

An Improved Convolutional Neural Network Framework For Efficient Motor Imagery Electroencephalography (EEG) Classification Using Common Spatial Pattern (CSP)

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ABSTRACT

This study develops an optimized Convolutional Neural Network (CNN) architecture based on the Common Spatial Pattern (CSP) method to improve the classification performance of motor-imagery-based brain-computer interface (BCI) systems. The use of brain activity is to communicate and control external devices by people with motor limitations has demonstrated encouraging outcomes for motor-imagery-based BCIs. However, the electroencephalography (EEG) signals can be difficult to extract pertinent information from, which limits the classification accuracy of these systems. The CSP algorithm, which successfully extracts discriminative features from multi-channel EEG signals, is combined in this study's unique approach with a CNN framework that makes better use of the learnt spatial filters. The preprocessing of the EEG data, use of the CSP algorithm to extract pertinent features, and training of the CNN with an optimized architecture make up the technique. Using publicly accessible benchmark datasets, the performance of the proposed strategy was assessed and compared to current state-of-the-art techniques (DNN). Improvements in classification accuracy (i.e., 98.80% was achieved against the 88.10%) of the existing approach (DNN-FBCSP), decreased computing complexity, and greater usability of motor-imagery-based BCIs are predicted consequences of this research, which was ultimately developed assistive technologies for people with motor disorders.

Keywords: Motor imagery MI, Electrooculography EEG signals, Common spatial pattern CSP, Convolutional neural network CNN, Deep neural network DNN, Brain computer interface BCI.

1.0 INTRODUCTION

Motor imagery based brain computer interfaces (BCIs) are a promising technology that allows persons with movement impairments to use their brain activity to engage with their surroundings. When performing motor imagery tasks such as visualizing left- or right-handed motions, these BCIs use scalp-captured electroencephalography (EEG) signals to decode the user's intents. These signals can be used by machine learning algorithms to classify the planned activities and translate them into commands that operate external devices. However, it is challenging to accomplish accurate and trustworthy categorization due to the high complexity, unpredictability, and noise of EEG signals (Thomas, et al. 2019).

Feature extraction is a crucial step in motor imagery-based BCI systems, which extracts relevant information from the EEG, signals to differentiate between different mental tasks. The Filter Bank Common Spatial Pattern (CSP) algorithm is one of the many feature extraction techniques that have been put forth; it has produced promising results. CSP extracts frequency domain spatial filters to enhance the discriminative information in EEG

data related to motor imagery. The ensuing classification step usually depends on traditional machine learning models, which might not fully capture complicated spatial and temporal relationships, even though deep learning methods are better at doing so (Abdulkader, 2022).

Since brain impulses are used as inputs for brain-computer interfaces, many non-invasive and invasive approaches have been developed. Both non-invasive techniques like electroencephalography (EEG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), and local field potentials (LFP) are available, as well as invasive techniques like functional near-infrared spectroscopy (FNIRS), grid recordings from the cortex (ECoG), and multi-unit activities (S. Zhang, 2019). Of all the methods discussed, EEG-based systems have been extensively studied and put into practice because of their properties that allow for portability, flexibility, and non-intrusiveness. Motor imagery is a prominent use of EEG-based BCI systems, in which the device uses the motor cortex's activity while the user imagines moving their limbs. Machine learning algorithms are widely employed to model high-definition

datasets and generate predictions on data regarded as an experience in order to record and interpret these movement related brain activity.

Much progress has been made in the last few years in using BCI in biological systems, including the identification and diagnosis of cancers and neurological conditions (Thomas, et al. 2019).

Feature extraction, categorization, signal preprocessing, and signal acquisition are the parts of a BCI system (Abdulkader, 2022). When a voluntary task is finished, the brain's electrical activity is recorded by signal acquisition. Procedures for acquiring signals usually have two approaches: non-invasive and invasive. As part of the invasive signal acquisition process, which involves surgery, electrodes are placed on the surface of the brain. Obtaining the signal without requiring any surgical procedures is known as non-invasive acquisition.

As a communication strategy, motor imagery (MI) has been extensively used in non-invasive BCI (Mengxi Dai et al. 2020). The power of EEG signals in certain frequency bands changes when one imagines moving hands, feet, or the tongue, according to (J. Mellinger, 2021), the Brain Sensors and Signals. An increase in the EEG signal's power within a certain frequency band is known as an event-related synchronization (ERS). On the other hand, a drop in EEG signal strength is referred to as an Event-Related Desynchronization (ERD) (Lotte F et al., 2022). For instance, when a left-hand movement is imagined, the motor cortex's contralateral ERD (i.e., the left motor cortex for hand movements on the right) is activated in the μ (about 8-12) and β (about 16-24) bands during movement imagination, and this results in an ERS in the β band shortly after the movement imagination concludes. A novel MI pattern classification based on the direction of both hands' movement was recently proposed by (S. Zhang, 2019). To distinguish between the directions of the hands' movements, they employed a support vector machine (SVM) and the common spatial pattern (CSP) technique for feature extraction. In order to increase the accuracy of EEG MI classification, (S. U. Amin, 2019) suggested combining CNNs with various features and architectures. This technique would enhance the convolutional neural network (CNN) models. These methods, however, either produce poor accuracy results or take a long time for the motor imagery system to mature.

The term Brain-Computer Interface (BCI) refers to a technology that allows people to communicate with external devices by measuring brain signals and converting them into an interactive application command, (Shuaibu Z. and Li. Q., 2020), despite the fact

that motor-imagery-based BCIs have advanced significantly. By granting people suffering from myotrophic lateral sclerosis (ALS), paralysis, and muscle impairment an alternative means of communication that converts the way they think into a command for the control of devices around them without doing anything physically, brain-computer interface (BCI) applications seek to lessen their limitations. Comparing invasive techniques that assess a patient's brain signal via brain surgery, non-invasive electroencephalography (EEG) is by far the most popular method for obtaining the user's brain signal because it carries less risk and is simple to set up for BCI. (Lotte, F. et al., 2022). For the past thirty years, EEG signal processing has been a significant and fascinating topic. According to (Långkvist, M. et al., 2020), it has been applied to a variety of tasks, such as assessing sleep stages and managing mobile robots. It was once employed in clinical neurology for purposes like diagnosing epilepsy, identifying epileptic seizures, and locating epileptic form discharges. (Song, Ye. et al., 2022). If traditional feature extraction methods and machine learning models underutilize the capabilities of deep learning techniques, the effectiveness of motor-imagery-based BCIs may be compromised. On the other hand, one of the most well-liked and effective approaches for machine learning issues including pattern recognition, picture categorization, and object detection is the convolutional neural network (CNN). (Chan K. et al., 2019). Consequently, to boost classification accuracy in motor-imagery-based BCIs, a better technique is needed that effectively blends the benefits of CNNs and the CSP. The main contributions of the proposed method are:

- i. Reviewed challenges and limitations of using CSP and CNN for classification performance based BCI system, with a focus on extracting discriminative features from EEG signals.
- ii. Designed CNN framework architecture that integrates the CSP filters.
- iii. Developed the CNN model that incorporates the CSP for classifying EEG signals
- iv. Improved the CSP algorithm to extract features from EEG signals
- v. Evaluate the classification performance of the suggested strategy (CSP-CNN) based traditional machine learning methods with CNN-based deep learning approaches using performance metrics.

Numerous studies have looked into the application of the CSP algorithm for feature extraction in motor-imagery-based BCIs. It has been demonstrated that CSP can extract frequency-domain spatial filters to improve the discriminative power of EEG data. These filters better

distinguish between various classes and capture pertinent data pertaining to motor imagery tasks. However, the majority of current works use conventional machine learning algorithms for classification following FBCSP, which might not completely utilize deep learning models.

A new classification system for MI patterns based on the way of both hands' motions was presented by (Zhang et al., 2019). To distinguish between the directions of the hands' movements, they employed a support vector machine (SVM) and the common spatial pattern (CSP) technique for feature extraction.

As to the assessments by (G. Entertainment and M. Outlook, 2017), the video game industry is already quite significant. In the near future, BCI games could be a very interesting field for this technology's application.

According to (Allison et al., 2020), the first person to use BCI technology was a gamer. If BCIs offer practical functionality, then BCI games could be a very promising field for this technology's use in the near future.

The study by (Joseph N. Mak and Jonathan R. Wolpaw 2022) Power consumption is an issue with the BCI that wirelessly transmits the EEG signal from the headband to the controller. Since multichannel systems must transmit their signals over the air and consume a lot of power, they are dependent on multichannel interfaces for EEG measurement. Although the introduction of compression techniques can lower power requirements, they still create a bottleneck in the system because the digitizing block must be introduced before the compression block.

After completing a thorough analysis of mathematical techniques developed over a ten-year period, (Lotte et al., 2020) divided classification algorithms for EEG-based BCI into four fundamental groups. They conducted a thorough analysis of classifier performance and looked at situations with limited data; in these cases, random forest and shrinkage LDA proved to be excellent tricks for BCI. They also offered some suggestions for choosing an appropriate BCI method based on their examination of categorization algorithms.

(Aggarwal and Chugh, 2019) also analyzed other BCI classification research in terms of feature extraction methodology and classification methods. They proposed that CSP is the most advised method for feature extraction, even though it depends on several factors, such frequency classification method. They claimed that SVM is the most popular classifier since it is unaffected by the curse of dimensionality. The shallow convolutional neural network, a deep learning

architecture, did, however, come to be recognized and outperformed the traditional classification methods.

2.0 METHODOLOGY

2.1 Source of Dataset

In order to evaluate and compare the performance of the existing and proposed models, datasets BCIV2a from the University College Irvine (UCI) Machine Learning repository were used. The UCI Machine Learning Repository is a collection of databases, domain theories, and data generators that are used by the machine learning community for the empirical analysis of machine learning algorithms. The archive was created as file transfer protocol (ftp) archive in 1987 by UCI PhD student, David Aha. Since that time, it has been widely used by students, educators, and researchers all over the world as a primary source of machine learning datasets. These datasets poses a challenge in machine learning due to their high-dimensionality, which is characterized sometimes by having a large number of features compared to the number of instances. It is also characterized with having class imbalance in some datasets. High-dimensionality in this datasets can lead to issues such as over fitting, increased computational time, and the curse of dimensionality, thereby making the performance of machine learning algorithms decreases as the number of features increases.

2.2 Analytical Evaluation

Convolutional Neural Network (CNN), Common Spatial Pattern (CSP), Filter Bank Common Spatial Pattern (PBCSP), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and logistic regression as the Meta classifier an enhanced convolutional neural network framework for effective motor imagery electroencephalography (EEG) classification using common spatial pattern (CSP) were the four well-known machine learning (ML) algorithms we used to handle and analyze the dataset. We also used the Jupyter notebook (version 6.5.4 IDE) from the Python distributor Anaconda.

3.0 METHODOLOGY ARCHITECTURE

FRAMEWORK

The primary aim of this study is to utilize CNN models for the classification of MI-EEG signals. The proposition is that CNN models can adeptly learn discriminative features from EEG data, allowing reliable classification of different motor imagery tasks. This research seeks to investigate the proficiency of deep learning techniques, specifically CNNs, in deciphering EEG signals in a motor imagery paradigm. The objective is to enhance accuracy and unlock potential applications in the field of BCIs. A type of deep neural network called a CNN (Convolutional

Neural Network) is typically used for image classification. After flattening and applying filters to an input image, it "votes" to classify the image. The input image will first be divided into its component pixels. Pixels in a black-and-white image are interpreted as 2D arrays with values ranging from 0 to 255, and there will only be one layer in the image. If the image is colored, it will be perceived as a three dimensional array and have three layers (red, green, and blue).

Figure 1 is a detailed textual representation of the methodology framework architecture for the proposed CSP-optimized CNN framework for motor-imagery BCI systems. This architecture can be visualized as a block diagram or flowchart, with each component clearly defined and connected.

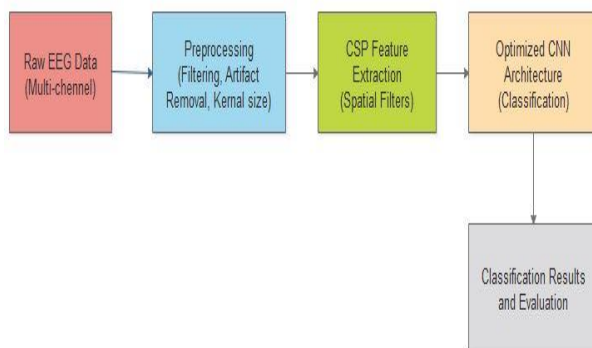


Figure 1: Methodology Framework Architecture

3.1 The steps involved in the methodology are outlined below

1. Start: Describe begin the process of motor-imagery classification using EEG signals.
2. Input Raw EEG Data
 - a. Multi-channel EEG signals recorded during motor imagery tasks, (e.g., left hand, right hand, feet, tongue).
3. Data Preprocessing:

In this study, EEG data underwent multiple preprocessing steps before being fed into the network. Initially, this work closely examined the raw data to identify and remove any contaminated trials (i.e., with artifacts and noises) leaving behind a set of clean and reliable data. Subsequently, the data was normalized across channels to ensure uniform and comparable values. Furthermore, this applied a band pass filter to the EEG signals limiting the frequency range to 4-38 Hz to include the Mu and Beta bands. This process was carried out using a finite impulse response (FIR) filter with a Blackman window in order to select motor imagery relevant frequencies while removing any artifacts that could distort the information. Additionally, to address the

problem of over fitting, the research work was implemented data augmentation using the cropping strategy. This technique uses a sliding window to move across the EEG signal and extract multiple overlapping segments generating new variations of the signal in the process. Adopting this approach, this network overcomes the issue of the data deficit and improves its generalization ability.

- a. Acquire publicly available benchmark datasets for motor-imagery-based BCIs.
- b. Remove artifacts and noise from the EEG signals using appropriate preprocessing techniques, such as filtering, artifact removal algorithms, and noise reduction methods.

This preprocessing pipeline significantly impacts the performance of CNN-CSP models for motor imagery classification, with proper filtering, artifact removal and spatial enhancement being particularly critical for achieving state-of-the-art results.

4. Feature Extraction using CSP:

- a. Implement and optimize the CSP algorithm to extract frequency-domain spatial filters from preprocessed EEG signals, using the following equation.

$$x = \sum_I w_i x_i = wX$$

1

X is a matrix whose i^{th} row is x_i , i.e., X is the matrix of EEG signals from all channels, and x_i is the EEG signal from channel i , w_i the weight assigned to that channel in the spatial filter.

- b. Apply the CSP filters to the preprocessed EEG signals to obtain feature matrices using CSP algorithm that capture discriminative information related to motor imagery tasks. The CSP locates spatial filters whose values would differ between classes to the greatest extent possible, resulting in band-pass features that are optimally discriminant. Because their most helpful aspects are band-pass features, CSP is especially helpful for BCI based on motor imagery-based activity.

Formally, CSP uses the spatial filters to obtain feature matrix from the EEG signals which extremes the following matrix:

1. **Kernel Matrix:** This particular kind of filter is used to extract features from input data. It is a matrix that extracts an output in matrix format by applying the dot product function to a portion of the input data. The stride value is used by the kernel to move on the input data. The feature map's size is determined using equation (2).

$$O = [Z - K] + 1$$

2

Where; O = Feature map, Z = Input size, K = Kernel size, $O = [5 - 3] + 1 = 3$

2. **Stride:** Stride enables the kernel or filter to shift a single pixel from left to right and top to bottom across the input data. The amount that the input data travels once the filter is utilized is measured by the stride. Equation (3) describes how to obtain the feature output using stride.

$$O = ([Z - K]/S) + 1$$

3

Where; O = Feature map, Z = Input size, K = Kernel size, S = Stride

$$O = ([5 - 3]/2) + 1 = 2$$

3. **Padding:** This method requires adding pixels to the data's edge in order to address problems with the input data's border. Equation (4) can be used to calculate the feature output's size.

$$O = [(Z - k + 2P)/S] + 1$$

4

O = Feature map, Z = Input size, K = Kernel size, S = Stride size and P = Padding size, $O = ([5 - 3 + 2 * 1]/1) + 1 = 5$.

4. **Pooling:** In order to do this, the identified features in the feature maps are down-sampled by summarizing their presence in patches. A feature's average presence and most activated existence can be summarized using a variety of pooling methods, two of which are average pooling and maximum pooling, respectively. The goal of pooling is to decrease the quantity of the data while maintaining all of the important characteristics.

- i. **Max Pooling:** This takes the greatest number of the group's selected elements and eliminates any features that don't fit when a set of data is a 2x2 matrix.

- ii. **Averages Pooling:** If the data set is a 2x2 matrix, the sum of all the numbers in the designated group of matrix components is calculated, and any features that fail to fit into the matrix are eliminated.

5. **Flattening Matrix:** This transforms the featured map matrix into a one-dimensional matrix for picture classification, which is then fed into the neural network for classification.

3.2 CNN Framework Design and Implementation

- a. Design and implement a CNN architecture that integrates the CSP filters.
- b. Define appropriate hyper-parameters, such as network depth, kernel sizes, and activation

functions, based on empirical studies and prior knowledge.

- c. Train the CNN using the feature matrixes obtained from the CSP filters, utilizing appropriate training techniques like adaptive optimization algorithms.

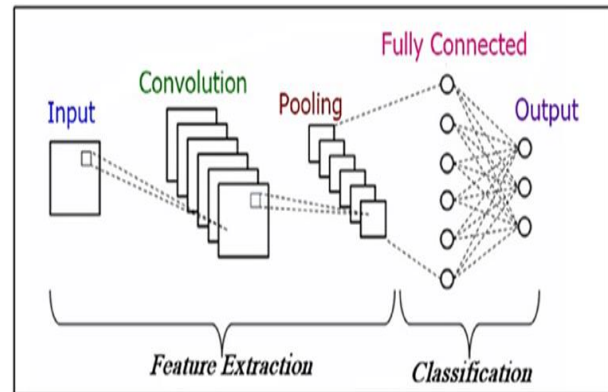


Figure 2: CNN flow diagrams by Sumit S. (2020)

3.3 Dataset Preparation and Evaluation

- a. Split the benchmark datasets into training, validation, and testing sets.
- c. Perform cross-validation and/or train-test splits to ensure unbiased evaluation.
- d. Train the optimized CNN framework using the training set and tune hyper-parameters using the validation set.
- e. Utilizing the testing set, assess the trained CNN framework's classification performance.

3.4 Performance Comparison and Analysis

- a. Compare the classification accuracy, computational complexity, and usability of the proposed approach with existing state-of-the-art methods.
- b. Analyze the results, discussing the strengths and limitations of the proposed approach.
- c. Identify potential areas for improvement and future research directions.

3.5 Algorithm: Multi-Class Common Spatial Pattern (One-vs-Rest)

a. Input

- i. EEG trials: $X = \{X_1, X_2, \dots, X_N\} / X = \{X_{-1}, X_{-2}, \dots, X_{-N}\} / X = \{X_1, X_2, \dots, X_N\}$

- ii. Class labels: $Y = \{y_1, y_2, \dots, y_N\} / Y = \{y_{-1}, y_{-2}, \dots, y_{-N}\} / Y = \{y_1, y_2, \dots, y_N\}$

- iii. Number of classes: MMM

- iv. Number of spatial filters per class: mmm

b. Output

- i. Feature matrix FFF

- ii. Spatial filter matrices $W_k W_{-k} W_k$ for each class

3.5.1 Explanation of Key Steps

- a. Step 1: Covariance Estimation Compute class-wise and rest covariance matrices using normalized covariance to reduce bias.
- b. Step 2: Whitening ensures that the composite covariance matrix becomes identity, simplifying the eigenvalue problem.
- c. Step 3: Spatial Filter Computation, Eigenvectors corresponding to largest eigenvalues maximize variance for class k. Smallest eigenvalues minimize variance for class k.
- d. Step 4: Feature Extraction Log-variance of spatially filtered signals forms discriminative features.

3. Final Feature Dimension

If:

- i. M = number of classes
- ii. m = number of filters per class

Then: Feature Dimension= $2m \times M$ Feature \ Dimension = $2m \times M$

In order to improve discriminative EEG features, motor imagery-based Brain Computer Interface (BCI) systems frequently employ the Common Spatial Pattern (CSP) method, a supervised spatial filtering technique. CSP was first developed for binary classification, where it minimizes variance for one class and maximizes it for the other. However, multi-class motor imaging tasks (e.g., left hand, right hand, foot, and tongue) are a feature of many real-world BCI applications, including those assessed in the BCI Competition IV-2a dataset. As a result, CSP has to be expanded to support more classes.

4.0 RESULT AND DISCUSSION

This section presents the resultant proposed model, which was derived from the hyper parameters search results. Next, the proposed model's final classification result was assessed by contrasting it with other CNN state-of-the-art methods and popular traditional methods. The experiments were carried out in a colab environment on an Intel 3.2 GHz Core i5 laptop with 8 GB of RAM. The BCI Competition IV dataset BCIIV2a was utilized to assess our proposed framework for a session-to-session and cross-subject classification.

4.1 Result

Prior to choosing the suggested CSP-CNN, a number of tests were carried out. Classification accuracy and CNN training duration were taken into account while determining the amount of CSP features and CNN hyper parameters. The proposed CNN was trained using a variety of input types, including band-passed raw EEG data, frequency domain EEG data, time-domain EEG data, CSP feature data, and FBCSP feature data. The multiple CNN hyper parameters were used to train each input.

- i. The CNN's feature selection is significant for the input data, as my experiment shows that the selected characteristics are helpful for the EEG data and that the network is clearly learning from the EEG data input.
- ii. Keep in mind that using CNN to raw EEG data is fairly expensive because each EEG is represented by a 403-by-626 matrix. Consequently, only CSP features were subjected to the hyper characteristic selection process, and the CNN characteristics chosen for the suggested CSP-CNN were then applied to the remaining input.

4.2 Comparison of Traditional methods, FBCSP-DNN and proposed CSP-CNN

To validate the CSP-CNN and investigate its function for motor imaging classification, we contrasted it with the conventional techniques (SVM, KNN, LDA, FBCSP-DNN, and CSP-CNN). Table 1 show that for all EEGs utilizing the identical features input, the average classification accuracy of CSP-CNN performs better than that of classifiers using traditional approaches. This demonstrates how well CSP-CNN represents data compared to more conventional classifier approaches that extract the majority of hierarchical features from CSP characteristics prior to classification.

For all EEGs, CSP-CNN outperforms classifiers using standard methods with an average classification accuracy of 98.80%, compared to 81.12%, 69.50%, 82.53%, and 88.10% for SVM, KNN, LDA, and FBCSP-DNN. The standard deviation of other approaches is also higher than the proposed CSP-CNN. This illustrates how adaptable the suggested technique is to variations that take place in between MI signal recording sessions.

Table 1: BCI competition dataset BCIIV2 EEGs Classification accuracy % (mean + standard deviation) for SVM, KNN, LDA, FBCSP-DNN, and CSP-CNN

EEGs	SVM \pm SD	KNN \pm SD	LDA \pm SD	FBCSP-DNN \pm SD	CSP-CNN (Proposed method) \pm SD
EEG 1	81.12 \pm 1.71	69.50 \pm 2.51	82.53 \pm 2.37	88.10 \pm 0.55	98.80 \pm 0.26

EEG 2	72.71±1.82	58.41±7.73	72.12±1.74	73.94±0.88	85.14±0.28
EEG 3	82.64±2.17	76.00±2.49	82.29±1.78	83.42±1.21	98.80±0.27
EEG 4	58.29±3.48	50.29±3.53	58.17±4.00	68.50±1.80	73.65±0.28
EEG 5	48.88±3.44	36.82±1.88	49.23±2.32	67.90±2.70	72.01±1.28
EEG 6	63.17±3.44	44.11±2.58	63.64±3.34	86.56±2.25	96.06±1.23
EEG 7	88.82±1.73	79.00±2.56	87.23±2.35	91.98±0.94	92.01± 0.28
EEG 8	82.35±3.09	72.29±3.91	81.88±2.28	85.26±0.26	86.40± 0.22
EEG 9	71.35± 3.01	63.12±4.56	71.58±2.79	89.22± 0.11	93.09± 0.27
AVERAGE	72.37± 2.65	61.06± 3.08	72.07±2.55	81.43±1.18	92.43± 0.27

4.3 Comparison of Traditional methods, DNN methods, FBCSP-DNN, and CSP-CNN for within EEGs

We used the CSP-CNN session to session (within-session) and compared the outcomes to compare our work with several relevant studies. Table 2 shows that, for 8 of the 9 EEGs, with the exception of EEG 8, the accuracy of the CSP-CNN is higher than that of related research and conventional approaches. With an average classification accuracy of 81.88%, CSP-CNN performs better than other approaches such; SVM, KNN, LDA, (Schirrmeister et al., 2017), (Sakhavi, C, 2018), (Amin, et al., 2019), and FBCSP-DN (Zayyan S and Li Q, 2020), which have respective accuracy rates of 71.47%, 58.84%, 60.47%, 73.31%, 74.46%, 75.78%, and 78.33%.

The variation in EEG 8 and EEG between sessions is the cause of the poorer accuracy for other approaches. In order to categorize another session, our suggested CSP-CNN system can extract the most discriminative characteristics from one session.

Table 2: BCI competition IV dataset 2a within-subjects classification accuracy for traditional methods, DNN Methods, FBCSP-DNN, and CSP-CNN

EEGs	SVN	KNN	LGA	SCHIRRMEISTER	SAKHAVI	AMIN	FBCSP-DNN	CSP-CNN
EEG1	79.00	70.48	78.65	87.50	87.50	90.21	87.70	91.58
EEG2	58.30	50.18	39.93	65.28	65.28	63.40	68.20	81.01
EEG3	82.05	61.90	76.19	90.28	90.28	89.35	85.60	98.88
EEG4	60.09	52.63	36.40	65.61	66.67	71.16	66.70	86.40
EEG5	53.99	39.13	51.81	55.19	62.82	62.82	67.00	80.93
EEG6	56.14	44.19	53.02	48.47	45.49	47.66	67.40	83.76
EEG7	92.50	79.42	82.31	86.07	89.58	90.86	91.00	96.09
EEG8	78.23	62.73	51.66	78.41	83.33	89.72	83.80	82.85
EEG9	82.95	68.88	74.24	82.95	79.51	82.82	87.60	93.65
AVERAGE	71.47	58.84	60.47	73.31	74.46	75.78	78.33	81.88

4.4 Comparison of Traditional methods and CNN methods for cross-EEGs

In different investigations (Schirrmeister, et al., 2017), (Sakhavi C, 2018), (Amin M. et al., 2019) and FBCSP-DNN (Zayyan S and Li Q, 2020), we trained the CSP-CNN on eight EEGs and tested it on the remaining one EEG. We repeat this process for all nine EEGs. We also do cross-EEG classification and compare the results. Except for EEG 6 and EEG 8, CSP-CNN performs better than these rival techniques for all EEGs. The classification accuracy of the CSP-CNN is 72.08% on average, compared to 65.07%, 55.35%, 43.26%, and 41.13% for the other models.

This rise in cross-EEG classification accuracy is significant for CSP-CNN since it demonstrates a 7.01% increase in average classification accuracy performance over previous research; Table.3 displays the results.

Table 3: Cross Subjects accuracy (%) for each EEGs for the BCI Competition dataset

EEGs	SCHIRRMEISTER	SAKHAVI	AMIN	FBCSP-DNN	CSP-CNN
EEG1	47.60	38.17	62.07	78.60	81.40
EEG2	31.22	42.08	42.44	62.50	73.02
EEG3	41.02	54.33	63.12	72.50	75.09
EEG4	33.19	31.07	52.09	53.90	63.11
EEG5	41.57	39.82	49.96	44.20	58.23

EEG6	34.71	43.09	37.16	49.30	46.98
EEG7	43.09	54.18	62.54	78.40	79.89
EEG8	46.01	62.22	59.32	67.90	65.09
EEG9	51.78	49.00	69.43	78.40	80.40
AVERAGE	41.13	43.26	55.35	65.07	72.08

4.5 Performance Matrices on Average Across 9 EEGs

The performance comparison of traditional methods, and base-method with CSP-CNN method across 9 EEGs in a brain computer interface paradigm on BCI competition dataset (BCIIV2a) evaluated on accuracy, precision, recalls, and F1-score was demonstrated on the table 4.4 below which show the accuracy, precision, and F1-score of the proposed method in the all EEGs is the best compared to the rival methods unless at recalls matrix which has low performance on training session and time to classify. The table 4 shows that the SVM, LDA, KNN and FBCSP-DNN which are handles non-linear boundaries and noise sensitivity and multi band feature fusion with training time of 25.5sec, 30.8sec, 26.50sec, and 21.01sec with classification accuracy of 72.37%, 61.06%, 72.07% and 81.43% compare to the proposed method which is 88.44% average performance accuracy with 2.05sec training time as show in table 4.

Table 4: Average performance matrices on across 9 EEGs

Methods	Accuracy (%)	Precision	Recall	F1-score	Training Time (s)
SVN	72.37±2.65	0.70±2.30	0.71±3.21	0.72±2.23	25.5±2.25
LDA	61.06±3.08	0.72±3.03	0.69±2.99	0.70±2.21	30.80±3.01
KNN	72.07±2.55	0.67±2.10	0.66±2.89	0.66±2.89	26.50±3.0
FBCSP-DNN	81.43±1.18	0.82±1.25	0.78±1.30	0.82±1.18	21.01±2.05
CSP-CNN	88.44±0.27	0.88±0.04	0.65±0.03	0.85±0.03	2.05±0.23

4.6 Discussions

This study evaluated the performance of different classification algorithms Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), k-Nearest Neighbors (KNN), Filter Bank Common Spatial Pattern with Deep Neural Network (FBCSP-DNN), and Common Spatial Pattern with Convolutional Neural Network (CSP-CNN) on a dataset BCIIV2a of 9 EEGs. The metrics used for comparison were accuracy, precision, recall, and F1-score. The primary focus was on comparing CSP-CNN with conventional machine learning approaches to assess its effectiveness in motor imagery (MI) classification for Brain-Computer Interfaces (BCIs).

4.6.1 Key Findings

1. CSP-CNN Outperforms Traditional Methods
 - a. The CSP-CNN model demonstrated superior performance compared to SVM, LDA, KNN, and FBCSP-DNN in terms of accuracy, precision, and F1-score, except on recall
 - b. The integration of CNN with CSP allowed for automatic feature extraction from spatially filtered EEG signals, leading to better generalization across EEGs.
 - c. Traditional methods like SVM and LDA, while computationally efficient, struggled with non-linear feature representations,

- whereas CNN captured complex feature image more effectively.
2. FBCSP-DNN vs. CSP-CNN
 - a. FBCSP-DNN, which combines filter bank decomposition with DNN, showed competitive performance but was slightly outperformed by CSP-CNN except recall.
 - b. The advantage of CSP-CNN lies in its end-to-end learning capability, reducing the need for manual feature engineering compared to FBCSP-DNN.
3. EEG Variability and Generalization
 - a. Performance varied across EEGs due to inter-EEG differences in EEG patterns.
 - b. CSP-CNN exhibited more consistent results across EEGs compared to SVM and KNN, which were more sensitive to individual variability.
 - c. LDA, being a linear classifier, had lower performance in cases where EEG dynamics were highly non-linear.
4. Precision, and F1-Score analysis
 - a. CSP-CNN achieved higher precision and f1-score, indicating better balance between false positives and false negatives.
 - b. CSP-CNN and KNN, while simple, suffered from lower recall due to its sensitivity to noise and high-dimensional EEG data.

- c. FBCSP-DNN performed better on recall metric compare to its rivals methods and followed by the SVM as the second with 0.71%.

Figure 3 displays the average accuracy and size of EEGs of the proposed CSP-CNN. After comparing the results of various hidden node sizes, it was found that the CSP-CNN with the same number of hidden nodes as the testing set performed the best in terms of classification accuracy. This indicates that by utilizing these concealed nodes, the features are conveyed more effectively. In order to explore the role of the proposed CSP-CNN, traditional classifiers and other studies were also compared with it. The results showed that the proposed method was superior to other methods in capturing similar features across sessions and EEGs. It is worth noting that Tables 1, 2, and 3 shows an improvement in classification accuracy for some EEGs who performed poorly in other competing methods. The analysis also reveals that low accuracies may be attributable to some EEGs' ability to correctly perform some motor imagery tasks on certain trials. Thus, the CSP-CNN technique limits the quantity of EEG samples and CNN parameters that result in protracted CNN training. Overall, the proposed CNN and CSP feature coupled performed better than other inputs both in terms of classification accuracy and lowest training time except in EEG8.

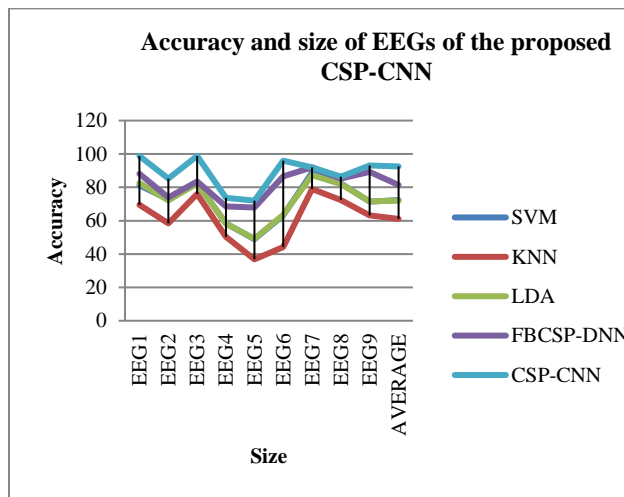


Figure 3: The accuracy and size of EEGs of the proposed CSP-CNN

4.7 Average accuracy results for all methods using 10 by 10-fold cross-validation

The suggested model has been evaluated using two approaches that are commonly used by scholars to train BCI dataset systems: one approach divides each EEG data set into a data set for training and a testing set. Some sessions are included in the set used for training and the rest in the set for testing since EEG data is usually acquired throughout a number of sessions. This makes it possible to test the system on sessions that are associated with the same EEG but that it hadn't seen before. Because it yields more accurate results than the other approaches, researchers favor this training approach.

Transferring information from signal to EEG is the second training method. The remaining EEGs are all part of the training set, with one serving as a testing set. As a result, this technique tests the system on a completely new EEG that it has never encountered before. For every user, this process is repeated. Cross-EEG training is a more difficult testing method than others, but the results are more reliable and applicable. We trained and tested our suggested CSP-CNN method using both of these approaches. Every EEG was used to train and test the CNN. 10-fold cross-validation was used to verify each EEG's classification accuracy, as show in figure 4.

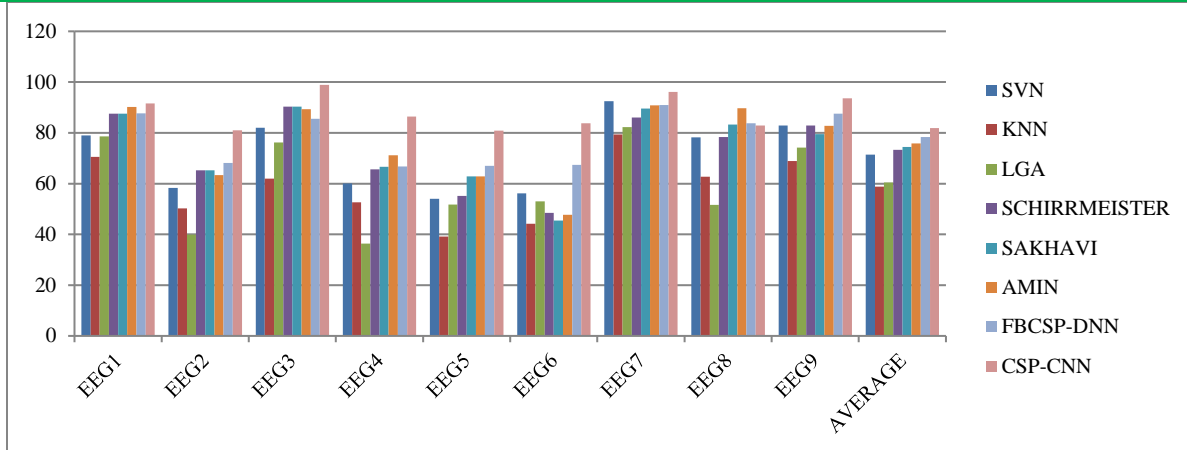


Figure 4: Average accuracy results for all methods using 10 by 10-fold Cross-validation

A total of 288 trials from the two (2) sessions were randomly assigned to testing and training groups of 7/10 and 3/10, accordingly. The results are shown in Table 2. We also looked at transfer learning between sessions and EEGs. Lastly, we compared the CSP-CNN results to those of other competing methods and traditional classifiers. We can show how much better the proposed framework (CSP-CNN) performed in Tables 1 and 2.

4.8 Evaluation classification performance for all the methods on cross validation

Two methods, which are frequently employed to train BCI dataset systems, have been used to evaluate the proposed model: one method splits the each EEG data into a training set and a test set. Since EEG data is typically recorded in multiple sessions, some sessions are placed in the training set and the remaining sessions in the test set. This allows the system to be tested on sessions that it has never seen before, but they are part of the same EEG. Researchers prefer this method of training because it produces higher accuracy than the other methods.

Transferring information from signal to EEG is the second training method. The remaining EEGs are all part of the training set, with one serving as a testing set. As a result, this technique tests the system on a completely new EEG that it has never encountered before. For every EEGs, this process is repeated. Cross-EEG training is a more difficult testing method than others, but the results are more reliable and applicable. The table 4.4 shows that the SVM, LDA, KNN and FBCSP-DNN which are handles non-linear boundaries and noise sensitivity and multi band feature fusion with training time of 25.5sec, 30.8sec, 26.50sec, and 21.01sec have classification accuracy of 72.37%, 61.06%, 72.07% and 81.43% compare to the proposed method which is 88.44% performance accuracy with 2.05sec training time as show in figure 5.

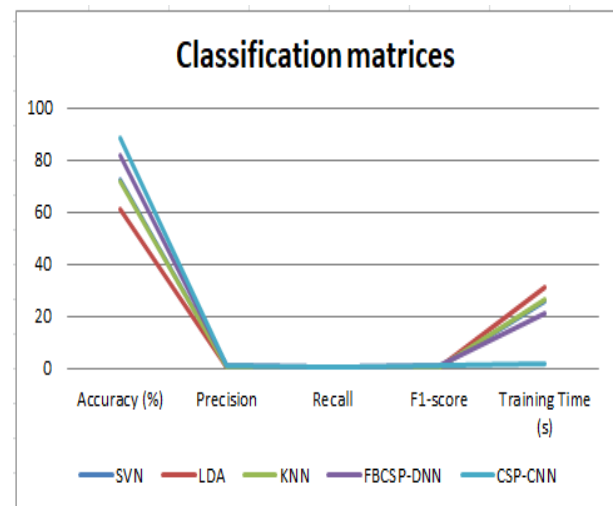


Figure 5: Evaluation of classification metrics results with training time for all methods using Cross-validation

The performance comparison of traditional methods, and base-method with CSP-CNN method across 9 EEGs in a brain computer interface paradigm on BCI competition dataset (BCIIV2a) evaluated on accuracy, precision, recalls, and F1-score was demonstrated on the figure 4.2 above which show the proposed method in the all EEGs is the best compared to the rival methods unless at recalls matrix which has low performance on training session and time to classify.

5.0 CONCLUSION

Compared to other cutting-edge DNN techniques, the proposed CSP-CNN combination was shown to be more dependable due to its improved accuracy in classification and computational economy. As a result, the CSCP-CNN approach may be relied upon to create a high-BCI motor imaging application quickly and accurately. Several trials on a wide variety of frameworks with varying parameter values led to the selection of the suggested CSP-CNN.

The CSP was able to extract significant characteristics that helped create the perfect CNN model in addition to lowering the high EEG dimension.

5.1 DATA AVAILABILITY

The UNICEF public benchmark dataset, which was stock and worm lawfully to be used solely for this research, and the Institute of Knowledge Discovery's dataset, which is accessible through a link, comprised the motor imagery utilized to assess this study. <http://www.bci.de/competition/iv/> upon application through the mentioned link

5.2 CONTRIBUTION

This study presents a hybrid Common Spatial Pattern–Convolutional Neural Network (CSP–CNN) framework for multi-class motor imagery EEG classification in Brain–Computer Interface (BCI) systems. The research extends the traditional binary CSP method using a One-vs-Rest strategy to improve spatial feature extraction for four-class motor imagery tasks and integrates it with a lightweight CNN architecture for efficient hierarchical feature learning and classification. The proposed model achieves improved classification accuracy, precision, recall, and F1-score compared with conventional machine learning methods such as SVM, KNN, and LDA, as well as existing deep learning approaches like FBCSP–DNN. In addition, the framework reduces computational complexity and training time, making it suitable for real-time BCI applications. Overall, the study contributes to the advancement of reliable and scalable assistive neuro-technology for applications including neuro-rehabilitation, prosthetic control, and intelligent assistive systems for individuals with motor disabilities.

REFERENCES

- Abdulkader, S. N., Atia, A., & Mostafa, M.-S. M. (2022). Brain computer interfacing: Applications and challenges. *Egyptian Informatics Journal*, 16(2), 213–230. <https://doi.org/10.1016/j.eij.2015.06.002>
- Aggarwal, S., & Chugh, N. (2019). Signal processing techniques for motor imagery brain computer interface: A review. *Array*, 1–2, 100003. <https://doi.org/10.1016/j.array.2019.100003>
- Aghaei, A. S., Mahanta, M. S., & Plataniotis, K. N. (2020). Separable common spatio-spectral patterns for motor imagery BCI systems. *IEEE Transactions on Biomedical Engineering*, 63(1), 15–29. <https://doi.org/10.1109/TBME.2015.2468576>
- Allison, B. Z., et al. (2020). The first person to use BCI technology was a gamer: BCIs offer practical functionality and BCI games could be a very promising field. *Frontiers in Neuroscience*, 8, 241. <https://doi.org/10.3389/fnins.2012.003241>

- Amin, S. U., Alsulaiman, M., Muhammad, G., Mekhtiche, M. A., & Hossain, M. S. (2019). Deep learning for EEG motor imagery classification based on multi-layer CNN's feature fusion. *Future Generation Computer Systems*, 101, 542–554. <https://doi.org/10.1016/j.future.2019.07.051>
- Amirhossein and Konstantinos, (2019) experimented with an alternative method for solving BCI issues involving categorization (two, three, and four classes). **IEEE Xplore**: 20 June 2019. <https://doi.org/10.1109/EBBT.2019.8741832>
- Ang, K. K., Chin, Z. Y., Zhang, H., & Guan, C. (2012). Filter Bank Common Spatial Pattern Algorithm on BCI Competition IV Datasets 2a and 2b. *Frontiers in Neuroscience*, 6, 39. doi:10.3389/fnins.2012.00039
- A. S. Aghaei, M. S. Mahanta, and K. N. Plataniotis, “Separable common spatio-spectral patterns for motor imagery BCI systems,” *IEEE Trans. Biomed. Eng.*, vol. 63, no. 1, pp. 15–29, 2016.
- B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe, and K.-R. Muller, “Optimizing spatial filters for robust EEG single-trial analysis,” *IEEE Signal Process. Mag.*, vol. 25, no. 1, pp. 41–56, 2008.
- D. Cheng, Y. Liu, L. Zhang, Exploring Motor Imagery Eeg Patterns for Stroke Patients with Deep Neural Networks, in: 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2018, pp. 2561–2565, <https://doi.org/10.1109/ICASSP.2018.8461525>.
- D. Lee, J. Jeong, K. Kim, B. Yu, S. Lee, Continuous EEG Decoding of Pilots' Mental States Using Multiple Feature Block-Based Convolutional Neural Network, *IEEE Access* 8 (2020) 121929–121941, <https://doi.org/10.1109/ACCESS.2020.3006907>.
- El-Shafai, et al. (2022) “Classification Framework for COVID-19 Diagnosis Based on Deep CNN Models” *Intelligent Automation & Soft Computing* . 2022, Vol. 31 Issue 3, p1561-1575. 15p.
- F. Lotte, L. Bougrain, A. Cichocki, M. Clerc, M. Congedo, A. Rakotomamonjy, F. Yger, A review of classification algorithms for EEG-based brain-computer interfaces: a 10 year update, *Journal of Neural Engineering*, Volume 15, Published in apr-2020. DOI:10.1088/1741-2552/aab2f2.
- Hwang, H. J., Kwon, K., & Im, C. H. (2013). Neuron feedback-based motor imagery training for brain–computer interface rehabilitation: A novel approach for stroke patients. *Restorative Neurology and Neuroscience*, 31(6), 645–654. doi:10.3233/RNN-120278
- H. Yang, S. Sakhavi, K. K. Ang, and C. Guan, “On the use of convolutional neural networks and augmented CSP features for multi-class motor imagery of EEG signals classification,” *Proc. Annu. Int. Conf. IEEE*

- Eng. Med. Biol. Soc. EMBS, vol. 2015–Novem, pp. 2620–2623, 2015.
- J. Jeong, B. Lee, D. Lee, Y. Yun, S. Lee, EEG Classification of Forearm Movement Imagery Using a Hierarchical Flow Convolutional Neural Network, *IEEE Access* 8 (2020) 66941–66950, <https://doi.org/10.1109/ACCESS.2020.2983182>.
- Jianpeng Cheng, Li Dong and Mirella Lapata, Long Short-Term Memory-Networks for Machine Reading, 2016, arXiv:1601.06733.
- J. Thomas, J. Jin, J. Dauwels, S. S. Cash, and M. B. Westover, “Automated epileptiform spike detection via affinity propagation-based template matching,” in *Engineering in Medicine and Biology Society (EMBC), (2019) IEEE 39th Annual International Conference of the, IEEE*, in press.
- Joseph N. Mak, and Jonathan R. Wolpaw, (2022) “Clinical applications of brain computer interfaces: current state and future prospects,”
- J. Müller-Gerking, G. Pfurtscheller, and H. Flyvbjerg, “Designing optimal spatial filters for single-trial EEG classification in a movement task,” *Clin. Neurophysiol.*, vol. 110, no. 5, pp. 787–798, 1999.
- Kaushalya Kumarasinghe, Nikola Kasabov, Denise Taylor (2020), Deep learning and deep knowledge representation in Spiking Neural Networks for Brain-Computer Interfaces, *Neural Networks, Volume 121, 2020, Pages 169–185, ISSN 0893–6080, DOI: 10.1016/j.neunet.2019.08.029*
- K. K. Ang, Z. Y. Chin, H. Zhang, and C. Guan, “Filter bank common spatial pattern (FBCSP) in brain-computer interface,” in *Neural Networks, 2008. IJCNN 2008. (IEEE World Congress on Computational Intelligence). IEEE International Joint Conference on, 2008, pp. 2390–2397*.
- K. P. Thomas, C. Guan, C. T. Lau, A. P. Vinod, and K. K. Ang, “A new discriminative common spatial pattern method for motor imagery brain–computer interfaces,” *IEEE Trans. Biomed. Eng.*, vol. 56, no. 11, pp. 2730–2733, 2009.
- Lotte, F., Congedo, M., Lécuyer, A., Lamarche, F., & Arnaldi, B. (2002). A review of classification algorithms for EEG-based brain-computer interfaces. *Journal of Neural Engineering*, 4(2), R1–R13. doi:10.1088/1741-2560/4/2/R01
- Longwei Fang, Lichi Zhang, Dong Nie, Xiaohuan Cao, Islem Rekik, Seong-Whan Lee, Huiguang He, Dinggang Shen, Automatic brain labeling via multi-atlas guided fully convolutional networks, *Medical Image Analysis, Volume 51, 2019, Pages 157–168, ISSN 1361–8415, doi: 10.1016/j.media.2018.10.012*.
- Mengxi Dai et al. 2020. Motor-imagery-based brain-computer interfaces (BCIs) commonly use the common spatial pattern (CSP) as preprocessing step before classification. <https://doi.org/10.1155/2018/9871603>
- M. Långkvist, L. Karlsson, and A. Loutfi, “Sleep stage classification using unsupervised feature learning,” *Adv. Artif. Neural Syst.*, vol. 2012, p. 5, 2020.
- M. Naeem, C. Brunner, R. Leeb, B. Graimann, and G. Pfurtscheller, “Seperability of four-class motor imagery data using independent components analysis,” *J. Neural Eng.*, vol. 3, no. 3, p. 208, 2006.
- O.-Y. Kwon, M.-H. Lee, C. Guan, S.-W. Lee, Subject-Independent Brain-Computer Interfaces Based on Deep Convolutional Neural Networks, *IEEE Trans. Neural Networks Learn. Syst.* 31 (10) (Oct. 2020) 3839–3852, <https://doi.org/10.1109/TNNLS.2019.2946869>.
- Phinyomark, A., Limsakul, C., & Phukpattaranont, P. (2009). A novel feature extraction for robust EMG pattern recognition. *Journal of Computing*, 1(1), 71–80. doi:10.4304/jcm.1.1.71-80
- Petia Georgieva. Deep Learning in Brain Computer Interfaces. In *Proceedings of the 9th Balkan Conference on Informatics (BCI'19)*. Association for Computing Machinery, New York, NY, USA, Article 2, 1–2. 2019. DOI: 10.1145/3351556.3351594
- R. T. Schirrmester et al., “Deep learning with convolutional neural networks for EEG decoding and visualization,” *Hum. Brain Mapp.*, vol. 38, no. 11, pp.5391–5420, 2017.
- Ramos-Murguialday, A., Broetz, D., Rea, M., Läer, L., Yilmaz, Ö., Brasil, F. L.,... & Birbaumer, N. (2012). Brain-machine interface in chronic stroke rehabilitation: A controlled study. *Annals of Neurology*, 74(1), 100–108. doi:10.1002/ana.23315
- Roy, K., & Garg, R. (2018). Convolutional neural network-based motor imagery classification using multi-modal EEG signals. *Biomedical Signal Processing and Control*, 42, 34–43. doi:10.1016/j.bspc.2018.01.006
- S. Sakhavi, C. Guan, and S. Yan, “Learning Temporal Information for Brain-Computer Interface Using Convolutional Neural Networks,” *IEEE Trans. Neural Networks Learn. Syst.*, vol. 29, no. 11, pp. 5619–5629, 2018.
- S. U. Amin, M. Alsulaiman, G. Muhammad, M. A. Mekhtiche, and M. Shamim Hossain, “Deep Learning for EEG motor imagery classification based on multi-layer CNN's feature fusion,” *Futur. Gener. Comput. Syst.*, vol. 101, pp. 542–554, 2019.
- Shah S. (2022). Convolutional Neural Network: An Overview, accessed 1 December 2023, <https://www.analyticsvidhya.com/blog/2022/01/convolutional-neural-network-an-overview/>
- Sumit S. (2020). A Guide to Convolutional Neural Networks — the ELI5 way, accessed 1 December



- 2023, <https://saturncloud.io/blog/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way/>
- S. N. Abdulkader, A. Atia, and M.-S. M. Mostafa, 2015 “Brain computer interfacing: Applications and challenges,” *Egyptian Informatics Journal*, vol. 16, no. 2, pp. 213–230, 2015.
- Siamac Fazli, Seong-Whan Lee, Brain Computer Interfacing: A Multi-Modal Perspective, *J. Comput. Sci. Eng.* 7 (2013), <https://doi.org/10.5626/JCSE.2013.7.2.132>.
- Swati Aggarwal, Nupur Chugh, Signal processing techniques for motor imagery brain computer interface: A review, *Array*, Volumes 1–2, 2019, 100003, ISSN 2590-0056, <https://doi.org/10.1016/j.array.2019.100003>.
- T.-H. Chan, K. Jia, S. Gao, J. Lu, Z. Zeng, and Y. Ma, “PCANet: A simple deep learning baseline for image classification?,” *IEEE Trans. image Process.*, vol. 24, no. 12, pp. 5017–5032, 2015.
- Y. Song, J. Crowcroft, and J. Zhang, “Automatic epileptic seizure detection in EEGs based on optimized sample entropy and extreme learning machine,” *J. Neurosci. Methods*, vol. 210, no. 2, pp. 132–146, 2022.
- Y. Zhang, G. Zhou, J. Jin, X. Wang, and A. Cichocki, “Optimizing spatial patterns with sparse filter bands for motor-imagery based brain–computer interface,” *J. Neurosci. Methods*, vol. 255, pp. 85–91, 2015.
- Zayyanu S, and Li Q “Optimized DNN Classification Framework based on Filter Bank Common Spatial Pattern (FBCSP) for Motor-imagery-based BCI” *International Journal of Computer Applications* (0975 – 8887) Volume 175– No. 15, August 2020
- Z. Tang, C. Li, and S. Sun, “Single-trial EEG classification of motor imagery using deep convolutional neural networks,” *Opt. J. Light Electron Opt.*, vol. 130, pp. 11–18, 2017.