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Motor Imagery EEG Signal Processing Using Common Spatial Patterns (CSP) and Python-Based Artificial Intelligence

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ABSTRACT

Brain–Computer Interface (BCI) systems create a direct communication channel between the human brain and external devices, bypassing conventional neuromuscular pathways. These systems interpret brain activity typically captured via electroencephalography (EEG) to infer user intent and execute commands accordingly. In this study, we focus on the classification of motor imagery (MI) signals, a widely used paradigm in BCI applications, which involves users imagining specific limb movements without actual muscle activation. EEG data corresponding to these imagined movements were preprocessed and analyzed using the Common Spatial Patterns (CSP) algorithm, a spatial filtering method that enhances class-discriminative features by maximizing variance differences across mental tasks. Subsequently, these features were classified using machine learning techniques implemented in the Python 3.7 environment. The EEG datasets used for training and evaluation were obtained from PhysioNet, a widely recognized repository hosted by the Massachusetts Institute of Technology (MIT). The aim of this work is to support the development of real-time, non-invasive BCI systems, with potential applications ranging from neurorehabilitation to the control of assistive devices such as prosthetics and exoskeletons. Additionally, the results offer insight into the implementation of neural signal processing algorithms on embedded systems, paving the way for the development of brain-controlled microchips and next-generation human–machine interfaces.

1. INTRODUCTION

Brain–Computer Interface (BCI) systems provide a direct communication link between the human brain and computers. In such systems, a user can control a device such as a wheelchair simply by imagining the desired action. By processing the brain's electrical signals (EEG), the computer can interpret what the user is thinking and execute commands accordingly. This technology holds significant promise for stroke patients, as it can assist in neural rehabilitation and serve as an effective aid in motor recovery training.

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The range of BCI applications extends beyond healthcare to include navigation, military services, robotics, virtual gaming, and communication systems. One of the most widely used techniques for decoding motor imagery (MI) from EEG data is Common Spatial Patterns (CSP). CSP is a feature extraction algorithm that employs spatial filters to maximize the variance between two classes [1,2]. This method has been extensively used for EEG-based MI feature extraction in BCI systems [3,4]. The classification accuracy of MI signals largely depends on the quality of features extracted from EEG signals. Notably, in various studies, binary MI classification accuracy has reached over 90%. However, multi-class MI classification still exhibits lower performance [5]. Another notable feature extraction approach is Sequential Forward Floating Selection (SFFS) [6]. After extracting features, classification can be performed using methods such as Linear Discriminant Analysis (LDA), which has shown good performance in combination with CSP [7].

EEG measurement is performed using a specialized cap equipped with electrodes that detect the brain's electrical activity. Typically, EEG testing is conducted alongside imaging scans such as CT or MRI, as well as laboratory tests, for diagnosing neurological conditions like epilepsy. EEG is non-invasive, painless, and safe, with no lasting side effects. Each electrode is labeled with a specific code, and different brain lobes are responsible for distinct cognitive and motor functions such as speech, memory, and language. By analyzing EEG recordings, abnormal brain activity and the affected regions can be identified. In partial (focal) seizures, only specific electrodes detect abnormal activity, whereas in generalized seizures, abnormal signals appear across all electrodes. Brainwave types in EEG are classified by frequency, each with a distinct name. Figure 1 illustrates a sample EEG measurement using a 64-channel system.

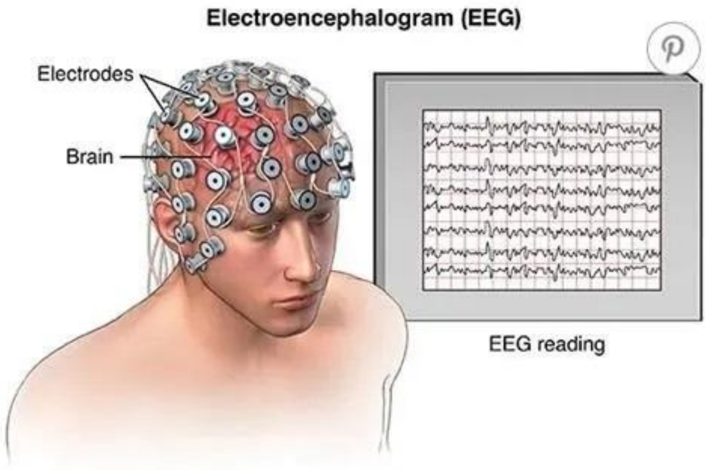

Fig. 1. Measurement of brain signals using electroencephalography (EEG) cap

2. FEATURE EXTRACTION USING THE COMMON SPATIAL PATTERNS (CSP) METHOD

The Common Spatial Pattern (CSP) is a mathematical technique in signal processing used to decompose a multivariate signal into additive subcomponents that exhibit the maximum variance difference between two time windows. This algorithm is commonly applied to detect abnormalities in EEG signals and to discriminate between classes in brain–computer interface (BCI) systems, particularly for binary motor imagery (MI) tasks. Due to the multi-channel nature of EEG data, CSP is especially effective for such signals.

CSP operates by applying spatial filters to the input signals in a manner that maximizes the variance in one class while minimizing it in the other. The algorithm then extracts features for the first class using the filtered signals. Conversely, another set of spatial filters does the reverse maximizing variance for the second class while minimizing it for the first thus enabling feature extraction for the second class. The mathematical foundation of CSP lies in linear algebra and multivariate statistical analysis.

CSP transforms EEG data from the time domain to the spatial domain using spatial filters. This transformation yields new features (components), which are linear combinations of the original EEG channels. The goal of the spatial filter is to find a set of spatial weights that best discriminate between two or more EEG data classes. For example, in a typical CSP analysis, EEG data may be divided into two classes: one representing a cognitive task (e.g., imagining left-hand movement) and the other representing a resting state (e.g., eyes closed). CSP then determines a set of spatial weights that maximally differentiate these two classes.

The spatial filter used in CSP is typically computed by solving a generalized eigenvalue problem, which involves finding the eigenvectors of a matrix that optimally separates two EEG classes based on their covariance matrices. These eigenvectors (spatial filters) project the EEG signals into a new space where the classes are optimally distinguishable in terms of variance. In essence, the resulting spatial filters are sets of weights applied to the EEG data to produce spatially filtered signals that highlight the differences between the classes. A summary of this process is illustrated in Figure 2.

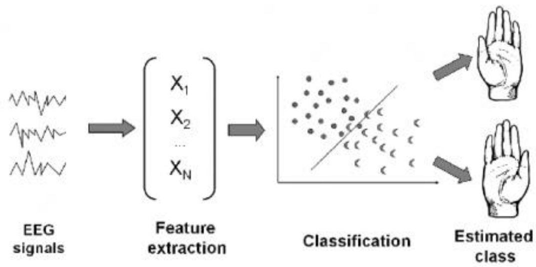

Fig. 2. Signal processing pipeline for motor imagery (MI)

From a computational perspective, let us assume that X1 and X2 are two time windows of a multivariate signal with dimensions *(n,t₁)* and *(n,t₂)*, respectively, where n denotes the number of channels (signals), and t_1 and t_2 represent the number of samples in each window. The CSP algorithm determines the spatial projection matrix W^T such that the ratio of variances (or second-order moments) between the two signal windows is maximized:

$$W = arg\,max_w \frac{\|wX_1\|^2}{\|wX_2\|^2} \tag{1}$$

The solution to the above optimization problem is obtained by computing the following two covariance matrices:

$$R_1 = \frac{X_1 X_1^T}{t_1} \tag{2}$$

$$R_2 = \frac{X_1 X_2^T}{t_2} \tag{3}$$

The process then continues with the diagonalization of the two matrices and spectral decomposition (i.e., factorizing the matrix into its canonical form such that it is represented in terms of its eigenvalues and eigenvectors). The matrix of eigenvectors is determined as:

$$P = [p_1 \dots p_n], \tag{4}$$

and the diagonal matrix D contains the eigenvalues:

$$D = \{\lambda_1 \dots \lambda_n\} \tag{5}$$

where the eigenvalues $\lambda_1,\lambda_2,\dots,\lambda_n$ are arranged in descending order. We then have the following decomposition:

$$P^T R_1 P = D \tag{6}$$

$$P^T R_2 P = I_n \tag{7}$$

where I_n is the identity matrix. This is equivalent to the spectral decomposition of $R_2^{-1}R$, yielding:

$$R_2^{-1}R = PDP^{-1} \tag{8}$$

Here, W_T corresponds to the first column of P; that is, $w = p_1^T$

3. IMPLEMENTATION OF THE METHOD

For the implementation of our approach, one could use simulated EEG signals; however, in this study we employ real recordings from a well-known public dataset. A cohort of healthy volunteers performed motor imagery tasks while their EEG was recorded. The raw EEG data were obtained from the PhysioNet database of MIT's Biomedical Engineering repository [9], and all processing was carried out in Python 3.1.

This dataset comprises over 1,500 one- and two-minute EEG recordings collected from 109 subjects. During each trial, a visual cue a target appearing either at the top or bottom of the screen was presented to the participant. If the target appeared at the top, the subject was instructed to imagine repeatedly opening and closing both fists; if the target appeared at the bottom, they were to imagine opening and closing both feet. After the cue disappeared, the subject returned to a relaxed state.

An example of a recorded EEG trial is shown in Figure 3. All signals were captured using a 64-channel electrode cap arranged according to the international 10–10 system (see Figure 4), with a sampling rate of 160 Hz. These high-density recordings provide the spatial resolution needed for effective CSP-based feature extraction and subsequent classification.

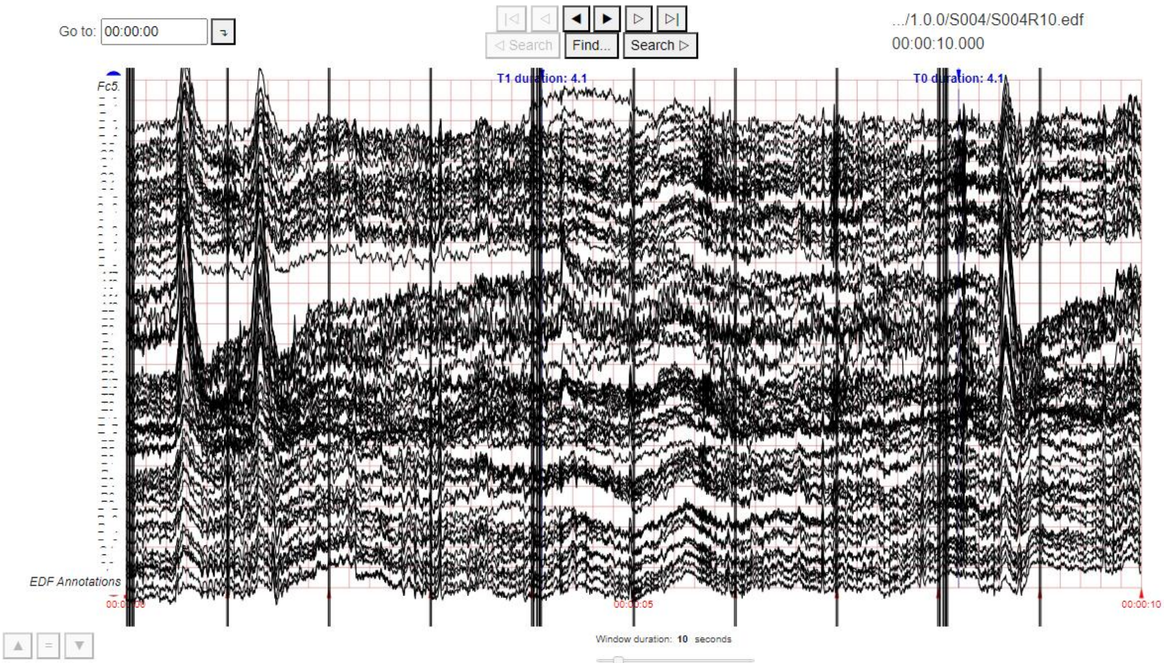

Fig. 3. A sample EEG recording obtained from a volunteer in the laboratory.

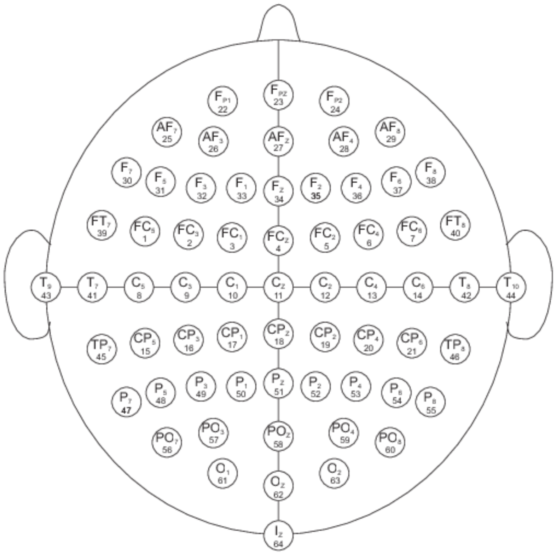

Fig. 4. The 64-channel electrode system in 10–10 configuration for EEG signal acquisition in the PhysioNet dataset

Signals are recorded from different channels. Source localization is typically performed using spatial and temporal filters. The use of a spatial filter, namely Common Average Reference (CAR), helps reduce the spatial blurring effect in the raw signal. To remove noise and preprocess the channels, a band-pass FIR filter with a passband of 7 to 30 Hz and a Hamming window is applied. The specifications of this filter are provided in Table 1. This frequency range covers the mu and beta bands, which are considered crucial in BCI systems. It has shown better performance compared to narrower bands in distinguishing motor imagery patterns and improving classification accuracy. Feature extraction is conducted using the Common Spatial Pattern (CSP) algorithm, followed by classification using Linear Discriminant Analysis (LDA). This statistical classifier applies a linear transformation using a weight matrix, where the weights are determined to maximize the between-class variance and minimize the within-class variance. High speed and no requirement for hyperparameter tuning are among the advantages of this classifier. The goal of this method is to project data such that samples from the same class are close together in the new subspace, while samples from different classes are well separated in other words, maximizing inter-class variance and minimizing intra-class variance. For training the machine learning model and reducing variance, Monte Carlo cross-validation is employed. In this technique, the data are randomly split into multiple partitions. Other validation methods, such as K-fold cross-validation, can also be used. Through channel analysis and application of the CSP filter, the topographic brain maps of the participants are obtained, as illustrated in Figure 5, clearly indicating the brain activation regions. Finally, the performance of the classifier is evaluated based on standard evaluation metrics. These metrics are derived from the four key components of the confusion matrix: true positives (i.e., correctly predicted positive instances), true negatives (i.e., correctly predicted negative instances), false positives (i.e., instances incorrectly predicted as positive), and false negatives (i.e., instances incorrectly predicted as negative). The onset of motor imagery is considered to occur at time zero. The overall classification accuracy over time for different subjects is depicted in Figure 6.

Table 1. FIR filter parameters used in the implementation

One-pass, Zero-phase, non-causal bandpass filter

Windowed time-domain	*Hamming Window*
Passband ripple	*0.0194*
Stopband attenuation	*53 dB*
Lower passband edge	*7 Hz*
Lower transition bandwidth	*2 Hz (-6 dB cutoff freq.: 6 Hz)*
Upper bandpass edge	*30 Hz*
Upper transition bandwidth	*7.5 Hz (-6 dB cutoff freq.: 33.75 Hz)*
Filter length	*265 samples (1.656 s)*

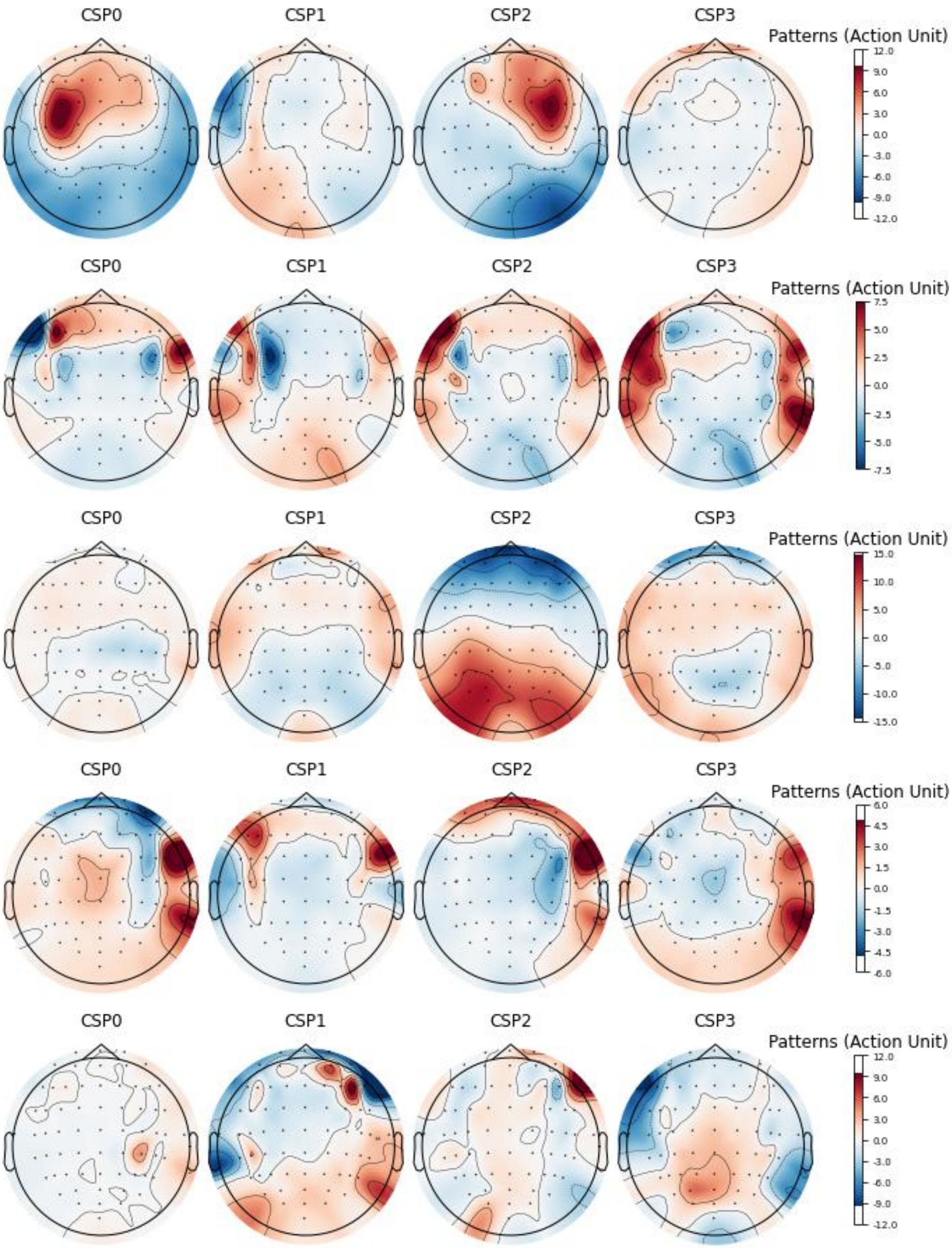

Fig. 5. Brain topographic maps resulting from CSP analysis (for five participants)

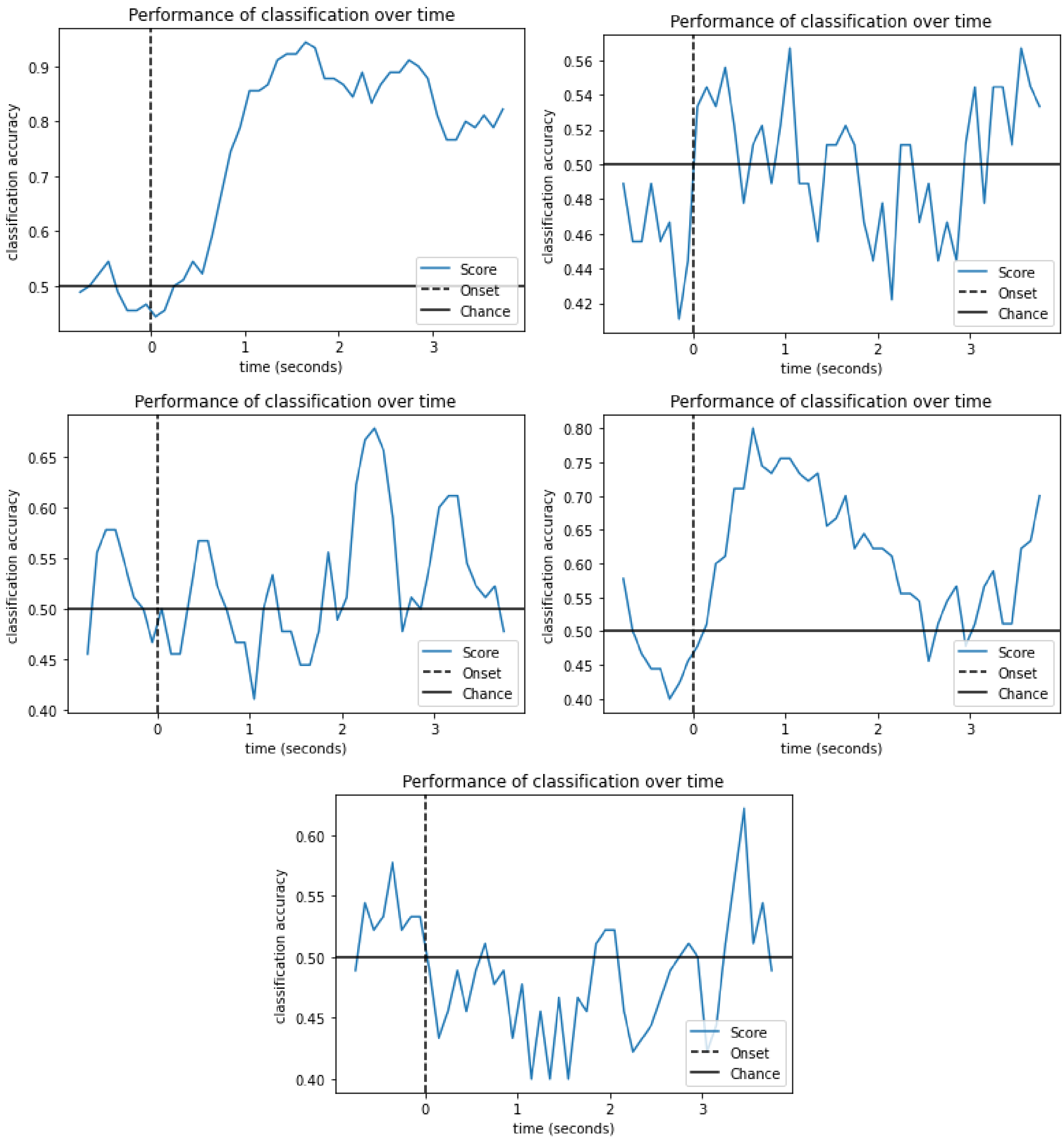

Fig. 6. The overall classification accuracy over time for different subjects (for the same participants – in order from left to right and top to bottom)

It can be observed that for the first participant, the classification accuracy reaches approximately 93%. By examining the plots for the other participants, it can be concluded that the implemented CSP-based model demonstrates acceptable performance and prediction accuracy.

4. CONCLUSION

This study aimed to extract features from EEG signals associated with motor imagery. The application of this research lies in assisting patients with various neurological and muscular disorders, as well as brain and spinal cord injuries. Temporal and spatial filters were used for preprocessing. The Common Spatial Pattern (CSP) method was employed for brain signal processing and feature extraction, followed by classification using Linear Discriminant Analysis (LDA). The proposed method was simulated and implemented in Python 3.7 using the MIT biomedical

engineering dataset.
The findings of this study can be utilized in Brain-Computer Interfaces (BCIs) and brain-implanted chips for human-machine interaction.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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