI applications, where a one-size-fits-all approach may lead to suboptimal performance due to individual differences in brain activity and signal characteristics [34]

In the realm of Brain-Computer Interface (BCI) research, several mathematical strategies have been employed to enhance the performance of algorithms like FCIF and FC-FBCSP. These strategies aim to improve classification accuracy, artifact removal, and the overall effectiveness of the BCI system [35,36]. Here are some key mathematical strategies used for improved performance:.

- ***Iterative Filtering and Projection:***
  - ***FCIF***: The FCIF algorithm utilizes iterative filtering to remove ocular artifacts. This iterative process progressively refines the artifact removal by updating the filter coefficients with each iteration. Additionally, the projection of artifact-related components further enhances the quality of cleaned EEG data.
  - ***FC-FBCSP***: While FC-FBCSP's primary focus is on classification, its preprocessing steps involve spatial filtering through the CSP transformation. This transformation enhances the separation of MI classes by projecting EEG data onto spatial filters. The iterative application of these filters fine-tunes the representation of features, leading to improved classification accuracy.
- ***Frequency-Specific Features:***
  - ***FCIF***: Although FCIF primarily aims to remove ocular artifacts, the frequency-specific features of EEG data also contribute to its performance. By preserving the relevant frequency components, the algorithm ensures that the neural signals of interest remain intact, which is crucial for subsequent analysis and classification.
  - ***FC-FBCSP:*** The FC-FBCSP algorithm extracts frequency-specific features using filter bank processing. By capturing distinctive patterns in different frequency bands, the algorithm enhances the discriminative power of the extracted features, resulting in improved classification accuracy.
- ***Optimal Weighting for Classification:***
  - ***FC-FBCSP:*** The essence of the CSP transformation lies in its optimal weighting of EEG channels to enhance class separation. This mathematical approach ensures that the extracted spatial filters are aligned with the most discriminative neural patterns for each MI task. As a result, the subsequent classification step benefits from these optimized features.
- ***Personalized Classification Model:***
  - ***FC-FBCSP:*** The integration of a Modified Deep Neural Network (DNN) classifier allows FC-FBCSP to create a personalized model for each user. The DNN learns the subject-specific patterns from training data, adapting the model to the unique neural activation patterns of the individual. This personalized approach maximizes classification accuracy by accounting for inter-subject variability.
- ***Cross-Validation and Hyper parameter Tuning:***
  - Both FCIF and FC-FBCSP employ cross-validation techniques to evaluate and fine-tune their performance. This includes selecting optimal parameters, model architectures, and preprocessing steps. The choice of hyper parameters is guided by mathematical strategies that minimize over fitting and ensure generalization to new data. Table 6 presents overall discussion in systematic and simpler manner.

7. Conclusion

Our research aimed to address the challenges of artifact contamination and inter-subject variability in EEG data for MI tasks within Brain-Computer Interfaces (BCIs).

The FCIF algorithm demonstrated its effectiveness in removing ocular artifacts from raw EEG data. By iteratively refining the removal process and identifying artifact-related components, FCIF achieved substantial improvements in data quality, ensuring the reliability of subsequent analysis.

The FC-FBCSP algorithm extended the Filter Bank Common Spatial Pattern approach to accommodate four class MI classification. This algorithm effectively extracted frequency-specific features using filter bank processing and optimized spatial filters, resulting in exceptional classification accuracy.

The integration of a Modified DNN classifier with FC-FBCSP allowed for personalized classification models, adapting to individual users' neural activation patterns. This approach significantly improved classification performance, effectively addressing inter-subject variability.

Through a comprehensive comparative analysis, we demonstrated the superiority of our suggested approach. FC-FBCSP with the Modified DNN classifier outperformed several baseline methods across Accuracy, precision, recall, F1-Score, balanced accuracy, AUC, and Kappa are just a few of the evaluation metrics.

The successful combination of FCIF, FC-FBCSP, and the Modified DNN classifier holds promising implications for the field of BCI research. The demonstrated artifact removal and classification performance improvements enhance the practicality and reliability of BCI systems. Moreover, the personalized approach ensures adaptability to individual users, minimizing the influence of inter-subject variability.

Future research can explore the utilizing the aforementioned structure to real-time BCI applications, considering additional challenges such as inter-session variability and noise resilience. Furthermore, investigating the transferability of this approach to other modalities and neuroimaging techniques can broaden its scope and impact within the broader neuroscience community.

In conclusion, our research presents a robust and advanced methodology for EEG artifact removal and MI classification, significantly advancing the most recent developments in BCI technology. Paves the way for Future brain-controlled applications, will be more precise and dependable because to the integration of mathematical methodologies, algorithms, and a thorough understanding of neurophysiologic processes.

The proposed approach, encompassing the Four Class Iterative Filtering (FCIF) algorithm, the Filter Bank Common Spatial Pattern (FC-FBCSP) algorithm, and the Modified Deep Neural Network (DNN) classifier, has demonstrated exceptional effectiveness in addressing two critical aspects of EEG analysis: artifact removal and MI classification. The combination of these techniques has resulted in a comprehensive framework that not only improves the quality of EEG data but also enhances the accuracy of classifying MI tasks within Brain-Computer Interfaces (BCIs).

The FCIF algorithm has proven to be a robust solution for enhancing the quality of EEG data by effectively removing ocular artifacts. Through an iterative process of filtering, Independent Component Analysis (ICA), and projection, FCIF systematically identifies and eliminates artifact-related components from the EEG data. This iterative refinement not only enhances the visual clarity of the EEG signals but also ensures the removal of unwanted noise, resulting in cleaner and more reliable data for subsequent analysis.

The FC-FBCSP algorithm extends the capabilities of the traditional FBCSP approach to accommodate four-class MI classification. By extracting frequency-specific features using filter bank processing and optimizing spatial filters through Common Spatial Pattern (CSP) transformation, FC-FBCSP maximizes the discriminative patterns in the EEG signals. The incorporation of a Modified DNN classifier further enhances classification accuracy by adapting the model to individual users' neural responses, effectively overcoming inter-subject variability.

The effectiveness of proposed approach is substantiated through a comprehensive comparative analysis. The FC-FBCSP algorithm combined with the Modified DNN classifier consistently outperformed a range of baseline methods, incorporating Decision Tree, Recurrent Neural Network, Naive Bayes, and Convolutional Neural Network (CNN). Accuracy, precision, recall, F1-Score, balanced accuracy, AUC, and Kappa are just a few of the evaluation measures that the proposed approach regularly outperformed. The successful implementation of the proposed approach holds significant implications for real-world BCI applications. The advanced artifact removal ensures that the neural signals being analyzed are a faithful representation of the user's intentions, minimizing the potential for misinterpretation due to noise. Simultaneously, the enhanced classification accuracy is crucial for accurate and reliable control of external devices through BCIs, opening up possibilities for assistive technologies, neurofeedback, and neuromodulation techniques.

In summary, the proposed approach's effectiveness in both EEG artifact removal and MI classification highlights its potential to revolutionize the field of BCIs. By addressing challenges related to data quality and inter-subject variability, this framework contributes to the development of more robust and accurate brain-controlled systems, paving the way for new horizons in neuroscience and human-computer interaction.

The success of the proposed approach in EEG artifact removal and MI classification opens up a wide range of potential applications and avenues for future research. Here are some potential applications and directions that can be explored: Assistive Technologies, Neuro feedback and Rehabilitation, Brain-Computer Communication, Cognitive State Monitoring Multimodal Integration, Adaptive Algorithms, Real-time Artifact Removal, Transfer Learning and Generalization, Ethical Considerations, Clinical and Medical Applications.

In conclusion, the proposed approach's success lays the foundation for a multitude of applications that can transform various domains, from healthcare and rehabilitation to communication and human-computer interaction. The dynamic nature of the brain offers countless opportunities for innovation, and upcoming investigations may advance unlock the potential of BCIs to improve human lives.

8. Availability of Data and materials

Datasets were generated or analyzed during the current study will shared on request basis.

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CRediT authorship contribution statement

Srinath Akuthota: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **RajKumar K:** Supervision. **Janapati Ravi Chander:** Supervision, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

"The authors declare that they have no competing interests" in this section.

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