

ARTIFICIAL INTELLIGENCE IN MOTOR IMAGERY-BASED BCI SYSTEMS: A NARRATIVE REVIEW

S.F. Nasim^{1*}, S. Fatimah¹ and A. Amin²

¹Department of Computer Science and IT, NED University of Engineering & Technology, 75270, Karachi, Sindh, Pakistan.

²Department of Computer Science and Engineering, NED University of Engineering & Technology, 75270, Karachi, Sindh, Pakistan.

*Corresponding Author's Email: sfaizaadnan@gmail.com

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ABSTRACT: Artificial intelligence concepts using machine learning models are implemented in medicines to examine medical data and gain insights to improve decision-making. This paper provides a narrative review of "Motor Imagery based brain-computer interface systems". The essential techniques of machine learning and deep learning are reviewed and compared based on computation and test data accuracy. Various preprocessing and feature extraction techniques are highlighted in this paper, which include FFT-LDA, Wavelet Packet Decomposition (WPD), CSP Algorithm, Fisher ratio algorithm, Discrete Wavelet Transform, and Filter Bank Common Spatial Pattern (FBCSP). This method collects outcomes with multiple perspectives of the MI-BCI and optimizes it. Necessary details of Algorithms applied are also compared to give an insight into MI techniques.

KEYWORDS: EEG signal, Motor imagery (MI), Fourier transform (FFT), Classification Models.

1.0 INTRODUCTION

The Brain-computer interface is a technique that decodes brain activity based on EEG signals. It is a system that creates a direct link between the human brain and the computer, allowing the tasks to be performed without using muscles and peripheral nerves. BCI system creates a device that makes individuals control the automated systems without

using muscles but rather completely by thoughts. An electroencephalogram or Brain computer-based system measures specific features of an individual's brain signal, which correlates with their intention to affect control. [12] The system then translates such features into control signals to control external devices. Such technology is especially used in the medical field for neuro-muscular disorder patients, such as patients with "Amyotrophic Lateral Sclerosis (ALS), brainstem stroke, brain or spinal cord injury, cerebral palsy, muscular dystrophies, and multiple sclerosis". [15]

One of the most used methods to record the brain's electrical activity is EEG. It requires electrodes to be placed on the individual's scalp to capture brain waves quickly and with high temporal resolution. However, most studies show that it also has a high noise level and low spatial resolution, making extracting useful information from EEG signals challenging for BCI systems. [15]

The condition of cerebral mental processing in which an individual models a physical activity or stimulates a motor action is known as motor imagery (MI). MI is the mental repetition of a motor act, such as "leg motions, tongue movements, hand movements, and finger movements", without any clear motor activity. BCI has made extensive use of MI. According to a research, it has been observed that the impact of MI training on learning and holding a foot sequence task has been explored already with thirty right-footed subjects between the ages of 22 and 37 years (mean: 27.4 ± 4.1 years) and randomly assigned to one of three groups, as it practised a serial response time task with a sequence of three dorsal flexions and three plantar flexions with the left foot. MI training works to develop motor performance, and that mental implementation may induce nonspecific effects as well.

For recording motor imaginary brain activity, various acquisition strategies are available. Because of its high temporal resolution, non-invasiveness, simplicity of installation, and low start-up costs, EEG is the most investigated possibility for non-invasive interface BCI designs. The scientists predicted that a good model of this occurrence might be employed as a valid character in categorization by visualizing a mental exercise. MI categorization is a tough and delicate topic since EEG recordings have a poor signal-to-noise ratio (SNR) and contain undesirable information such as artefacts. Signals that are not considered in ML algorithms in the main signal can be termed noise, artefacts, or interference. To remove noise in ML preprocessing steps will be applied in order to get clean data set, so there will o early

stopping in ML. To solve these issues, MI classification has also attracted several researchers. In this paper, we will analyze different feature extraction methods from EEG signals and propose a collection of methods that provide improved results for EEG-based motor imagery classification.

2.0 MATERIALS AND METHODS

The BCI system relies on pattern recognition. As a result, multiple research papers have looked at different classification and feature extraction methodologies and methods for MI task recognition. [4] The overall block diagram for the process is shown in Fig 1 and is concluded by reviewing different research papers.

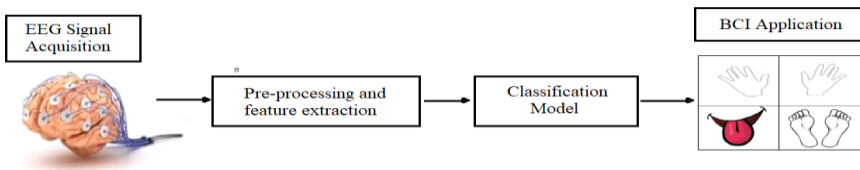


Fig 1: Feature Extraction

All the studies incorporated EEG signals with different data acquisition methods in their research. Table 1 includes the difference between the collected data sets of the studies:

3.0 RESEARCH METHODS

Preprocessing of acquired signals is necessary to reduce any noise or artefacts captured during the acquisition process. [4] These undesirable signals include the interference created when the device is mounted on the individual, EMG signals resulting from muscular contractions, and ocular artefact resulting from eye movement or blinking. This undesired noise in the EEG dataset will cause misinterpretation of the findings and incorrect conclusions; thus, they shall be filtered. The most used preprocessing method is using bandpass filters.

The identification of patterns is an essential component of the BCI system. This process is necessary because the EEG data set is typically

very large; that is, it may contain 250-time samples per second of EEG data leading to indiscriminate differences between distinct MI orders in the EEG signal, feature extraction is required.

This process aims to filter the raw EEG data signals from the unwanted background noise. [4] The EEG signals are divided into different frequency bands such as “alpha, delta, beta, gamma, and theta” bands. The frequency range of motor imagery lies within the alpha or beta band range. Hence, the signal processing of EEG signals should be processed in terms of frequency. Fourier transform (FFT) is applied to convert raw time-domain EEG signals into the frequency domain. Table 2 shows the chart of several preprocessing and feature extraction techniques explored by various researchers for MI task recognition.

Table 1: EEG signals data

Year Published	EEG Acquisition	No of the Participants in MI	MI Tasks:	No of Trials per Movement
March 2019	Dataset from “BCI Competition IV provided by B.Blankertz , C. Vidaurre, and K.-R. Müller from Berlin” was used	4 (healthy)	Hand movements, Foot movement	100
December 2020	BCI competition IV-2a	9 (Healthy)	Eyes open, eyes closed, Eye movement, Foot movement	72
December 2020	Multichannel EEG amplifiers with 64 channels were used to record EEG	5 (healthy)	Six different combinations of hands and feet movements.	60
June 2021	The Emotiv headset was used to collect the EEG dataset.	42	Hands movements, Feet Movements, Tongue movements, Eye movement	48
July 2021	Sixteen electrodes headset was used to record EEG signals per 10-20 intl. system.	57	Eye movements, Hand Movements	120

Isa et al. (2018) suggested applying “Linear Discriminant Analysis (LDA)” to the features obtained from FFT in order to develop better computational efficiency of the AI model. LDA reduces the number of

dimensions in a dataset resulting in the optimization of class separability by finding the feature subspaces. This method also reduces the chances of overfitting the data set.

However, Zheng et al. (2020) suggested an algorithm for feature extraction using transfer learning. This algorithm solves the long calibration time problem and lack of MI commands and increases the accuracy of the model. Because Spatial filters are used in feature extraction, making the algorithm more physiologically plausible in poor performers. Transferring source data from the old MI command makes this algorithm capable of performing efficiently for fewer training samples of the new MI command. However, this method is only suitable for discriminating between two classes [12].

Table 2: Preprocessing/feature extraction techniques

Year Published	Preprocessing techniques	Feature Extraction Methods
March 2019	Not Applied	FFT-LDA feature extraction
December 2020	EOG interference noise was removed. To increase SNR, EEG signals were filtered through the "Butter-worth" bandpass filter	"Wavelet Packet Decomposition (WPD)" method and "spatial characteristics using the Common Spatial Pattern (CSP)" method
December 2020	Noise caused by muscle movement and bias was removed by the Reference method. Dataset was filtered through a bandpass filter	CSP Algorithm and Fisher ratio algorithm
June 2021	Each channel was resampled to 128 Hz, and the dataset was filtered through a low pass filter.	Method of "Discrete Wavelet Transform with Maximum Overlap"
July 2021	The data set was filtered for the ML model but not for the DL model	"Filter Bank Common Spatial Pattern (FBCSP)" method

“Discrete Wavelet Transform with Maximum Overlap” method was suggested by Abdul Wahab (2021) to categorize the theta and delta patterns of very low and high frequencies of brain activities during mediation, learning, sleeping or focus mode. According to him, “in MODWT, the relative tolerance is independent of the detailed elements but can change when approximation or detail elements change”.

4.0 RESULTS

In this paper, classification is the technique applied to identify different sample classes in the data set. For motor imagery, different classes are a form of movement involving the left and right hands, the feet, and the eyes. To classify the MI signals, machine learning is widely used. But in recent years, more attention to the development of deep learning resulted in CNN and ANN-based classification models for motor imagery BCI systems. Table 3 shows the comparison chart of several studies and their resulting outcomes.

5.0 CONCLUSION

For a BCI system to work ideally for all the users, it is critical to develop a “classification” model that can differentiate task-related patterns of each individual with high accuracy. This article reviewed various research improving the effectiveness of machine learning techniques in Motor imagery-based BCI systems and deep learning needs in enhancing the motor imagery BCI system’s performance (Table 3). By comparing the results and accuracies of all the models on test data, it is found that the task transfer learning method works best for feature extraction. This algorithm solves the long calibration time problem and lack of MI commands and increases the accuracy of the model.

The SVM classifier yields the best results out of all the ML algorithms. However, the highest level of accuracy was attained with the CNN model, which outperformed all the ML classification models and ANN model. The CNN model is also trained and tested for raw data; thus, it eliminates the need for preprocessing and feature extraction but requires a large data set. In conclusion, deep learning classifiers have more potential MI-BCI apps for all users in the future. This situation is contrasts with ML-based BCI systems, which need a significant amount of feature extraction and preprocessing yet are prone to inaccuracies and are not suitable for some users.

Table 3: Comparative Studies

Year Published	Algorithm applied	Necessary detail	AI Feature	Outcomes	Metrics/Reference type
March, 2019	Classification	Classifiers: SVM, k-NN, Naïve Bayes, Decision Tree, Logistic Regression	ML	When compared to accuracy measurement, the area under the curve measurement yields a better result with "SVM, Logistic Regression, and the Naïve Bayes classifier" producing the best results with an accuracy of 89.09%"	Accuracy, AUC
December 2020	ANN CNN	Activation functions for ANN: Relu, Selu, Elu, tanh Activation function for CNN: Softmax	DL	ANN and CNN are both comparable as running classification on test data from 22 EEG channels yields the accuracy of 82.93% with CNN and 81.03% with ANN	Accuracy
December 2020	Classification	SVM classifier with "Gaussian radial basis function" as the kernel function	ML	The algorithm performs better, especially for datasets with fewer training samples and poor performance.	Accuracy
June, 2021	Classification	SVM classifier with several kernel functions	ML	The average accuracy achieved for SVM is 98.81%, with cubic SVM yielding the highest results with an accuracy of 97.77%	Accuracy
July 2021	Classification CNN	LDA classifier 2D CNN model with Relu as an activation function	ML DL	The average test accuracy of the CNN model is greater than CSP+LDA classifiers, and it outperformed CSP+LDA by 18.38% as per the t-test.	Accuracy Pairwise t-test

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