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Research article

Real-Time BCI Scheme to Assisting Disabled Persons Using Motor Imagery EEG Signal Classification

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ABSTRACT

Electroencephalography (EEG) signal-controlled Brain-computer interface (BCI) schemes have created hope for physically impaired people to lead a stress-free life. It is quite challenging to preprocess EEG signals and make them eligible for use in neuro-robotics applications as there exist various categories of artifacts in the raw EEG signal. As physically disabled people need to perform real-time actions, this study proposes a real-time BCI scheme that is usable and efficient for neuro-robotics applications in their rehabilitations. The ultimate goal is to classify hand, foot, and tongue motions as four-class motor imagery (MI) task-related impulses using the more efficient classification technique in this study. The proposed approach achieves state-of-the-art levels of accuracy and a kappa score of 77.41% and 0.70, respectively, on the benchmark dataset taken. Classifiers such as Skl-ANN, SVM, LDA, and others have been evaluated for the experimental subjects. It is believed that the higher classification accuracy and lower processing load of the proposed BCI system will make it acceptable for usage in real-world settings to facilitate the rehabilitation and reintegration of physically impaired persons.

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Introduction

Numerous individuals experience physical handicaps such as limitations in the mobility of organs, vision impairments, skeletal injuries, and other physical defects caused by accidents making life stressful. Brain-computer interface (BCI) gives a non-muscular mode for interacting with the world around utilizing invasive or non-invasive techniques. Through the blessings of applying human brain signals in neuro-robotics, the physically disabled can lead a stress-free life and perform human activities as an average person can.

The brain-computer interface (BCI) strategy has recently evolved as a cutting-edge means for individuals to interact with computing devices along with other smart technical equipment. BCI allows users to control devices only through electroencephalographic (EEG) impulses that tap into the neurological activity of the cognitive cortex, rather than relying on physical movements via muscle and nerve signals. Motor imagery-based BCI is a significant human-computer interaction methodology among others for interpreting neural activities by detecting motor imagery task-related EEG signals in human brain-computer paradigms. The brain rhythms are typically broken into certain frequency bands: delta: 0.5–4 Hz, theta: 4–8 Hz, alpha: 8–12 Hz, beta: 12–30 Hz, and gamma: > 30 Hz. Electroencephalography (EEG) is the most preferable in recording brain signals because of its prominence over others.

The raw EEG signal consists of different artifacts like Environmental artifacts, Physiological artifacts, and Motion artifacts. These contaminated EEG signals need to be preprocessed and removed the artifacts for further use. The EEG signal usage is quite challenging as there is a tiny signal-to-noise ratio (SNR) in brain signals. After properly preprocessing and feature extraction, the signal can be applied to classify motor imagery (MI) movements like the hands, feet, and tongue. Classification of MI signals here refers to deciding which class the signal belongs to base on the discriminative characteristics.

Over the course of the last several years, there has been a noticeable interest in EEG signal processing, motivating a growing number of academics to

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concentrate their dedication to research on this area of study. Some of the methodologies have been highlighted in cutting-edge research works on EEG signal classification. Tasks requiring the use of the imagination to move the left and right hands, feet, and tongue have been the focus of a great deal of BCI research. The wavelet decomposition (WD) extension is known as WPD. This method uses a number of bases, and the choice of base will affect the classification performance and address the DWT's lack of set time-frequency decomposition (Xue et al., 2004). Feature extraction and classification strategies are the primary areas of research in pattern recognition. Common Spatial Patterns (CSP), Filter-bank CSP (FBCSP), Principal Component analysis (PCA), Independent Component Analysis (ICA), and Riemannian methods are all types of feature extraction techniques. Techniques like Linear Discriminant Analysis (LDA), Support Vector Machines (SVMs), and Convolutional Neural Networks (CNNs) are frequently used for classification.

To parse MI-EEG from the BCIC-IV-2a dataset, Ma et al. (2023) presented a convolutional neural network (CNN) with a method of attention that integrates spatial and spectral details from multi-view EEG data. Interdependencies between discriminative characteristics are captured by the temporal attention mechanism. Grosse-Wentrup & Buss (2008) noted that CSP by means of joint approximation diagonalization (JAD) has similar to independent component analysis, or ICA, while applied to multiclass schemes of thought. They also provided a method for choosing independent components (ICs) that approximately achieve maximum the mutual information across ICs and class labels. As a result, prior class probabilities can be taken into account and heuristics for multiclass CSP are no longer necessary. In contrast to the multiclass CSP, the proposed approach increases the mean rate of classification accuracy about 23.4% when utilized on dataset IIIa for the 3rd BCI competition.

Combining a CNN with an effective channel attention (ECA) subsystem was the strategy put out by (Tong et al., 2023). Channel weights are assigned by the ECA subsystem according to their category relevance. During a four-class classification goal, experiments were carried out using the BCI Competition IV dataset, and an average accuracy of 75.76% occurred using all 22 channels. Alnaanah et al. (2022) demonstrated CNN models like Basic, CNN1D, CNN2D, CNN3D, TimeDist, CNN1DMF and evaluated on Physionet and BCI Competition IV-2a dataset. Among them CNN1DMF model achieves best accuracy of 58.0% and 69.2% for Physionet and BCI Competition IV-2a datasets, respectively. The limitation is CNN2D, CNN3D, and TimeDist have low accuracy and kappa values here. Also high complexity of models leads to overfitting and longer training times.

In this research, we utilize the BCI competition IV 2a dataset to classify four exclusive MI tasks: left-right hand movements, foot movement, and tongue motion (Tangermann et al., 2012). As classification accuracy plays a vital role in neuro-robotics research, enhancing classification accuracy is essential. A highly accurate classified EEG signal instruction can be parsed in neuro-robotics applications to rehabilitate physically disabled people. Movement of the hands, legs, eyes, tongue, and other body parts causes shifts or changes in the EEG signal. Furthermore, we also see differences in the EEG signals when a person attempts to imagine such a movement, i.e., motor imagery movement. For our experiment, we separated left, right, foot, and tongue motions, as well as those performed with motor imagery. The primary objectives of the research are pointed in the following:

- To find the best technique of gaining artifact-free EEG signal.
- To classify four-class motor imagery signals such as left-hand, right-hand, foot, and tongue movement.
- To test the accuracy factors of the scheme.

This work is arranged into sections accordingly, beginning with the Introduction, which discusses the BCI idea and our purpose. The literature review part discusses relevant research analysis and study concepts. The Materials and Methods section describes our proposed strategy, the dataset, experimental configuration, and the experimental procedures. The stated methodology's output is shown in the Results and Discussion section. The performance-measuring criteria are also mentioned. The results are analyzed using several comparison charts. The conclusion summarizes and completes the work. Future employment information is also presented. The Data Availability declaration and the Acknowledgment portion are inserted suitably following the Conclusion part of the writing.

Literature Review

Over the course of the last several years, there has been an increase in interest on EEG signal processing, leading a growing number of academics to concentrate their efforts in this area of study. There is a significant body of research available on EEG signal. From among the numerous published works, we selected a limited handful that dealt with the EEG signal feature extraction and classification.

Tasks requiring the use of the imagination to move the left and right hands, feet, and tongue have been the focus of a great deal of BCI research (Ang et al., 2012), (Chin et al., 2009). Feature extraction and classification strategies are the primary areas of research in pattern recognition. Common Spatial Patterns (CSP), Filter-bank CSP (FBCSP), Principal Component analysis (PCA), Independent Component Analysis (ICA), and Riemannian methods are all types of feature extraction techniques (Feng et al., 2019). Techniques like Linear Discriminant Analysis (LDA), Support Vector Machines (SVMs), and Convolutional Neural Networks (CNNs) are frequently used for classification.

The previously described Riemannian techniques have been integrated with SVM classifiers, resulting in a classification accuracy of 75% on the BCI IV II a dataset (Yger et al., 2017). Schirrmeister et al. (2017) presented a method that combines the sliding time windows approach with a convolutional neural network (CNN) to acquire the temporal and spatial characteristics of EEG signals, therefore expanding the training set capacity and enhancing the classification performance. In addition to MI identification tasks, this technique has also been used to facial recognition and other disciplines. Previous studies have flaws. Same algorithm affects various participants differently.

Table 1: Summary of the literature review

Authors	Used Techniques	Dataset	Applications
Yger et al., 2017	MDM – Riemannian Kernel	Not Specified	Real-time programs employing adaptive approaches.
Schirrmeister et al., 2017	FBCSP – ConvNets	BCI Competition IV Dataset 2a	ConvNet-driven EEG interpretation systems in real-world uses
Dose et al., 2018	1D – CNN	Physionet MI Dataset	User-Friendly BCI Systems
Hou et al., 2020	ESI – CNN	Physionet MI Dataset	User-Friendly BCI Systems
Uktveris & Jusas, 2017	FFT – CNN	BCI Competition IV Dataset 2a	Improved Rehabilitation Systems
Nguyen et al. (2017)	CSP – PSO – FLS	BCI Competition IV Dataset 2a	Improved Rehabilitation Systems
Zouch & Echtioui, 2022	WPD – CSP – 3CNN	BCI Competition IV Dataset 2a	User-Friendly BCI Systems
Hu et al., 2023	CS – CNN	BCI Competition IV Dataset 2a	Future Research Guide

Kumar et al. (2016) and Yang et al. (2015) proposed the usage of multilayer perceptron (MLP) as a classifier. Dose et al. (2018) suggested a DL model that achieved a global average accuracy of 68.51% by making use of CNN layers for the purpose of learning generalized features and dimension reduction, in addition to making use of a traditional fully connected (FC) layer for classification. Extreme learning machines were utilized by Gao et al. (2016) for the purpose of enhancing the classification of motor imagery BCI data. The classification of motor imagery (MI) tasks was accomplished by Hou et al. (2020) using a combination of the scout EEG source imaging (ESI) approach and the convolutional neural network (CNN). Pfurtscheller et al. (2006) demonstrated that foot and tongue motor imageries had a more tenuous decrease in energy than left- and right-hand motor imageries; hence, they are more likely to form an energy pattern in particular channels and frequencies. Therefore, it is necessary to develop a method that can extract temporal data and interact with static energy features to construct a classifier that can then handle a broader range of motor imageries; one possible and relatively novel approach could be the deep learning subfield of machine learning. These techniques have the ability to uncover previously unnoticed characteristics in a greater variety of data. Convolutional Neural Network (CNN), initially suggested by Lecun et al. (1998) is the approach that has achieved promising results in various domains. Compared to shallow classification algorithms, CNNs have proven to be effective when applied to the classification of EEG data. Uktveris & Jusas (2017) conducted a classification of four-class motor imagery using a variety of feature extraction approaches, with an average accuracy of 68%, making their work among those aiming to classify various motor imageries.

Several attempts were made to use deep learning, namely a convolutional neural network, to find out what limits a single classifier's effectiveness. However, despite deep learning's success in a wide range of applications, multiclass EEG-MI classification has not yet achieved state-of-the-art levels of accuracy. It is important to fine-tune deep learning's hyper-parameters and setup, as well as address other challenges including the volume of training data required. Additionally, the hyper-parameters and setup for deep learning models are unique for each participant in many of the earlier research (Olivas-Padilla & Chacon-Murguia, 2019; Xu et al., 2019; Amin et al., 2019). According to the results of earlier multi-class investigations, EEG-MI classification still has room for advancement since its performance as well as the kappa coefficient remains subpar. In their experiments, Nguyen et al. (2017) demonstrated the superiority of their proposed approach over competing approaches like LDA, k-nearest neighbor, ensemble learning, NB, AdaBoost, and SVM. They used the multiclass motor imagery dataset IIa from the BCI competition IV. Experiment results demonstrate the high accuracy of the CSP and FLS combo.

Among current methodologies for EEG data processing (e.g., time-frequency analysis and nonlinear dynamics methods, artificial neural networks (ANNs) are the most promising and efficient tools for classifying of single EEG trials. The effective implementation of ANNs requires the proper choosing of the parameters, which may vary greatly depending on the job and topic (Bashashati et al., 2015). As a result, one of the important difficulties for the development of effective ANN-based BCIs is the optimization of EEG inputs (dimensionality reduction, filtration, etc.) and channel selection.

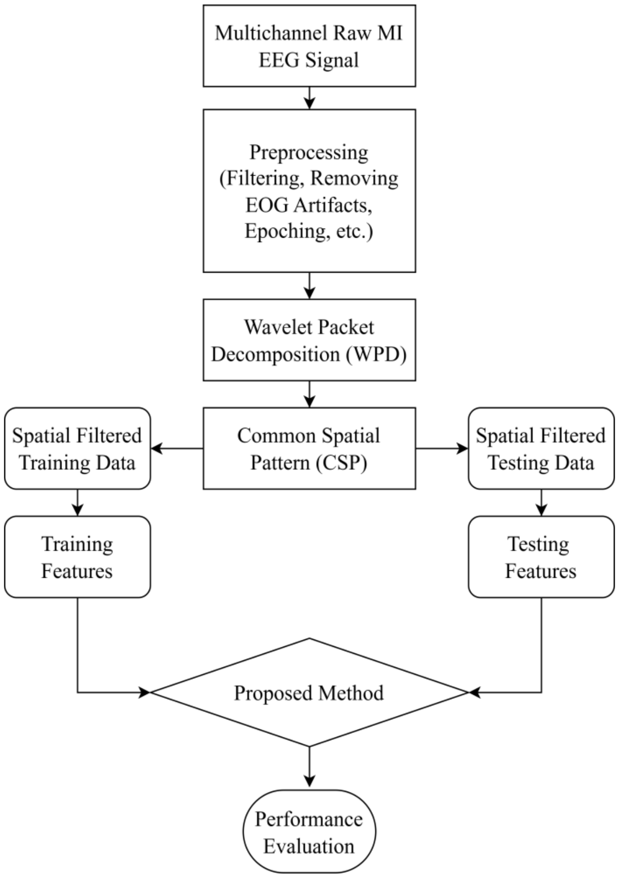

Figure 1: Block diagram of the proposed methodology

Recently, neural network-based classifiers that do better in data-rich, non-linear clustering tasks like MI decoding were brought up as a possible way to make the CSP algorithms better. In particular, the Sequential Backward Floating Selection method and a radial basis function neural network (RBFNN) were suggested as a possible better algorithm for BCIs. These two methods would be used to choose the best CSP features (Bhatti et al., 2019). Recent studies show that several machine learning (ML) approaches, particularly deep learning (DL), are gaining favor regarding EEG-based MI classification (Yu et al., 2022). Zouch & Echtioui (2022) came up with a method based on combining three CNNs. When evaluated using the nine individuals from the BCI Competition IV 2a dataset, this approach got a remarkable accuracy score of 64.75%. The CS-CNN technique solves the shortcomings of contemporary approaches and offers a strong framework for MI-EEG classification, resulting in a substantial contribution to the area of BCI (Hu et al., 2023). The literature review is summarized in table 1.

Materials and Methods

This paper presents a strategy for MI-task distinction that employs WPD to separate signal packets that are received CSP to extract features, and a model based on machine learning to classify data. Introducing a series of preprocessing procedures enhances the signal-to-noise ratio (SNR). Figure 1 depicts the conceptual flow diagram illustrating the proposed scheme. Following are the particulars of the EEG dataset and the methodologies performed for this study.

Experimental Configuration

The experimental arrangement employed in this empirical study is outlined below:

Hardware	:	Laptop (8 GB RAM, 64 Bit)
Coding Language	:	Python
Coding notebook	:	Google Colaboratory (12 GB RAM)
Dataset	:	BCI Competition IV-2a
Toolbox	:	MNE-Python

Experimental Dataset

In this study, the BCI IV 2a dataset (Brunner et al., 2008) is employed for four-class MI task classification. Here, four subjects' EEG signals are taken, each consisting of 25 channels (3 EOG channels) of the recorded signal. Cue-based brain-computer interfaces involve four specific motor imaging tasks: left hand (class 1), right hand (class 2), foot (class 3), and tongue (class 4). There are 288 trials per session, with each class comprising 48 trials (12 per class). In all, there are 288 trials completed throughout each session (Tangermann et al., 2012).

Signal Preprocessing

The preprocessing is the initial step after preparing the dataset and loading the raw signal data. By this step, the dataset is ready to apply the proposed feature extraction method to extract important features. Based on the markers provided with the dataset, the data was contaminated by 3 EOG channel signals among 25 channels (Figure 2). So, we need to preprocess the dataset and make it suitable for further processing by good channels. Before the EEG pattern could be used for feature extraction, identification, and prediction, it had to go through several preprocessing steps.

Filtering

From the literature, we may deduce that the majority of motor-imaging-related brain activity occurs between 7 and 40 Hz or between 12 and 30 Hz (Joyce et al., 2004). That’s why we only need the signals that lie in that frequency range. Therefore, we filtered the raw EEG signal dataset for a subject by finite impulse response filter with Hamming window with 0.0194 passband ripple and 53 dB stopband attenuation where the lower passband frequency edge: is 7.00 Hz and upper passband edge: is 35.00 Hz. The filtering process also removes the physiological artifacts arising from eye blinks and movements (Figure 3).

EOG Artifacts Removing

After filtering the signal in a certain frequency range the EOG artifacts are removed (Figure 4). Three EOG channels are 'EOG-left', 'EOG-central', and 'EOG-right' which are contained in the dataset. After removing those the dataset only contains 22 good EEG channels. From these 22 EEG channels signal we would find our four class MI EEG activity such as Left-hand (LF), Right-hand (RF), Foot (F), and Tongue (T). The four class MI events annotations in the dataset are ‘769’, ‘770’, ‘771’, and ‘772’ for Left-hand (LF), Right-hand (RF), Foot (F), and Tongue (T) respectively (Brunner et al., 2008). This process removes the physiological artifacts arising from eye blinks and movements for providing a clean EEG signal. After filtering we also segment according to the event and extract epochs of 3s time period from the dataset into 288 events for all 4 classes.

Events Marking

There are many kinds of events, but we only need four types of events, namely (Figure 5): left-hand '769', right-hand '770', foot '771', and tongue '772'.

Events Epoch Averaging

After being stimulated by a flash or sound, the brains of subjects will produce different types of potentials, which are called evoked potentials. In order to solve these evoked potentials, we need to average the signals.

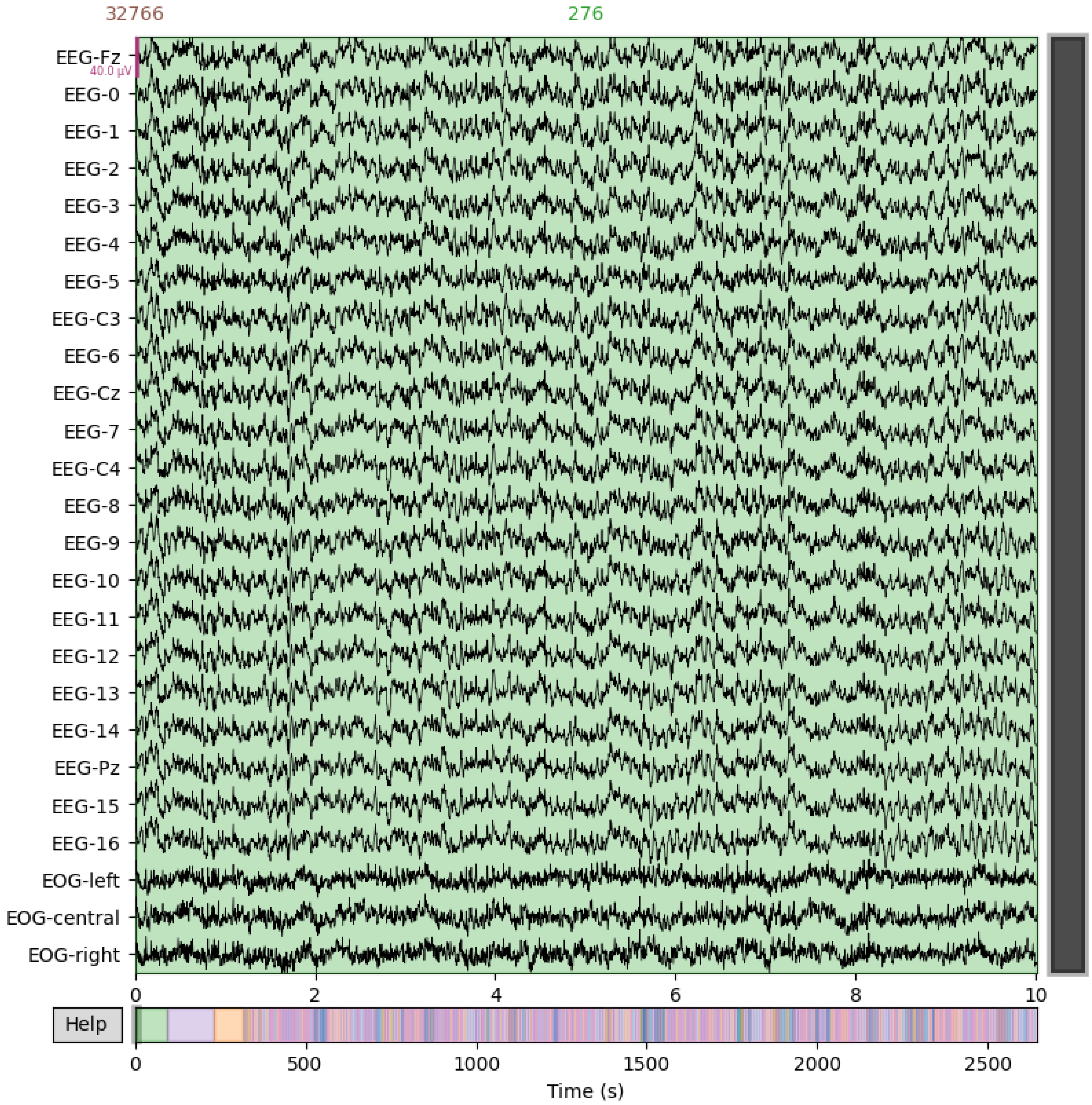

Figure 2: Raw EEG signal with EOG artifact. The 25 channels are shown in the vertical left side in the figure labeling the channel names. There exists 3 EOG channels which we have to remove

Wavelet Packet Decomposition (WPD)

Wavelet packet decomposition, sometimes known as WPD, is a method for processing signals that is based on the concept of wavelet transformations. Decomposing a signal into a collection of wavelet packets, which are sub-bands of the signal and include a variety of distinct frequency components, is a necessary step in the process. In order to acquire more sub bands, the WPD method first recursively divides the frequency range of the signal into smaller sub bands. After that, wavelet transformations are applied to each sub band in order to generate additional sub bands. This procedure will continue until the required degree of breakdown has been attained. After the signal has been broken down into wavelet packets, different kinds of processing and analysis can be carried out on each sub-band. For example, filtering, feature extraction, and compression are some of the possible operations. Since distinct frequency components can be manipulated independently thanks to this, signal processing can be made more efficient and precisely targeted. The method of wavelet packet decomposition finds usage in a diverse array of applications, such as the processing of audio and images, the compression of data, and the study of biological signals (Samar et al., 1999).

In this study, we employed Wavelet Packet Decomposition (WPD) function. Wavelet decomposition and wavelet packet decomposition are two distinct processes. Both of these instruments are suitable for the investigation of non-stationary data, such as our electroencephalogram (EEG), for example, which is a non-stationary signal. Wavelet Transform only decomposes the low-frequency component of the signal further, but Wavelet Packet Decomposition may decompose both the low-frequency and high-frequency parts of the signal. The signal is decomposed to level 5 with 'db4' wavelet. Eight frequency band coefficients are selected from the 4-32 Hz range. This is comparable to taking each channel of each epoch and decomposing it into a five layer binary tree for wavelet packet decomposition (Pawan & Dhiman, 2022). After this, convert labels by employing One Hot Encoder. It is a code in which one bit is 1 and the other bits are 0. For example, red, 100; Yellow, 010; Blue, 001.

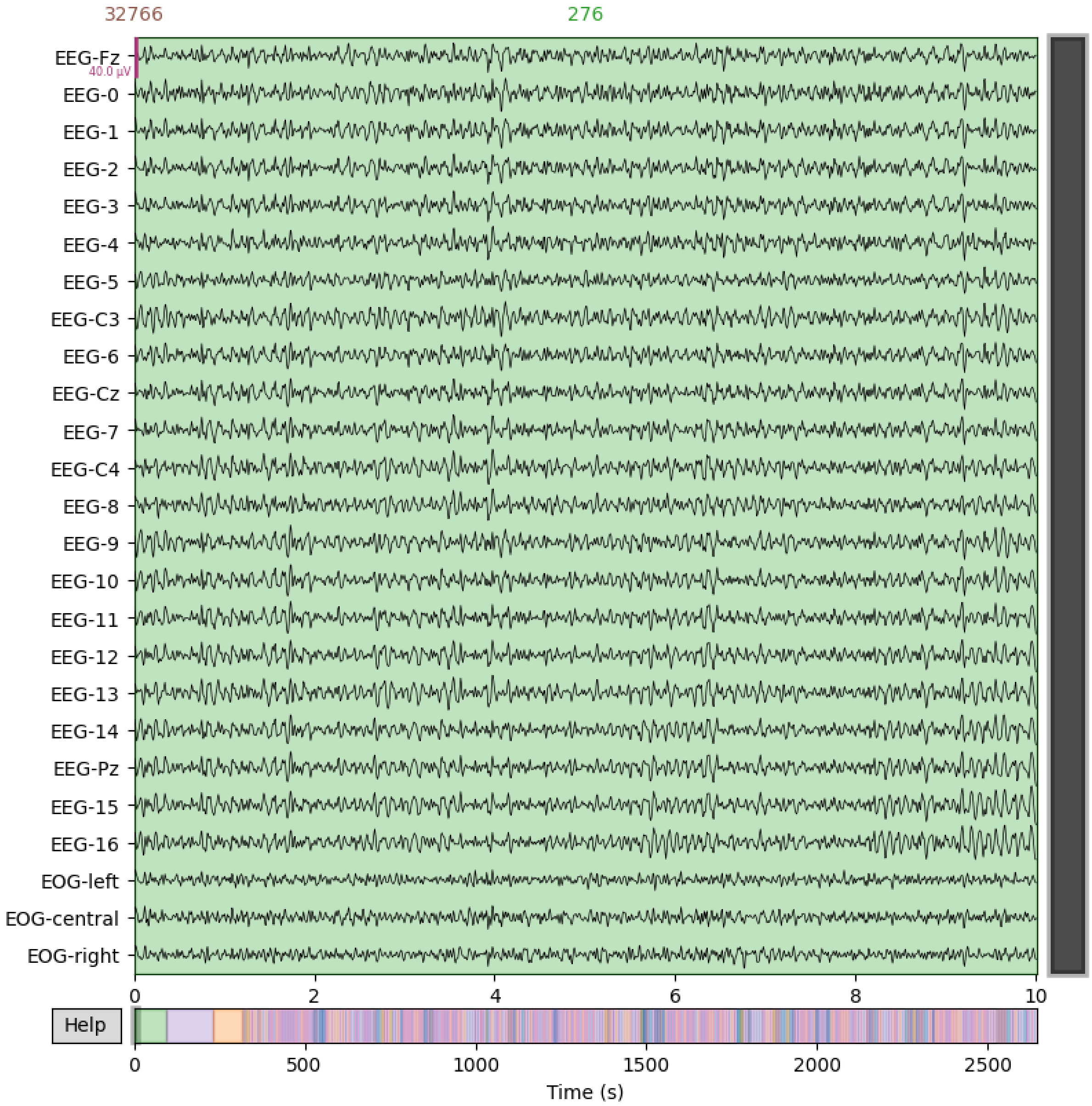

Figure 3: Filtered EEG signal with EOG artifact. The figure visualizes a clean signal with all the channels. The signal is smooth enough to extract features

Common Spatial Pattern (CSP)

Feature extraction is the most crucial step, since classifier performance would suffer if the features are not properly extracted. Extraction of features is the collecting of relevant information from a signal. Features are signal properties that may differentiate between distinct physical movements. Extraction of features from a huge amount of output data is referred to as feature extraction. To extract excellent features from the original signals, which would have a significant influence on the classification accuracy of EEG signals, it is crucial to use a precise approach for feature extraction. It has been shown that common spatial pattern (CSP) is a rather effective approach for feature extraction.

Multiclass CSP's goal is to categorize electroencephalogram (EEG) signals from several MI instances or classes. Most research has employed numerous modifications of two-class models to obtain multiclass the case of BCI which is needed in a real system. By breaking down the classification into many two-class sub-problems, multiclass issues may be handled. Joint approximation diagonalization (JAD) serves as the foundation for the expansion of CSP to multiclass issues (Grosse-Wentrup & Buss, 2008). JAD seeks to concurrently diagonalizable more than two matrices. Concurrent diagonalization of the average covariance matrices across all classes is the goal of CSP based on JAD. As a result, a single level is used to extract the discriminative characteristics for each multiclass paradigm.

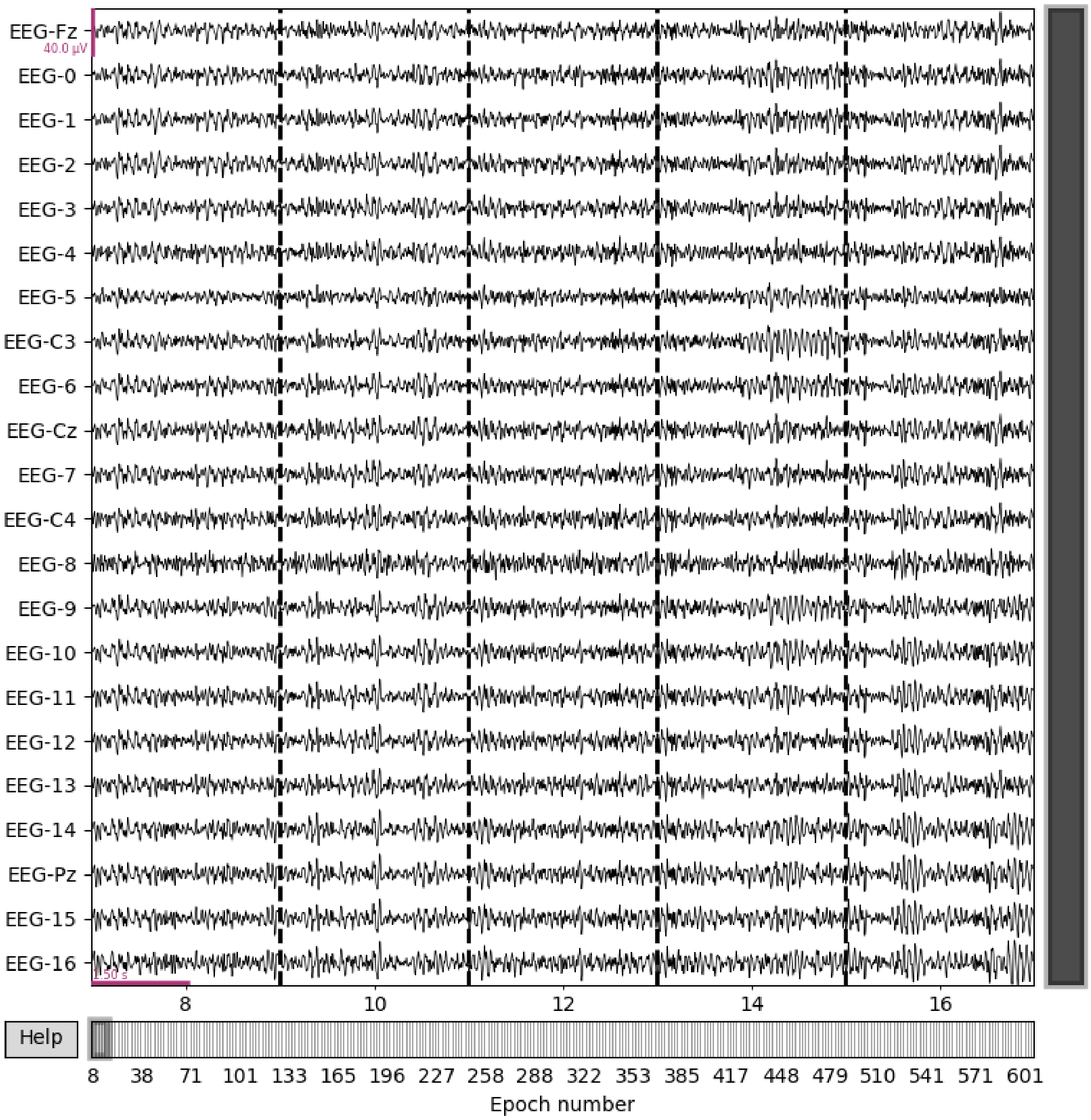

Figure 4: Epoched artifact free EEG signal where the 3 EOG artifact comprising channels are removed. Only 22 EEG channels are kept for feature extraction

Classifier Training and Testing

Classification is basically the identification of a class from a collection of features taken from signals. After extracting the necessary features, we must determine which movement is performed by a human. A classifier performs this function. A classifier is often a system that classifies certain data into multiple classes and the movement that corresponds to that portion of the EEG signal.

In this work, we first build the proposed ANN classifier by necessary components (Figure 7). After that, the CSP features are fed into the proposed ANN classifier to classify the four classes (Left-hand, Right-hand, Foot, Tongue) MI EEG signal. By decreasing the complexity of a learning model, ANN may generalize classification issues. The ANN is a powerful tool in high-dimensional environments, and it is especially useful in document classification and sentiment analysis, where the dimensionality may be exceedingly high (Sarker, 2021). Class separation is often nonlinear. The capacity of the ANN to apply fresh kernels provides for significant flexibility in decision boundaries, resulting in improved classification performance.

In our work, we built a three-layer ANN (Figure 7), wherein the first layer the dense layer input dimension is 32. To prevent overfitting and improve generalization ability, regularizers l2 and dropout are used. The ReLU is used here, which is a piecewise linear activation function that returns the input value unmodified if it is positive and zero otherwise. Since we must divide signals into four categories, the final layer (called the output layer) contains four output units. In this case, softmax is employed as the activation function. Optimizer: rmsprop, loss function: categorical cross-entropy, and metrics: accuracy were employed in the compilation process to determine efficacy. Once the model has been fitted, a forecast can be made, and the performance may be assessed by testing. The training and testing split is 80% and 20%, respectively.

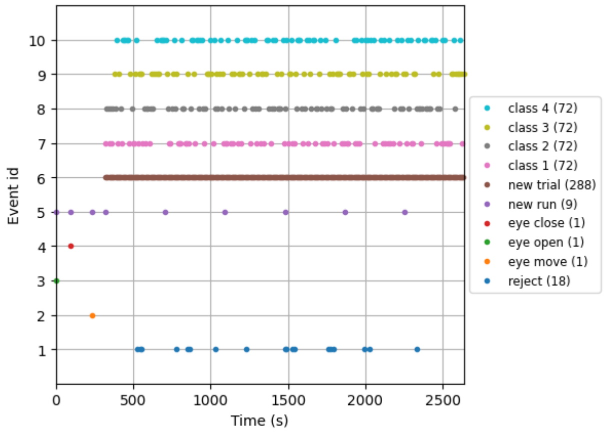

Figure 5: Signal events are marked here. From the events we need the four types of events which are marked with class 1, class 2, class 3, and class 4, respectively

Code Replication

To aid in understanding the procedure, a pseudocode replication of the methodology is included below in a nutshell.

1. Load and Preprocess EEG Data

 # Load Data
LOAD raw EEG data using `read_raw_gdf(filename)`
 # Preprocessing
FILTER raw EEG signal with a bandpass filter
MARK bad channels as `bads` in raw data (e.g., EOG channels)
SELECT only EEG channels, excluding bad channels and EOG channels
 # Event Detection
DETECT events from EEG data annotations using `events_from_annotations(raw)`
 # Define Event IDs
DEFINE event IDs for motor imagery tasks:
'left_hand' : 769 ...
 # Epoch Extraction
EXTRACT epochs from raw data with time window around each event

2. WPD

 # Define Wavelet Packet Decomposition Function
FUNCTION Wavelet_Packet_Decomposition:
APPLY wavelet packet decomposition using 'db4' wavelet on EEG signal
RETURN decomposition coefficients up to max level 5
 # Extract Features for Each Epoch
FOR each epoch in EEG data:
FOR each EEG channel:
COMPUTE wavelet packet decomposition coefficients
SELECT specific frequency band coefficients
STORE coefficients in the feature matrix `Bands`

3. CSP

SPLIT data into training and testing sets
 # Apply CSP Filters for Feature Extraction
FOR each frequency band in specified range:
INITIALIZE CSP filter
FIT CSP filter on training data and transform training data
TRANSFORM testing data using fitted CSP filter
 # Standardize Data
STANDARDIZE training and testing data using StandardScaler

4. Artificial Neural Network (ANN)

 # Define ANN Model Architecture
FUNCTION Define_ANN_Model:
INITIALIZE Sequential ANN model
ADD input layer with `num_units` and activation
ADD dropout layer with `dropout_rate`
 # Add Hidden Layers
FOR each layer in `num_layers`:
ADD dense layer with `num_units`, activation, and L2 regularization
ADD dropout layer with `dropout_rate`
 # Output Layer
ADD output layer with specified units and specified activation for classification

5. Model Training and Evaluation

 # Train ANN Model
INITIALIZE ANN model using `Define_ANN_Model()`
TRAIN ANN model
 # Predict and Evaluate
PREDICT classes
CALCULATE performance metrics: accuracy, kappa score, precision
STORE metrics in corresponding lists

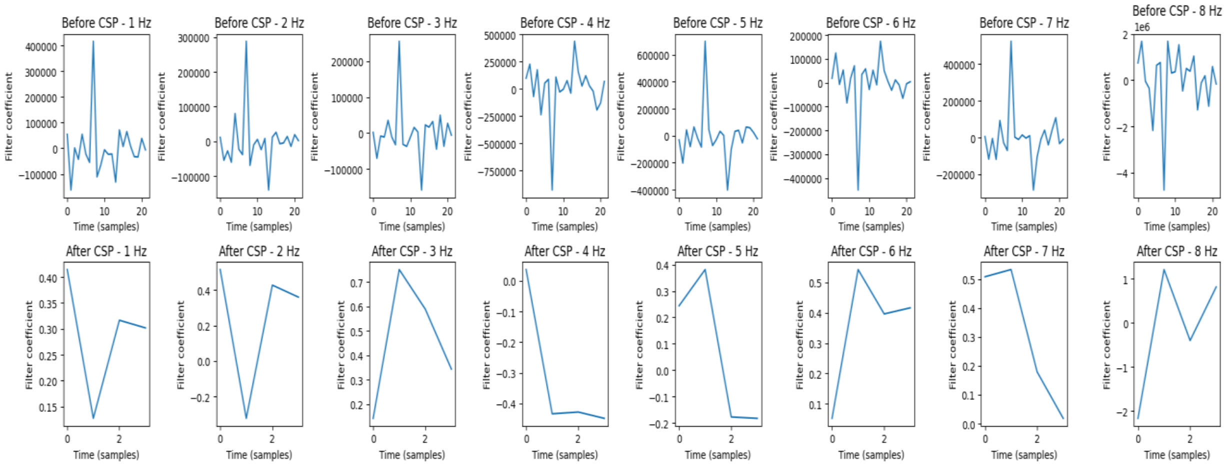

Figure 6: The 1st CSP filter is plotted before and after transformation as a function of time. The plot provides a visual representation of the CSP filters and their effect on the EEG data. The CSP filter is applied separately to each frequency band coefficient

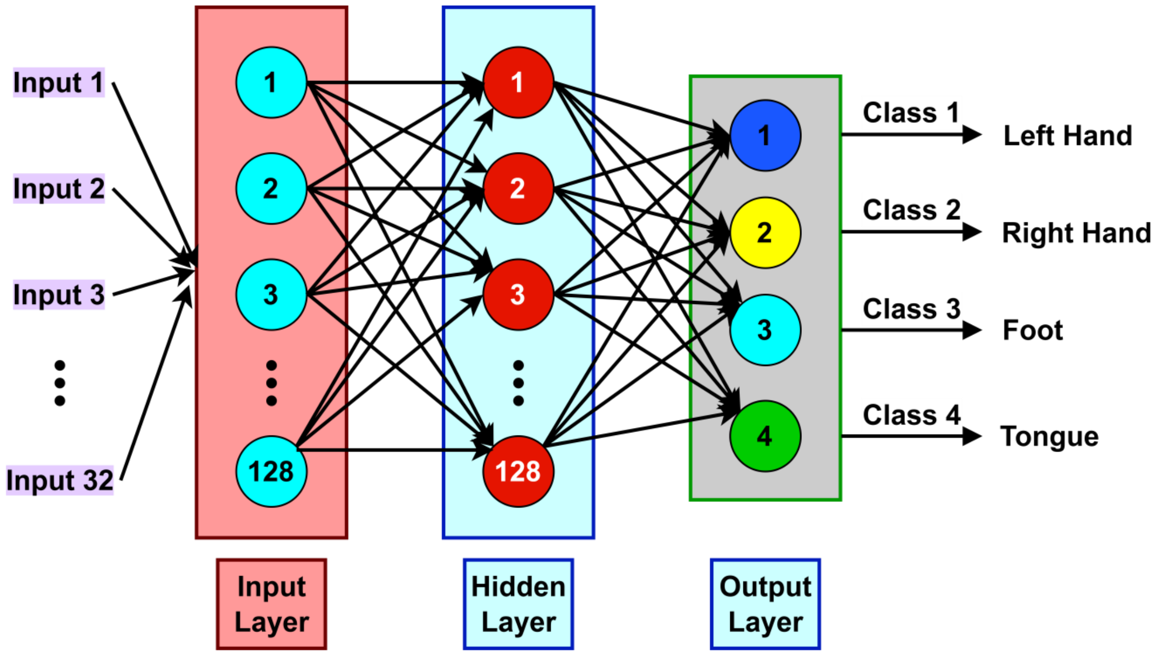

Figure 7: Proposed ANN classifier model structure

Results and Discussion

In this section, the experimental findings for MI task separation that have been accomplished on the BCI competition IV dataset 2a and proposed model performance will be presented.

Performance Metrics

The accuracy of the proposed approach in this study is assessed using Eqn. 1, the Kappa score is determined using Eqn. 2, and the precision is calculated by Eqn. 3.

$$acc = \frac{\sum_{i=1}^{M} \frac{TP_i}{S_i}}{M} \qquad (1),$$

Where TP_i represents the true positive that means the number of correctly classified samples in class i, S_i represents the number of samples in class i, and M means the number of classes.

Cohen's κ-score, which is calculated as:

$$\kappa = \frac{1}{M} \sum_{ac=1}^{M} \frac{P_{ac} - P_e}{1 - P_e} \qquad (2),$$

Where M means number of classes, P_{ac} is the actual rate of agreement, and the expected percentage likelihood of agreement is denoted by P_e.

Precision calculation equation is as like:

$$prec = \frac{TP}{TP + FP} \qquad (3)$$

Where TP is true positive and FP is false positive.

Subject Wise Cross Validation Result

To begin, we will illustrate the performance of the classification by the proposed method in accordance with the subjects (Fig. 8-11), respectively. Here, the evaluation result is shown for four subjects taken from the intended dataset, and 5-fold cross-validation is used.

Using the proposed strategy results in an average classification accuracy rating of 77.41% for the four subjects taken. The figures show that the subject A03's accuracy, precision value, and kappa score were all at 84.48%, 85.25%, and 0.79, respectively, which is the best result the proposed method could produce (Fig. 9). For the rest of the subjects, the proposed method outperforms cutting-edge techniques for classifying EEG data into four classes related to motor imagery.

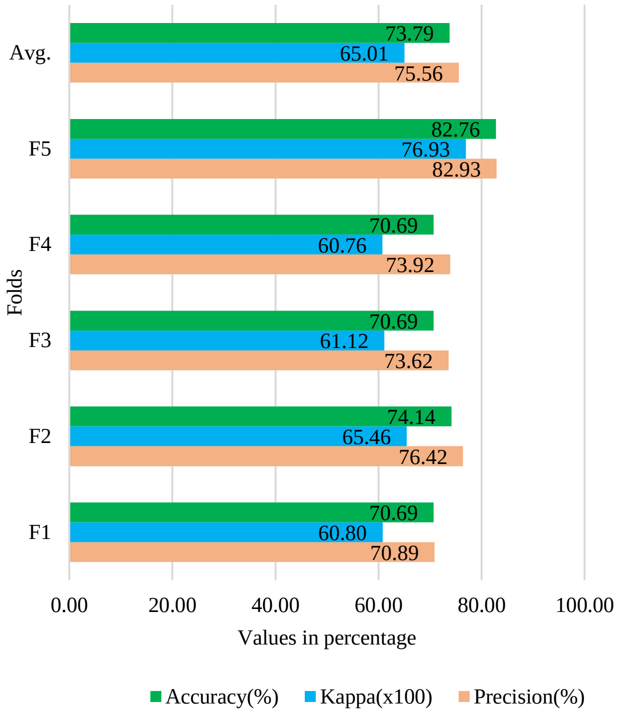

Figure 8: Classification result for subject A01

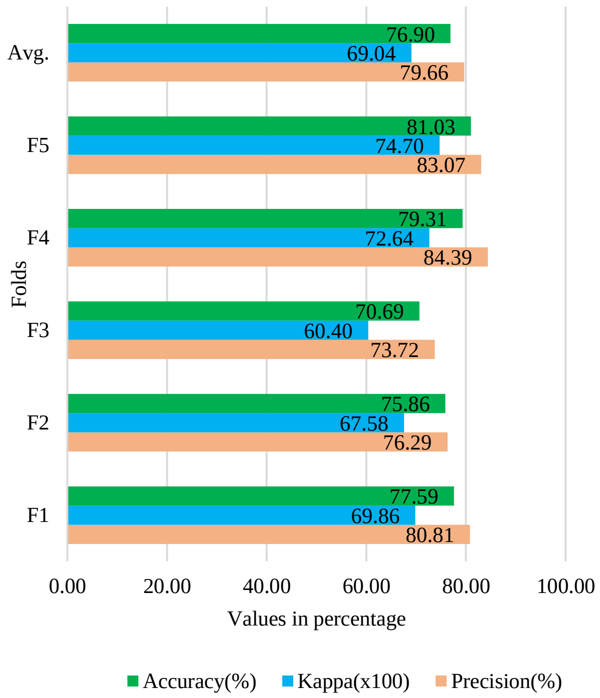

Figure 10: Classification result for subject A07

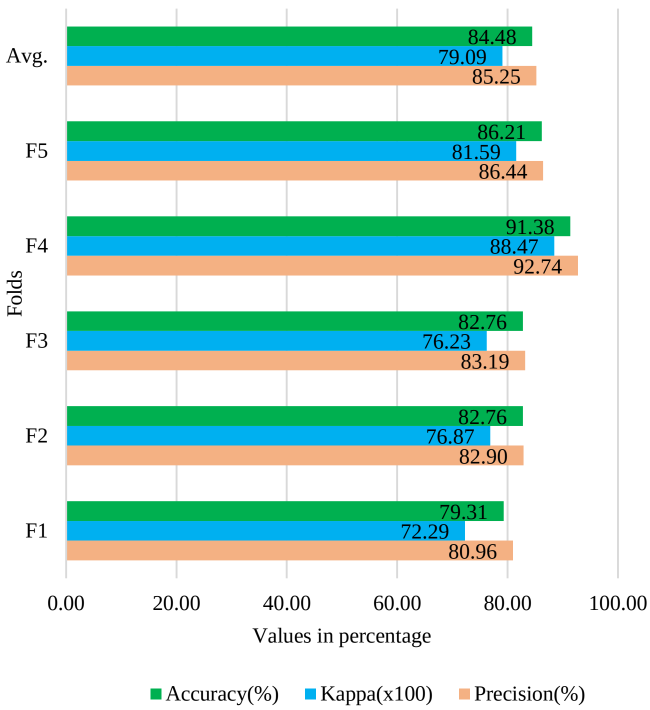

Figure 9: Classification result for subject A03

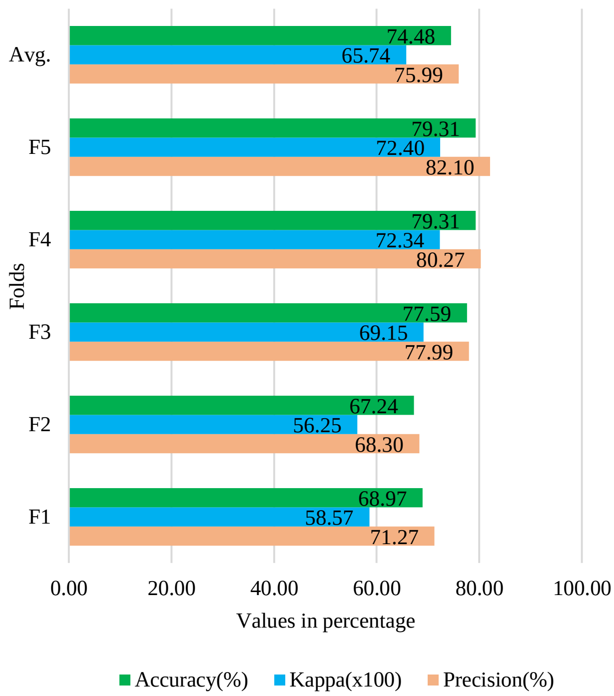

Figure 11: Classification result for subject A08

Comparative Analysis

The SVM, KNN, LDA, and Skl-ANN classifiers have been fitted to analyze the proposed method's classification efficiency. As we can see, the proposed model has a higher average accuracy than the others. The following (Fig. 12) compares the predictive power of the methods for classifying data.

The average classification accuracy rate while using the proposed model is 77.41%. However, when the SVM, KNN, LDA, and Skl-ANN classifier models are employed, the best average classification accuracy of 82.07%, 78.62%, 82.07%, and 81.31% is attained, respectively, for the subject A03. The proposed model outperforms the others by providing an accuracy of 84.48% for subject A03. This is why the proposed model performs better than state-of-the-art methods (Table. 2) for classifying EEG signals into four classes associated with motor imagery. With some further tweaking, we anticipate a more accurate classification in the near future.

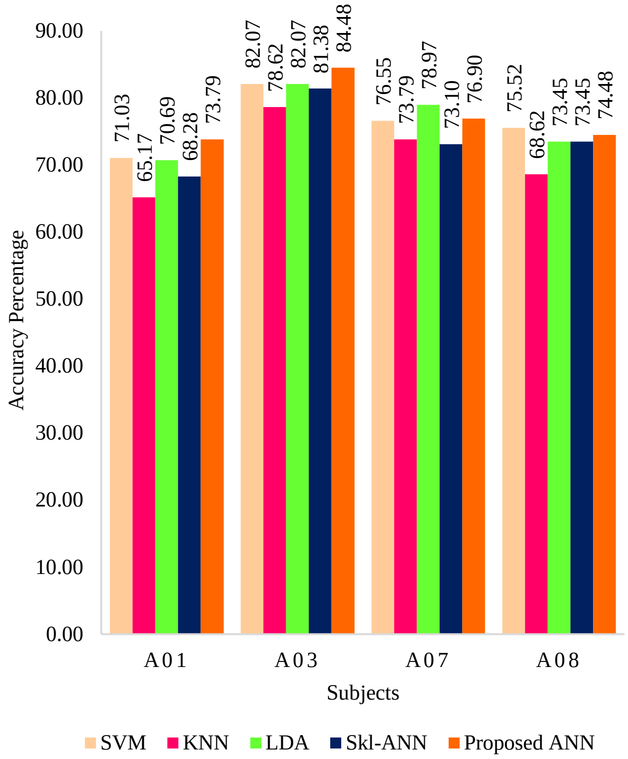

Figure 12: A comparative analysis of accuracy with other classification algorithms we experimented with for all the subjects tested is visualized in the chart above. Here, we observe that the proposed technique surpasses the others.

Table 2: A comparative analysis of the proposed method with others. Here, the proposed method attains maximum accuracy and kappa than others

Methods (4 Class MI EEG Classification)	Accuracy (%)	Kappa (%)
CNN+ECA (Tong et al., 2023)	75.76	-
CNN1DMF (Alnaanah et al., 2022)	69.20	59.00
CSP + 3CNNs (Zouch & Echtioui, 2022)	62.45	-
CSP+KNN (Nguyen et al., 2017)	67.86	59.31
Ensemble (Nguyen et al., 2017)	67.98	59.26
CSP+LDA (Nguyen et al., 2017)	71.24	63.49
CSP+NB (Nguyen et al., 2017)	70.38	62.33
CSP+SVM (Nguyen et al., 2017)	71.16	63.54
CSP+FLS (Nguyen et al., 2017)	72.96	65.71
Proposed	**77.41**	**70.00**

Limitations

This is done methodically and precisely to make the final result more palpable. Completed are data preparation, filtering, artefact removal, feature extraction, and classification chores. At last, the performance measures help to gauge it. Still, some of the obstacles still exist: extremely non-linear and prone to noisy EEG signals hamper accurate feature mining and classification tasks. For the need of thorough hyperparameter tweaking, the computational cost of optimizing the classification model is considerable. With future efforts, maybe the limitations ought to be transcended for greater impact outcomes.

Conclusion

The BCI) technology is a fascinating field of research and it is growing quickly. BCI schemes can facilitate people to control smart devices and interfaces without having to touch them physically. They do this by picking up and interpreting electrical signals from the brain. However, developing effective BCI systems requires overcoming numerous technical challenges, including how to process and interpret complex and noisy signals. With the proposed method, it has been seen that setting up the classifier with the right method is a big problem and unique feature extraction is also needed. Compared to other methods, the proposed method works better for the dataset without changing or adding to the recorded data. So, it is hoped that this idea will work better than the traditional way of using BCI in the real world.

Because EEG signals provide substantial contributions to biomedical science, rigorous analysis of EEG signals is required in the research field. One of the major issues in modern biomedical research is how to reliably classify MI movement-based electroencephalographic (EEG) data, which subsequently leads to the BCI system, which is critical for various motor handicapped patients. The future study will concentrate on more research into EEG signal processing and its relationship to various physiological movements. It will be attempted to apply the executed technique in real-world applications such as controlling certain hardware such as iron-hands or feet, wheelchairs, and a variety of useful amenities that benefit both impaired and non-disabled individuals in the BCI system. In future studies, it will be looked at ways to enhance this algorithm such that it produces better results than current EEG signal classification algorithms. The future step will also be turning the results of the classification into instructions that can be deployed on the BCI applications by interfacing robotic actuators. Before that, various performance assessment results will be assessed to evaluate how better the proposed approach is against the state-of-the-art model.

Data Availability

The BCI Competition IV 2a data (Brunner et al., 2008) used in this work is publically available and may be accessed on the recognized competition website at https://www.bbci.de/competition/iv/#datasets.

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Conflict of Interest

None of the authors present any conflicts of interest.

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