Measurement: Sensors 28 (2023) 100823

Contents lists available at ScienceDirect

Measurement: Sensors

journal homepage: www.sciencedirect.com/journal/measurement-sensors

Machine learning techniques for electroencephalogram based brain-computer interface: A systematic literature review

Pawan, Rohtash Dhiman *

Department of Electrical Engineering, Deenbandhu Chhotu Ram University of Science and Technology, Murthal, Sonipat, Haryana, 131039, India

ARTICLE INFO

Keywords:
Brain computer interface (BCI)
Deep learning (DL)
Electroencephalogram (EEG)
Feature extraction
Machine learning (ML)
Motor Imagery (MI)
Wavelet packet decomposition (WPD)

ABSTRACT

Brain-computer interface systems with Electroencephalogram (EEG), especially those use motor-imagery (MI) signals, have demonstrated the ability to control electromechanical devices with promising results. EEG being easy to record and non-invasive makes it a good choice for BCI systems. MI-based BCI systems compute neuronal activity and decipher these electrical impulses into gestures or effects, aiming to enable the person to communicate with their surroundings. This study summarises techniques of EEG signal processing used in the recent decade. This research paper presents an exhaustive survey on four aspects of EEG signals in BCI systems: signal acquisition, signal pre-processing, feature extraction, and classification. The most prominent time-frequency technique, wavelet transform (WT), and its updated version, wavelet packet transform (WPT), is primarily used in EEG-BCI systems for feature extraction. The development of artificial intelligence technology motivated researchers to classify motor imagery signals for BCI systems using machine learning (ML) and deep learning (DL) techniques. This literature survey paper explores more than 220 research papers related to ML and DL approaches to classify EEG signals for BCI systems. In order to identify prospective research areas for future investigation, present challenges are carefully considered, and suggestions are also provided for appropriate feature extraction and classification techniques. The authors expect that the investigation presented in this paper will help researchers to find accurate feature extraction, ML, and DL methods and these techniques will be supportive in devising an effective EEG-BCI system.

1. Introduction

Electroencephalogram (EEG) based brain-computer interface (BCI) system detects participant's brain activity and transforms their intents into commands without activating any peripheral nerve or muscle [1]. The COVID-19 pandemic has illuminated the requirements of persons with severe impairments in daily life transport, mobility, education, and healthcare. EEG-Based BCI system provides a better solution to disabled patients in COVID-19 pandemic situations by operating electronic devices such as wheelchairs [2]. To perform specific activities such as control home appliances and wheelchair, speech synthesizers, robotic arms, digital computers & gaming applications, elucidated brain activities are immediately deciphered into sequences of commands using BCI applications [3]. The BCI systems can be categorized into two modes: the first mode is synchronous BCI, which is a cued-based and computer-driven procedure, and asynchronous BCI is the second mode, which is not a cue-based, user-driven method. Brain activity can be investigated by non-invasive methods such as functional magnetic response imaging (fMRI), magnetoencephalogram (MEG), and electroencephalogram (EEG) [4] . The prominent BCI systems depend on EEG. The EEG-based BCI systems support different real-time implementations because it is simple to use and affordable in cost [5]. The BCI applications are generally using sensorimotor rhythms (SMR), event-related potentials (ERPs), visually evoked potentials (VEPs) and slow cortical potentials (SCPs). Among these, SMR with BCI systems deliver a large percentage of liberty in link with real-time and motor imaginary activities like tongue, hand, arm, and feet [6]. Motor imagery (MI) is a cognitive process during which an individual envisions performing a physical activity without moving their muscles. This phenomenal experience means that the subject is executing a specific action. Somatosensory and motor regions exhibit oscillatory activity, known as sensory-motor rhythms (SMR). Presently, EEG can identify different categories of MI signals. These MI signals can control the BCI system after sufficient training sessions. EEG signals activities related to sensorimotor rhythms based on MI-BCI systems are known as mu (8–13 Hz) and beta (14–30 Hz) rhythms [7]. With help of

* Corresponding author.
E-mail addresses: 18001902902pawan@dcrustm.org (Pawan), rohtash.ee@dcrustm.org (R. Dhiman).

https://doi.org/10.1016/j.measen.2023.100823
Received 16 January 2023; Received in revised form 9 May 2023; Accepted 12 June 2023
Available online 14 June 2023

electroencephalography, biological electrical signals produced by the cerebrum are recorded with electrodes set on the scalp using a 10–20 electrode system [8]. The fundamental component behind BCI systems is the biological electrical action of neurons. Millions of neurons are present in the cerebrum of the human brain. In the brain, when neurons fire or actuate, a voltage change is generated inside the brain's surface. This variation of voltage can be helpful for BCI systems for various applications. The brain signals distinguished between the five most crucial different frequency ranges, and these frequency ranges are delta (0.5–4 Hz), theta (4–7 Hz), alpha (8–15 Hz), beta (12–30 Hz), gamma rhythm (greater than 32 Hz) [9].

Signal acquisition, pre-processing, feature extraction, and classification are four important parts in EEG-BCI system. The most challenging part of BCI system is feature extraction. Extracted features indicate a piece of vital information encapsulated in the signal. In EEG-BCI system spatio-spectral feature extraction method has been given the appropriate results in the past several years [10] . For better investigation, EEG signals in the time domain should be converted into the frequency domain for better classification results [11]. Feature extraction techniques such as fast fourier transform (FFT), autoregressive model (AR), common spatial pattern (CSP) and wavelet transform (WT) have been applied for EEG-MI signals. The wavelet packet transform (WPT) effectively extracts appropriate motor imagery features due to its computational simplicity and offers best recognition rate [12]. The WPT technique is better for investigating EEG signals than AR model or FFT because it shows information in different time windows and frequency bands [13]. The main objective of classification process is to convert EEG signal features generated by feature extractor into commands [14]. BCI classification technique translates discriminatory features into, unlike motor imaging activities such as tongue movement, left-right movement, foot movement, etc. Several classification methods like artificial neural network (ANN), linear discriminate analysis (LDA), k-nearest neighbor (k-NN) support vector machine (SVM), gaussian naïve bayes (GNBs) & deep learning (DL) have been used for MI-BCI systems [15,16].

This literature paper is formatted as follows. Section 2 presented related research work. Then section 3 presents detail of Brain computer interface (BCI) module, including EEG signal acquisition, EEG signal pre-processing and feature extraction methods. Section 4 explain classifiers in EEG-MI-BCI systems. Section 5 explores the challenges for EEG-MI-BCI systems. Section 6 described suggested solutions for EEG-MI- BCI systems. Section 7 describes conclusion of this study.

1.1. Contribution of this literature paper

This work makes contributions in the following areas:

- This research aims to look into signal acquisition, signal pre-processing, feature extraction, and classification approaches used in MI-EEG-BCI applications.
- Analysis of the EEG data for motor imagery signals performed in MATLAB programming environment.
- To provide the review of research papers in the tabular form corresponding to EEG-MI BCI systems published from 2012 to 2022.
- To explore the application of ML and DL approaches in EEG-MI-BCI systems.

1.1.1. Role of machine learning techniques for EEG based MI-BCI systems

The goal of machine learning (ML) in EEG-based MI-BCI systems is to identify brain patterns related to a specific activity without relying on traditional statistical methods. The field of EEG based Research on MI-BCI started in the 1970s, and significant EEG studies were conducted on rat and monkey cortices at University of Washington School of Medicine to replicate their neurological activities. In the past, BCI research solely concentrated on studying brain activity and making medical diagnoses. However, technological advancements have led to numerous improvements in the BCI field over time. ML technology has enabled BCI applications to expand into various fields, providing a unique way to study brain activity. This includes identifying human motor imagery limb movement, recognizing emotions, and other applications. Recent advancements in low-cost microelectronics devices have made it easier for BCI users to utilize embedded circuits for complex tasks. Additionally, the rise of self-decision-making and more efficient ML algorithms have opened up new possibilities for pushing the boundaries of brain-controlled applications. The use of ML in BCI systems has motivated researchers to enhance the accuracy and significance of task performance.

ML is a crucial method for creating intelligent hardware, software, computers, and electronic devices that mimic human intelligence. Nowadays, ML is an essential aspect of computer science and statistics that involves using computers to perform tasks that are not explicitly programmed. It involves studying computer architectures and algorithms that can learn from observable data and allow for automated identified information that can be used to complete the intended activity. With the advancements of modern science, ML techniques have made significant strides and are extensively utilized in computer vision, robotics, face detection, natural language processing (NLP), motor imagery activity, data visualization and other medical applications. ML technology combined with BCIs can substantially improve the comprehension of intricate brain impulses and more accurately identify actions.

2. Literature survey

The concept of controlling prosthetic limbs using brain signals was investigated in 1971 [17]. Since then, brain-computer interfaces (BCIs) with electroencephalogram (EEG) have drawn full consideration among investigators due to their skill of cognizance of neural communications and ease of use, non-invasiveness, and low cost. Inspired by these attractive characteristics of BCI systems, various investigations have been carried out over last twenty years. This section presents past EEG investigations for motor imagery (MI)-BCI systems. Motor imagery, event-related potential (ERPs), and steady-state evoked potentials (SSEP) paradigms are used in BCI systems [18]. ERPs are responses in the brain that involve cognitive or motor sensory events. ERPs-based BCI often uses external touch and visual and auditory stimuli [19]. Constant-frequency visual stimuli, the brain generates typically electrical signal range between 3.5 and 75 Hz, activate the SSEP-based BCI system [20]. But recently, most researchers have focused on MI-BCI systems. MI refers to the cognitive process of imagining the movement of body parts without actually performing the activities [21]. It is near real movement execution, and sensorimotor areas' neural patterns changed specifically during MI activities. The BCI system decrypted the MI signal from the EEG, and this could be done using MI data and need feature extraction and classification to identify brain activity patterns. Different feature extraction approaches are required because the EEG spectrum varies over time [22]. The various feature extraction techniques include auto-regressive modeling (AR), independent component analysis (ICA), wavelet packet transform (WPT), principal component Analysis (PCA), hibert huang transform (HHT), fast Fourier transfer (FFT), discrete fourier transfer (DFT), short-time fourier transform (STFT), common spatial pattern (CSP) and empirical mode decomposition (EMD) have been employed MI BCI applications [23,24]. WPT is one of the most prominent time-frequency signal processing tools due to being suitable for non-stationary signals and delivering sophisticated frequency resolution [25]. In many fields, coefficients of WPT are used, and they are essential for noise reduction and signal compression [26]. The most important approaches, time domain, frequency domain, and time-frequency domain, have been investigated for feature extraction with unique advantages for EEG-based BCI systems. Time-frequency domain techniques provide optimistic outcomes for the MI-Brain computer interfaces [27]. WT has been used for feature extraction, and classification rate for left-right hand obtained 75.54% with spiking neural network (SNN) classifier [28]. A feature extraction approach has been used for classifying MI tasks based on CSP method [29]. A novel hybrid methodology used for selecting features based on differential evolution optimization technique to obtain the best feature subset and accuracy calculated by SVM [30]. The authors investigated signal processing techniques for BCI systems and used the CSP technique to extract ERS/ERD patterns from EEG [31]. Authors discussed [32] three popular signal processing techniques (EMD, DWT & WT) for decomposing signals in MI-BCI and k-NN algorithm used for classification**.** The author suggested feature extraction approaches with DWT and EMD and calculated approximate entropy [33]. In Ref. [34] suggested a novel adaptive technique for automatic feature extraction & selection for brain-computer interface using EEG signal. The model competent merges eminent feature extraction methods & automatically chooses features for the accomplishment classification process, and authors used three feature extraction approaches, hjorth parameters, power spectral density, and autoregressive, and proposed a technique estimated using EEG signals from 9 subjects during MI tasks. Recent advances in artificial intelligence (AI) technology, such as ML/DL, have enhanced brain activity analysis for BCI systems with better accuracy. Based on the feature vector, ML/DL classifiers attempts to detect the user's intent [35]. In DL techniques, convolutional neural networks (CNNs) are commonly used in MI-EEG recognition because of their capacity to extract the most distinguishing characteristics for classification [36]. SVM and LDA are two popular linear classifiers for MI data classification used effectively in BCIs [37]. ANN and k-NN are examples of Nonlinear ML classifiers, which also have good performance [38]. In Ref. [39] presented a comparative investigation of multiple ML/DL approaches for motor imagery identification using biological signals.

Some of the previous research work presented in tabular form in Table 1, describes feature extraction and classification, but the investigation of signal processing techniques and classification needs to be more detailed. Detailed study of signal processing modules required further clarification. It will be beneficial if all aspects of the BCI paradigm can be explained systematically. In this paper's authors have tried to fulfill the literature gap for MI-BCI systems. ML/DL techniques with time-frequency domain should be used to classify EEG-based MI-brain computer interfaces, which provide optimistic results. These techniques are not discussed in Table 1 informatics manner; the authors in this research paper involved a brief dialogue on feature extraction and artificial intelligence techniques for EEG-MI-BCI systems

3. Brain-computer interface (BCI) module

The Brain-computer interface system involves four modules: signal acquisition, pre-preprocessing, feature extraction, and classification [52]. Fig. 1 demonstrates modules of the brain-computer interface system & their applications. Task-specific time domain, frequency domain, and time-frequency-based features are derived using feature extraction methods from the EEG signal. The classification process aims to translate extracted features to output depending on application to represent user's intent.

3.1. EEG signal acquisition

Electroencephalography has existed for over a century. Hans Berger, a German psychiatrist, released his research article on electroencephalogram (EEG) in 1929 and developed the technology for recording electrical activity from the human brain [53]. One of the crucial elements of BCI-based system is measurement of brain oscillations. EEG-BCI system represents the user's neural activities of current tasks. Numerous signal acquisition techniques have been investigated. Invasive and non-invasive are two broad techniques of brain signal acquisition [54]. Invasive technology involves implanting electrodes within or on top of the user's brain via neurosurgery, while in non-invasive methods, an external sensor is used to monitor brain activity [55]. Here authors only focused on EEG-non-invasive technology. Electroencephalography captures electrical signals, i.e., EEG, inside the subject brain with sensors/electrodes mounted in a cap-like structure [56]. It offers distinct benefits over other methods for brain signal recording, making it suitable for commercial application. It is simple to use, portable, and reasonably priced. The recording of an EEG also offers the best temporal resolution [57]. However, when compared to other approaches, its spatial resolution, and its signal-to-noise ratio (SNR), are weak. Several strategies have been proposed to increase EEG spatial resolution and SNR. It has been suggested that the number of electrodes is raised to 256 [58]. The 10–20 international electrode location system has been released publicly [59]. The Fig. 2 shows the distance between consecutive pairs of sensors to either 10% or 20% of the diameter of the skull [60,61].

3.2. EEG signal pre-processing

Raw EEG data coexist with neural activity, non-physiological noise, and physiological artifacts. Consequently, it is necessary to carry out a pre-processing method to reduce noise, eliminate artifacts, and eventually enhance the SNR of the EEG data [62]. The assimilated signals are improved by the amplification process & digitized before they are applied to BCI application, and signal pre-processing aims to boost SNR and filter out undesired signals. SNR refers to the dimensionless ratio between signal and noise power. The non-stationary EEG signals are commonly in time series and divided into smaller segments, and these small segments are considered stationary signals. The amplitude of the EEG signal is approximately 200 μV [63]. The signal processing is statistically derived parameters that assess many aspects of EEG signal & permit numerical manipulations of actual data & correlation with other physiological data. Artifacts & noise in EEG signal needs efficient

Table 1
Recent EEG-BCI systems related work.

Reference	Aim of research work	Feature extraction technique	Classification technique	Accuracy
[40]	Right-left hand	DWT and EMD	SVM	95.10%
[41]	Cursor movement	AR and CWT	SVM	82.24%
			k-NN	57.90%
			LDA	55.92%
[42]	Right – left hand and foot	CSP	SVM	76.34%
[43]	Right – left hand and foot	CSP	SVM	96.02%
[44]	Tongue or left small finger	CSP	Bayesian linear discriminant analysis (BLDA)	99%
[45]	Imagination vowels	–	SVM	65% (BGWO) and 60.84% (GA)
[46]	Tongue or left small finger	Stockwell transform	BLDA	96%
[47]	Right-left hand	WT	LDA	Misclassification Rate: 0.1286%
[48]	Left-right hand and forward imagery	WT	SVM	85.54%
[49]	Both fists, Right- left fist movement and feet	WT	ANN	93.05%
[50]	Tongue, right-left hands and feet	DWT	CNN	96.21%
[51]	Left hand-right foot	WT	CNN	86.20%

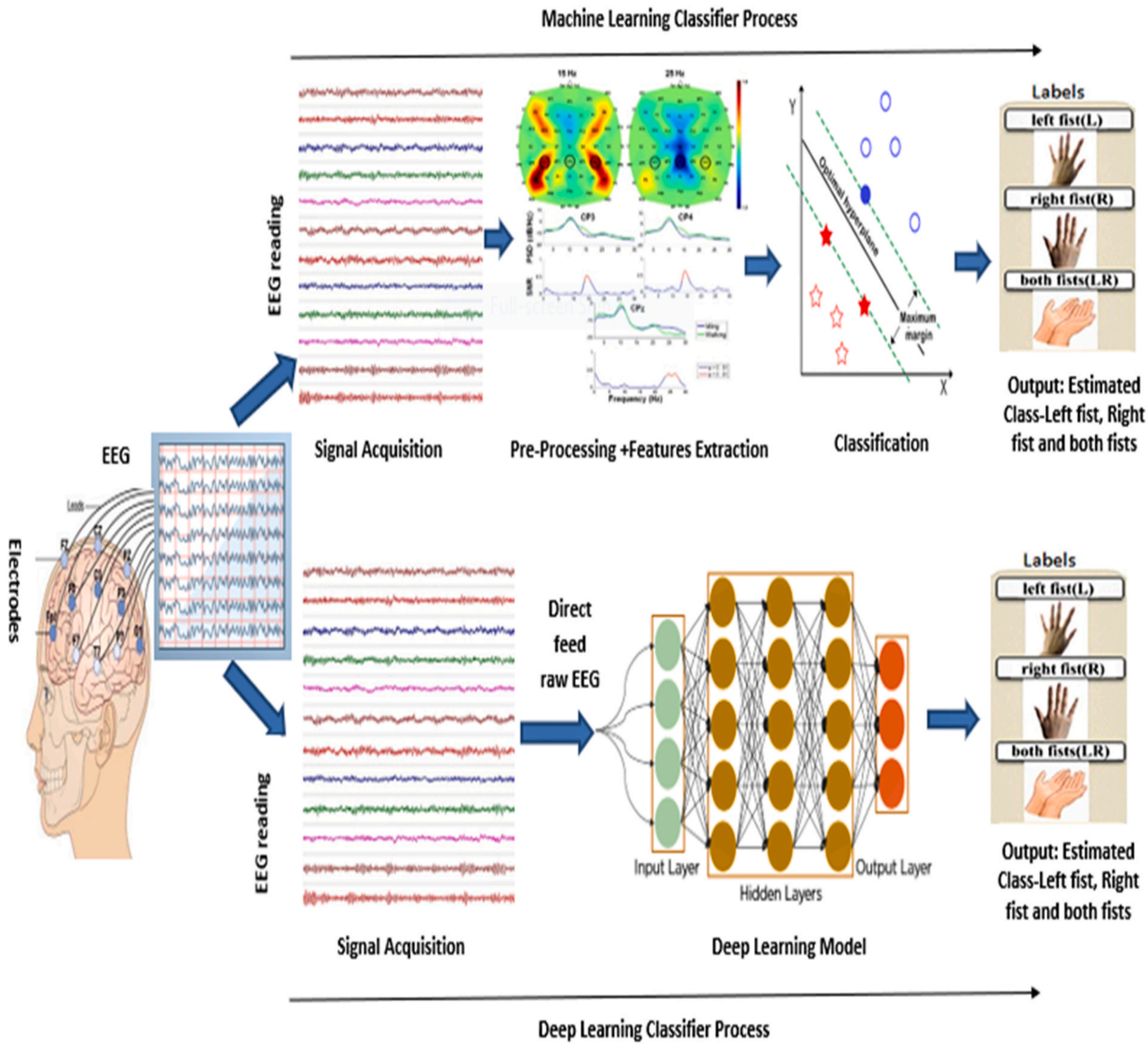

Fig. 1. EEG-Brain computer interface system.

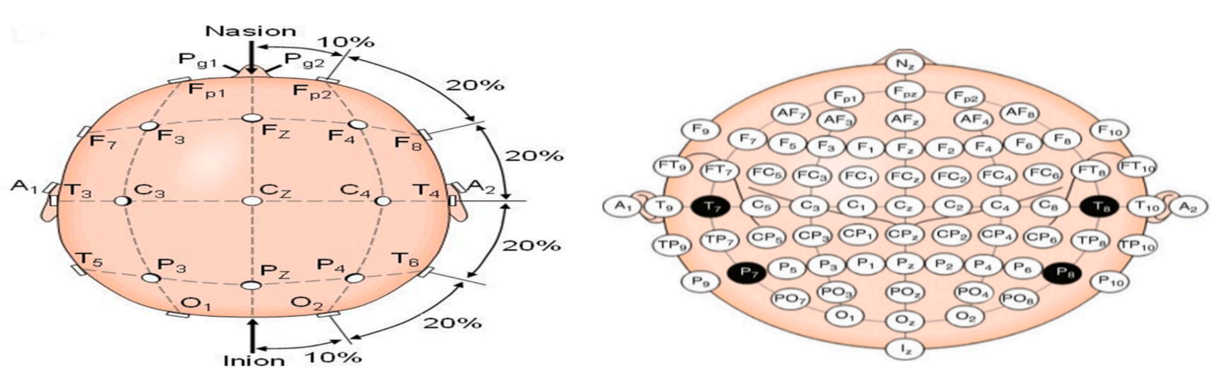

Fig. 2. Show 10–20 International electrodes placement system.

detection & elimination. The Notch filters (null frequency 50 Hz) reject strong power lines noise [64]. Nowadays, some BCI systems design does not consider artifact processing and will directly mark feature vectors. The feature will be derived from biological signals and can represent the subject's intent. That is why it is suggested that pre-processing be carried out on a biological signal before feature extraction to increase SNR. Spatial filtering and hamming approach can be applied for EEG signal windowing. These filters are designed to reduce classification errors [65]. The principal component analysis (PCA) and common average reference (CAR) are used to increase signal strength in BCI systems [66]. Generally, EEG signals are distinguished into five categories depending on frequency levels shown in Table 2 and some important signal pre-processing methods discussed in Table 3.

Table 2
EEG signals differentiated into five categories [67].

Band Name	Frequency in Hz	Source of Origin	Cognitive Activity
Delta (δ)	0.5–4	Found in parietal lobes and central cerebrum	Associated with sleep stages
Theta (θ)	4–8	Frontal, parietal and temporal lobes	Emotion recognition, Deep meditation and olfactory perception
Alpha (α)	8–13	Visual cortex	Determination of eye-closed relax condition and Drowsiness detection
Beta (β)	13–30	Motor cortex	Motor activity
Gamma (γ)	30–100	Somatosensory cortex	Attention, memory, Visual perception, learning

Table 3
Details of signal pre-processing methods.

S. No.	Technique	Characteristics
1	Common average reference (CAR) [68]	Increases SNR & It is utilized in recordings that have a lot of background noise.
2	Independent component analysis (ICA) [69]	It is computationally efficient, offers good performance, and gives better accuracy for large dataset, cannot be helpful to a few problems & needs extra computational efforts for decomposition.
3	Surface Laplacians (SL) [70]	Rigorous against artifact and noise is produced in areas uncovered by sensors or electrodes, sensitive to spline patterns & artifacts.
4	Principal component analysis (PCA) [71]	Decreases dimension & performance better than ICA.
5	Common Spatial Pattern (CSP) [72]	It produces better results for EEG- MI data & requirements multiple electrodes (>64).
6	Adaptive Filter [73]	It gives the best performance given input with overlapping spectra & required one or two reference signals.
7	Digital Filter [74]	It effortlessly eliminates noise, needs multiple frequencies.

3.3. Feature extraction

The multiple-thinking process generates various patterns of signals inside the human brain [75]. In the feature extraction stage, features can be derived from EEG signals in time domain, frequency domain, and time-frequency domain, and the most popular is time-frequency method [76]. The BCI system extracted features from the brain signal replicating resemblances to a certain class. The features are calculated properties of signals which hold discriminated information needed to differentiate various classes. The feature represents a unique characteristic that depends on the techniques and affects the classifier's performance. The primary signal processing stage for the BCI method is called feature extraction, and aim is to explore the EEG signals with a few significant values called features. Such particular features can seize vital information to explain mental conditions by rejecting artifacts & ignore non-relevant details. All extracted features are typically structured in a feature vector form. This investigation introduces a variety of linear and nonlinear feature extraction techniques, and Fig. 3 depicts an approach for the feature extraction process. Linear techniques included eigenvector, autoregressive (AR), independent component analysis (ICA), principal component analysis (PCA), wavelet transformation (WT), fast Fourier transform (FFT), and nonlinear methods including correlation dimension, Lyapunov exponent, various entropies, fractal dimension, phase spatial graphs, etc., [77,78]. The Heisenberg uncertainty principle tells us that it is hard to calculate signals in both time and frequency domains [79]. The time-frequency domain features offer better classification outcomes when compared with other approaches. Next, the sub-section describes the various feature extraction approaches.

3.3.1. Time domain techniques

Temporal information of signals easily captures by using time-domain analysis (see Table 4). EEG signal is a function of time so that features can be calculated in time domain. The important time domain statistical features are skewness, kurtosis, mean, standard deviation, and variance [80]. These features explore the distribution of EEG signals in terms of moments & amplitude. The time-domain method cannot calculate frequency information, so it is not frequently applied as a signal-processing method for EEG. For better results, it is added with other signal processing approaches. However, some investigations have been done with the help of time domain features with better results. There are two main time-domain EEG signal processing techniques: component analysis (CA) and linear prediction (LP) [81]. Normally, LP gives an assessed value equal to a linear combination of past output with current & past input value with past output and CA is an unsupervised technique in which data set is mapped to the feature set. All parameters in time domain techniques are completely dependent on time. The time domain technique constructs a link between physical time analysis & traditional frequency analysis. BCI systems can be used as feature extraction methods from EEG data from the time domain with mean absolute value, slope sign changes, zero crossings, & waveform length measured for classification [82]. Hjorth parameters are the characteristics based on the variance of EEG signal's derivatives. The first three signal derivatives are mobility, activity, and complexity, often employing Hjorth parameters [83]. Autoregressive (AR) is a time-domain method applied for feature extraction, and AR coefficients are used as a feature vector [84]. After signal pre-processing, data is entered into specific algorithms, allowing the most valuable information to be derived from EEG at this point, and the signal must have the best SNR ratio. Mathematical formulae of time-domain features utilized in

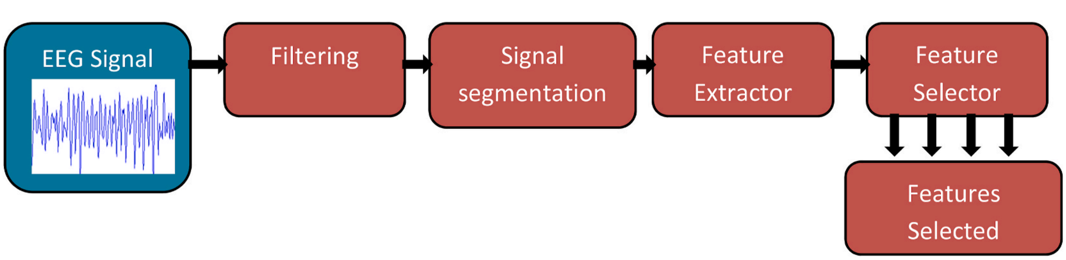

Fig. 3. An approach for the feature extraction process.

Table 4
Mathematical formulae of time-domain features for EEG [85].

S. No.	Feature	Mathematical expression
1	Mean (μ)	$\frac{1}{N}\sum_{n=1}^{N} f(n)$
2	Root mean square (rms)	$\sqrt{\frac{\sum_{n=1}^{N} \lvert f(n)\rvert^2}{N}}$
3	Standard deviation (σ)	$\sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(f(n)-\mu)^2}$
4	Variance (σ^2)	$\frac{1}{N-1}\sum_{n=1}^{N}(f(n)-\mu)^2$
5	Skewness (sk)	$\sqrt{\frac{1}{N-1}\sum_{n=1}^{N}\frac{(f(n)-\mu)^3}{\sigma^3}}$
6	Kurtosis (kt)	$\sqrt{\frac{1}{N-1}\sum_{n=1}^{N}\frac{(f(n)-\mu)^4}{\sigma^4}}$
7	Activity	variance(f(n))
8	Hjorth Mobility $h(t)$	$\sqrt{\frac{variance\ (df(n)/dt}{variance\ f(n)}}$
9	Hjorth Complexity $c(t)$	$\frac{mobility\ (\ df(n)/dt}{mobility\ (f(n))}$

Note: $f(n)$ is the *nth* sample in the EEG signal and $n = 1, 2, \ldots, N$.

brain-computer interface systems are shown in table no. 4, and all features use different techniques and affect the performance of classifiers.

3.3.2. Frequency-domain techniques

Frequency domain analysis is one of the most prevailing and standard techniques for MI BCI system [86]. The fast Fourier transform (FFT) converts the time domain EEG signal into the frequency domain after that, easily calculated features like mean & peak frequencies, standard deviation of power, relative power, maximum power, frequency of maximum power, etc. The FFT method provides an understanding of EEG signals in the frequency domain that can be used to extract features for motor imagery task identification [87]. In frequency domain techniques, power spectral density (PSD) feature is mostly used for EEG signals [88]. PSD is normally used to extract frequency characteristics of EEG, which permits distinguish of motor activities [89]. A limitation of the band power method is that it confines attention to a precise frequency band. With the help of the FFT method, split the epoch of the EEG signal into small segments & estimate PSD for each segment [90]. The periodogram is another mathematically well-organized approach to estimating the power spectrum [91]. This technique splits the complete EEG signal into a small chunk of data, called windows, then calculates the frequency of every small window signal [92]. The Yule-Walker AR and Burg's methods are important for calculating PDS. This method controls autoregressive (AR) parameters that display the EEG segments in the window. Statistical features such as, variance, skewness, kurtosis, etc., are also utilized in frequency domain. The relative powers of specific frequency bands are most often employed frequency-domain features in all aspects of EEG signal investigation. The non-parametric Welch's technique is also used in numerous BCI systems to optimize classification results [93].

3.3.3. Time-frequency analysis techniques

Time-frequency techniques provide promising results for non-stationary EEG signals due to the best time-frequency resolutions [94]. For EEG analysis, short-time Fourier transform (STFT) is used for time-frequency resolution with compromised [95]. Wavelet Transform (WT) was developed for feature extraction in 1984 by Morlet and Grossman [96]. Wavelet transform (WT) permits better flexibility, and features can vary over different time scales and is a very promising method for feature extraction for BCI systems [97]. The WT offers the best results as compared to STFT [98]. In the continuous wavelets transform (CWT) approach, the wavelet is changed effortlessly over the scale, and calculating wavelet coefficients for each possible scale could require substantial effort. DWT sampled version of CWT and computationally very competent without negotiating accuracy and performance [99]. The main step in employing wavelets is choosing a subset of wavelet coefficients significant in MI-BCI systems for classification results and identifying regions in the time-frequency plane where the EEG signal can be classified with high performance [100]. In the EEG-BCI system, wavelet packet decomposition (WPD) and its variant wavelet packet best basis decomposition (WPBBD) have been used as a feature extraction technique [101]. In WPD, signal is mapped onto an orthogonal wavelet basis function space, and the signal is first decomposed into low-frequency and high-frequency information. In successive layers, low-frequency information is again broken down into low- and high-frequency information. It is necessary to continue this decomposition procedure until the required results are achieved that depend on the dataset [102]. Fig. 4 represents the typical tree diagram of WPD at the 8th level. In this literature paper, authors used BCI competition IV -Dataset I [103] to demonstrate the EEG signal decomposition up to 8th level and obtained the wavelet nodes $2^8 = 256$. For the more detailed dataset researchers can visit the website: https://www.bbci.de/competition/iv/. Here presented, only two samples of EEG signal and Figs. 5 and 6 depict MATLAB representation of 7 nodes out of 256 at 8th level of WPD for subject "a" and "f." These 7 selected nodes are related to the 8–32 Hz frequency band, which is associated with motor imagery signals in BCI systems. Empirical Mode Decomposition (EMD) is a time frequency-based technique for decomposing pairs of signals in which one of them is used as a reference signal [104]. EMD was suggested in 1998 and has shown to be an excellent tool for studying biological data [105]. It is based on the Hilbert-Huang transform technique for decomposing nonstationary and nonlinear signals into constructive components (IMFs) with various frequency ranges [106]. EMD is used effectively for MI-BCI [107]. Further extensions of EMD, such as Multivariate EMD, have also been used in MI BCI [108].

3.3.4. Common spatial pattern (CSP)

H. Ramoser was the first to proposed the CSP approach for classifying multi-channel EEG for imaginary hand movement [109]. The CSP technique is generally employed for feature extraction in MI-BCI system. It is the transformation of EEG signals into a new space used by spatial filtering techniques where the variance of one of the groups is optimized while the variance of the second group is reduced [110]. The EEG signals have noise & over-the-fitting problems; several regularized common spatial pattern algorithms are shown to satisfy these issues [111]. The main advantage of the CSP approach [112] is that it does not entail priori choice of individual frequency bands, and the drawback of the CSP approach is that it involves several electrodes for better results [113]. However, the disruption of using additional electrodes/sensors can be justified by good results and the model's accuracy. The notable difficulty in the application CSP method is that it's very sensitive to artifacts in EEG signals. For calculating spatial filters, covariance matrices are a basic function [114]. Some research shows CSP approach does not give adequate MI-BCI classification results because different individuals displayed tasks in unlike frequency bands, and the intended frequency band is required. This implies that a wide frequency range, especially between 4 Hz & 40 Hz, can be included in the MI classification [115]. Various methods have been introduced to fine-tune particular frequency bands for the CSP technique; one of the best techniques is common spatio-spectral pattern (CSSP) which improves the outcomes for BCI applications [116]. Another extension of the CSP approach is filter bank common spatial Pattern (FBCSP), which comprises four stages: spatial filtering, frequency filtering, feature selection and classification [117]. The other variants of CSP methods are Discriminative FBCSP and SCSSP (Separable Common Spatio Spectral Patterns) applied to extract features and output delivered into several classifiers to improve BCI performance [118].

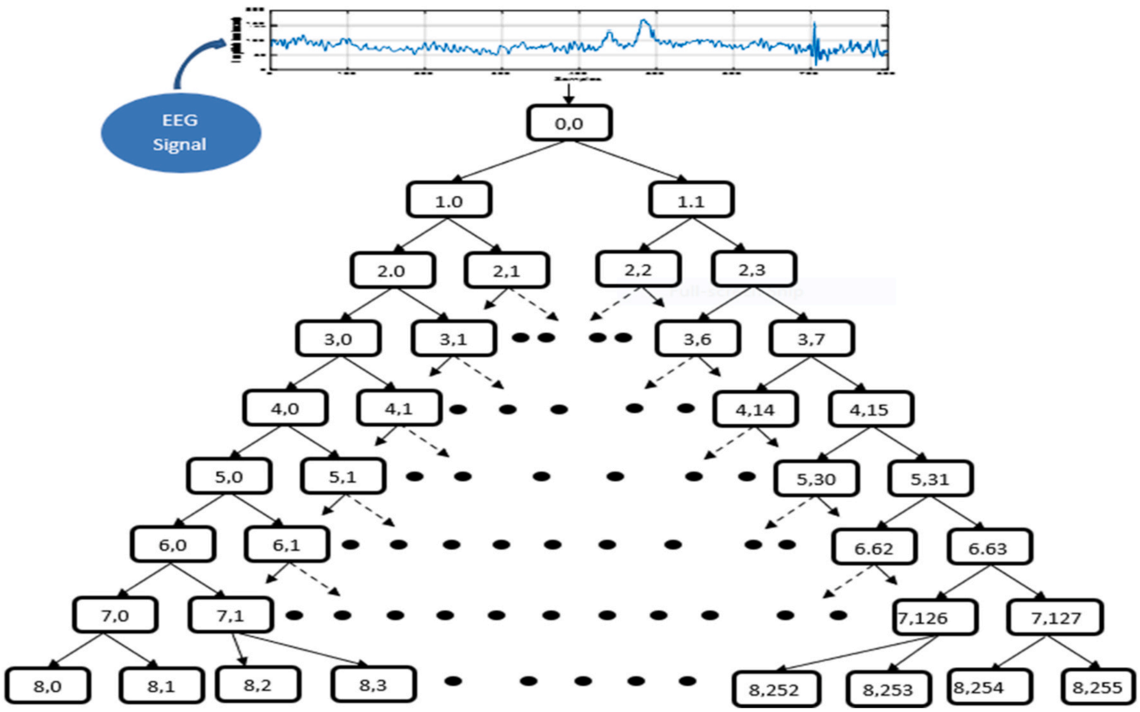

Fig. 4. WPD systematic tree diagram up to 8th level decomposition.

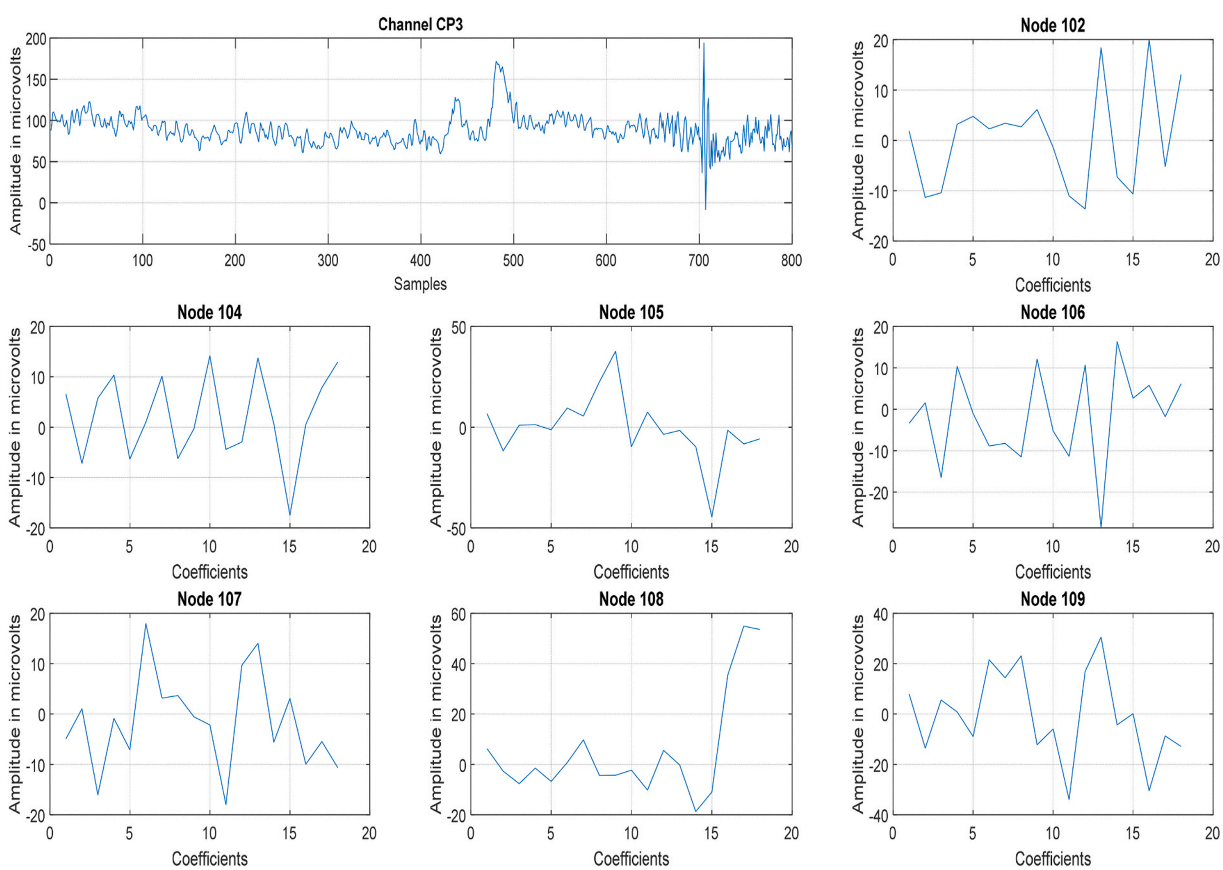

Fig. 5. Show MATLAB plot for subject "a" for EEG channel 43 as label CP3 and WPD nodes (8,102, 8104 to 8109) at 8th level (Dataset I of BCI competition IV).

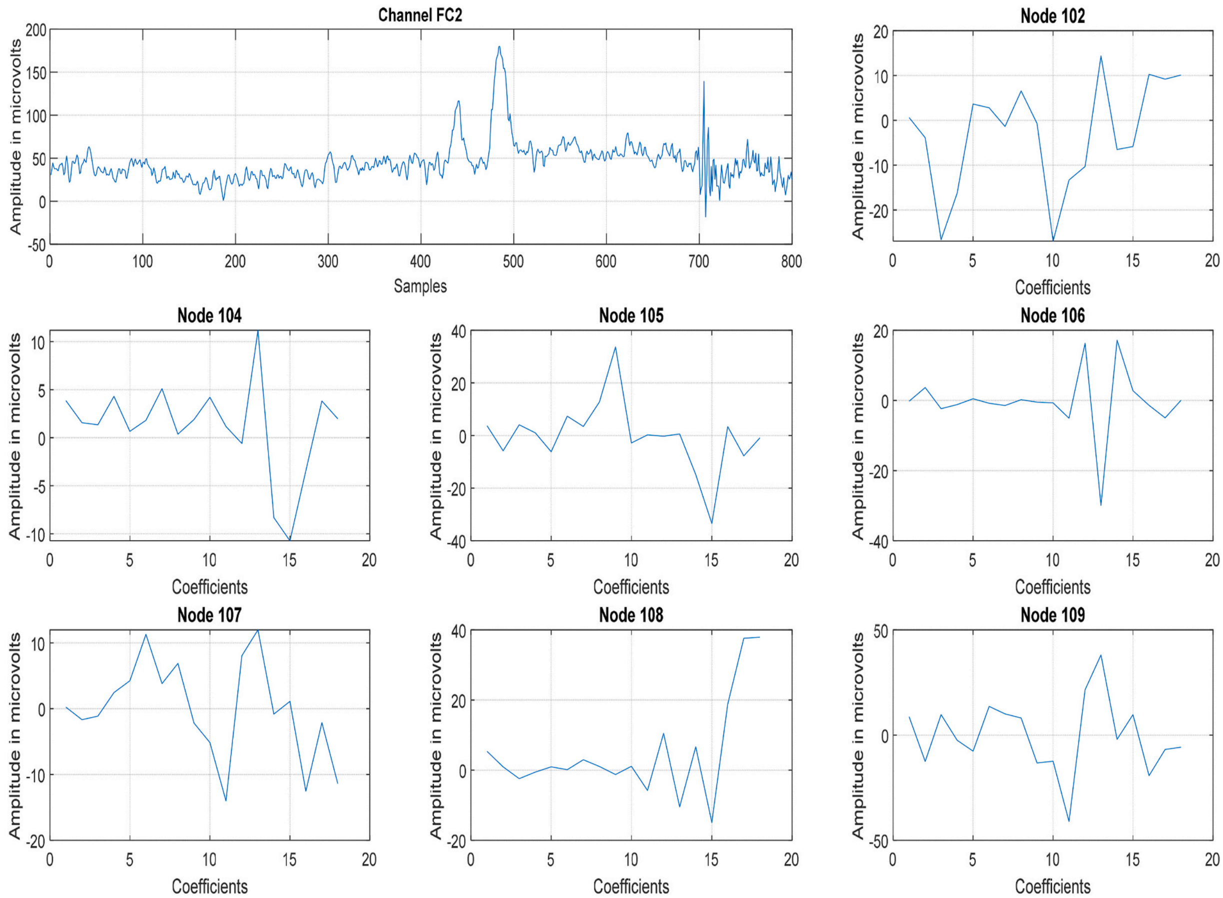

Fig. 6. Show MATLAB plot of subject "f" for EEG channel 14 as label FC2 and WPD nodes (8,102, 8104 to 8109) at 8th level (Dataset I of BCI competition IV).

3.4. Findings for feature extraction approaches

Electroencephalogram signals are chaotic and non-stationary; thus, an efficient feature extraction approach is essential for enhancing the accuracy of BCI systems. Artifacts are noise that substantially impairs extracting relevant information from EEG data. Section 3.3.1-3.3.4 explores the various feature extraction techniques for the EEG dataset, and feature extraction approaches such as the FFT, STFT, CSP, WT, and EMD have been studied. However, these approaches offer both benefits and disadvantages. CSP is mainly employed to feature the extraction of EEG data for BCI system. In CSP method, the spatial filter is used to analyze EEG data that create a new time series with one signal having a large variance and another having a less variance. This technique benefit is that no precise frequency band must be chosen in further, and drawback is that it is noise-sensitive and involves multi-channel analysis. To fix this issue for the EEG signal, only the energy features are considered for every channel. It ignores links between each channel's information. For analyzing EEG-motor imagery data, researchers nowadays concentrate on the most popular time-frequency approach, Wavelet transform, and its version, the Wavelet packet transform (WPT). The WPT algorithm is a powerful data-compression tool, and it is also capable of preserving signal quality thanks to its superb linear frequency-modulation approach. This technique has provided excellent accuracy in feature extraction for harmonic analysis. All feature extraction approaches have their proper places. While at same time, these have both positive and negative aspects. There is also the option of combining techniques and comparing them. Table 5 summarises the unique advantages and drawbacks of EEG signal feature extraction techniques.

4. Classifiers in EEG-MI BCI systems

The objective of classification is to predict target classes or variables from specified input. The intention of classifiers is to define the boundary between classes and label them based on their feature approximation. This section describes a comprehensive explanation of classifiers for MI BCI systems.

4.1. Support vector machine (SVM)

The linear SVM algorithm was proposed by Vapnik in 1963, while its non-linear version in 1992 [125]. In BCI research, SVM has gained tremendous popularity, which was initially introduced for data classification. SVM is a binary classifier that is often employed in the supervised approach. Its goal is to find the best hyperplane for separating the training data and achieving the minimal predicted risk. Nonlinear SVM employs kernel function to transform data into higher space to lower dimensional space, while linear SVM employs linear function as decision boundaries [126]. It is a robust technique that contains several parameters which could be customized to improve classification accuracy, as according to Ref. [127], hyperplanes can be used to define linearly separable classes.

$$f(x) = W_x^T + W_0 = 0 \tag{1}$$

$$k(x, y) = exp\left(\frac{-\parallel x - y\|^2}{2\sigma^2}\right) \tag{2}$$

Support vectors are data points that are nearer hyperplane and impact hyperplane's location and orientation, and they are vital components of the training dataset. Using the "kernel technique," it is feasible to set nonlinear decision boundaries with only a slight rise in

Table 5
Comparison of EEG-MI BCI feature extraction methods.

Approaches	Advantages	Drawbacks	Domain
Autoregressive Model (AR) [119]	It offers good spectral estimations and provides superior frequency resolution for short segments.	Model validity depends on the appropriate choice of AR coefficients, and it is slow and cannot always be used for real-time analysis.	Frequency domain
fast Fourier Transform (FFT) [120]	An effective methodology for stationary signal analysis. It is better suited to narrowband signals like sine waves.	Insufficient to analyses nonstationary EEG signals. It has a high noise sensitivity.	Frequency domain
Common Spatial Pattern (CSP) [121]	Multichannel data can be investigated using CSP. It provides the appropriate results for chaotic signals.	A lot of electrodes are required for good outcomes and Gaussian distribution is used to describe the data for each class. However, this hypothesis not true sometimes for EEG data.	Spatial Filters
Short-time Fourier Transform (STFT) [122]	It gives the frequency information of signal at each time point.	It does not provide the best results for non-stationary signals due to its fixed temporal resolution.	Time and frequency domain
Wavelet Transform (WT) [123]	WT is more suited for analyzing transient and abrupt signal changes (non-stationary).	An appropriate mother wavelet must be chosen.	Time and frequency domain
Empirical mode decomposition (EMD) [124]	It is well suited to nonstationary and nonlinear signal processing.	The main problem with EMD is mode mixing and it is sensitive to noise.	Time and frequency domain

complexity of the classifier. It entails implicitly projecting data to another space, usually with significantly larger dimensions, with the help of a kernel function, The Radial Basis Function (RBF) kernel $K(x,y)$, is often used in BCI research. For MI BCI, SVM has been employed [128]. In Ref. [129], SVM was also employed for ERP signal classification. In Ref. [130] the multiple kernels learning SVM algorithm was used to classify EEG data associated with cognitive tasks. SVM has been shown to be the most effective classifier for EEG. Different machine learning classifiers, including NBC, SVM, and LDA, were used [131] to classify MI activities. The SVM technique is used to classify various MI activities for the BCI system [132]. In Ref. [133] SVM classification technique is used to improve classification accuracy, and findings indicate that the SVM approach produces the most accurate classification results. Additionally, as shown by this approach, the overfitting error is small. One of the primary benefits of SVM is its adaptability based on optimizing its various parameters.

4.2. Linear discriminant analysis (LDA)

Fisher developed the linear learning approach known as the LDA classifier in 1936 [134]. LDA is a popular classification technique in BCI applications, and it has been implemented effectively in various MI-BCI applications [135]. It is a linear classifier that works on the assumption that two classes can be separated linearly. LDA splits the data using a hyperplane found by searching for a projection that satisfies the Fisher criterion. LDA uses projection $Y = w^T x$ to project information into data space, increase distance between classes [136]. LDA fundamental drawback is its linearity, which cannot produce optimal results when dealing with complicated nonlinear data [97]. LDA has been used to classify motor imagery activities [137]. In Ref. [138] adaptive LDA employed for classification of MI activities. Feature extraction and classification from EEG recordings were achieved using the CSP and LDA, respectively [139]. LDA is a basic and robust approach that allows researchers to classify data without using any additional parameters. This approach assumes two classes have a normal distribution. The Bayes theorem employed to determine the probability of belonging to every class using variance and mean [140]. In Ref. [141] compares three distinct classifiers based on SVM, ANN, and LDA for recognizing the MI activities. The findings reveal that the three classifiers perform well in classification accuracy, with SVM 82.6%, ANN 81.9%, and LDA 88.6% respectively. LDA is a linear classifier with low computation requirements that can be extensively employed in BCI investigations [142]. The Fisher classifier's goal is to transform high-dimensional data into low-dimensional data. As a result, lowering dimensionality is the key to resolving accuracy issues in the BCI system.

4.3. Artificial neural network (ANN)

ANN was first suggested in 1943 and since 1980s, ANN has been a popular topic in context of artificial intelligence techniques [143]. It abstractly replicates human brain neuron network in terms of information processing, creates appropriate models, and creates multiple networks based on various connection techniques. ANN is mostly used to handle large amounts of data and solve regression and classification issues. It pertains to a category of machine learning approaches. It has seen extensive usage in various applications, including the classification of physiological signals [143]. An SFNN (single-layer feed-forward neural network) and an MFNN (multi-layered feed-forward neural network) are examples of forward neural networks (FNN) [144]. The input and output layers of the SFNN are directly connected. The recurrent neural network (RNN) includes an MFNN-based feedback loop. The input neurons get feedback from the output layer neurons. The fundamental unit of ANN is the neuron, which is made up of input variable, activation functions, input variable weights, output variables, and deviation values. Neural networks are formed by input, hidden, and output layers [145]. SVM produces good outcomes but can only handle up to two class problems successfully in mostly cases. ANN classifiers work better but take large computational time, so there is a trade-off between accuracy and speed. ANN can offer a suitable trade-off, so it has been widely employed in BCI investigations. Various NN designs are used in BCI, and however Gaussian classifier is the one that was built exclusively for the BCI system [146]. Other NN designs used for the classification of MI problems include, multilayer perceptron (MLP), radial basis function (RBF), and SFNN that employs an online meta-neuron-based learning algorithm (OMLA) [147]. ANN offers several benefits, including high fault tolerance, and higher recognition accuracy. However, many parameters are involved, learning period is lengthy, and process is difficult to watch, reducing outcomes' appropriateness.

4.4. K-nearest neighbor (k-NN)

The k-NN approach is an effective nonparametric approach for BCI applications [148] and is a robust method for large, noisy data. Euclidean distance was employed [149] to calculate distance between other samples and the target sample.

$$d(a,b) = \sqrt{\sum_i^k (a_i - b_i)^2} \tag{3}$$

Where $d(a,b)$ represents a distance between a and b samples, k denotes a number of features and a_i, b_i denotes *ith* sample's feature. It has been used in to classify MI signals [150]. For classification, the euclidean distance between neighboring signals was measured. Then, the majority class of the test signal was chosen from the group of K neighbors. The k-NN classification algorithms allow for the construction of a simple, reliable, and accurate MI-BCI system. The k-NN approach was used in Ref. [151] to classify MI activities. It has been widely utilized in pattern recognition because of a number of benefits, including high generality and simplicity of implementation [152]. The most common use of k-NN approaches for problems with a large number of features. As a result, the general d-dimensional scenario receives special attention [153]. In Ref. [154] three unique classifier algorithms, LDA, QDA, and k-NN, were proposed to identify left and right limb movement. The results show that k-NN performed best, with an accuracy of 84.29%.

4.5. Mahalanobis distance (MD)

MD is a direction-sensitive distance classifier that employ statistics for every class. It is identical to maximum likelihood classification but suppose each class covariances are equal and therefore is a faster technique. MD-based classifiers [155] employ a Gaussian distribution (C, M_C) M for every prototype of class C. Then, MD using the d_m, a feature vector x is given to the class that has prototype closest (x). EEG patterns can be recognized using MD-based classifier [156].

$$d_m(x) = \sqrt{(x-\mu_x)M_c{}^{-1}(x-\mu_x)^T} \tag{4}$$

This a simple and effective classifier used in multiclass BCI systems. A linear MD-based approach used as a classifier of EEG data in BCI system [157]. Despite the remarkable outcomes it has produced, it is only rarely addressed in the BCI system to classify motor imagery data.

4.6. Naive bayes classifier (NBC)

NBC is a standard classification approach that uses Bayes' theorem to split data based on trained features [158]. Essentially, the framework assigns labels to a finite number of feature vectors. The naive Bayes technique has the drawback of treating all feature vectors as separate from one another regardless of any true correlation. Its key benefit is that it just needs a minimal number of training data to start accurately predicting features required for classification. NBC based brain computer interface used identified motor activities from EEG dataset [159]. NBC assumes that data has a distinct normal distribution. Although this method has been implemented to classify motor imagery effectively, even then NBC is not commonly used in BCI applications [160].

4.7. Hidden Markov model (HMM)

HMM is a sequence classifier used in MI EEG classification. It is a probabilistic classifier that depends on the Markov chain rule that can calculate possibility of detecting a specific sequence of feature vectors [161]. It is possible to describe the chance of observing a specific feature vector for every state of the automaton. It can be used in the BCI system's signal processing, gesture recognition, and pattern recognition [162]. HMMs algorithms are ideal for classifying time series and need less sample for training. HMMs have been used in classifying temporal patterns of EEG in BCI applications [163]. HMMs are not extensively employed in the BCI field, but this study showed they could be helpful for MI EEG-based BCI systems.

4.8. Deep learning (DL)

Deep learning is an extension of artificial neural network (ANN), and a subset of machine learning (ML) [164]. The DL denotes ANN processing, analysis, and learning of various hidden layer neurons. DL core structure are based ANN, convolutional neural network (CNN), deep neural network (DNN) with numerous hidden layers [165]. DL is an important field of ML that has currently become a hot research topic for brain computer interface (BCI) system. DL has found widespread use in the investigation and processing of physiological data [166]. This is a great strategy for researchers who want to classify EEG for BCI system. DL has shown promising outcomes in computer vision, and it has recently been used for categorizing motor imagery problems [167]. In Ref. [168] suggested a new technique for the MI EEG signal classification. In Ref. [169] proposed technique uses multilayer multiscale pooling and fusing to extract EEG signal characteristics that can be readily integrated into CNNs. Based on BCI competition IV dataset, CNN designs with multilayer pyramid pooling strategy improve classification accuracy. DNN is used to develop an automated and robust method for categorizing MI EEG signals. CNN and hybrid CNN designs provide great performance compared to other architecture [170]. The [171] study suggests a deep transfer VGG-16 CNN framework for MI signal classification. The results of the experiments showed that proposed framework has greater classification accuracy than other approaches, such as CNN, SVM, and ANN. In Ref. [172] a novel CNN-based time-frequency representation of MI EEG patterns has been proposed that integrates the one-dimensional CNN structure with the CWT. The classification method for MI data uses a CNN architecture and introduces a novel temporal representation of data. DL has recently gained interest from investigators and has effectively applied to various classification issues such as signal, voice recognition, and video classification [173]. Bioinformatics techniques have also been positively affected by deep learning. In recent years, numerous researchers have addressed deep learning models in biomedical applications, for example, using deep neural network (DNN) to classify MI activities [174]. DL technique for EEG-based BCI systems has been presented [175]. The deep belief network (DBN) classifier has accomplished a new scheme for identifying EEG patterns for better results than the conventional method [176]. A novel approach for motor imagery in BCI using deep residual CNN has been studied and identified limb movement activities with the best accuracy [177]. An important yet unsolved issue is how deep learning concepts could be applied for EEG classification to obtain a significant result. This study addresses this issue by reviewing previous research on applications of DL in BCI, and it is concluded that DL approaches give better results only with the large dataset, which needs more training than ML approaches.

4.9. Findings for EEG classification techniques

There are various techniques for classifying extracted EEG signal features. Every approach has advantages and disadvantages; explicit method must consider precise condition. The commonly used algorithms for classifying the features of EEG signals include SVM, LDA, ANN, k-NN, MD, NBC, HMM, and deep learning. SVM is a classic classification method mostly used in BCI systems for classifying EEG signals. Despite its robustness, it needs to gain previous knowledge of the distribution's features. The k-NN classifier can achieve excellent accuracy rates with suitable 'k' value for specific feature set. In recent years, ANNs and deep learning have risen to the forefront of interest to researchers. Most of the time, large EEG data processing is where deep learning technique is put to work mostly. It has a dynamic design and a high accuracy rate. It can thus be used in several situations. However, the drawback is obvious. A lot of data is necessary for training, which takes more time than machine learning techniques. Additionally, the design of the network structure affects performance. Based on more than 220 research papers presented in this investigation and respective references of these papers, Fig. 7 shows an analysis in percentage for feature extraction and classification techniques in the EEG MI-BCI system. Table 6 lists advantages and drawbacks of different classification techniques. Tables 7 and 8 present a comparison of various MI-BCI applications using machine learning and deep learning techniques, respectively.

The systematic research on feature extraction, machine learning (ML), and deep learning (DL) classification methods for motor imagery-based BCI systems is presented in subsections 3.3.1 to 3.3.4 and sections 4.1 to 4.8, Table 6, and Table 7. The findings obtained in these sections

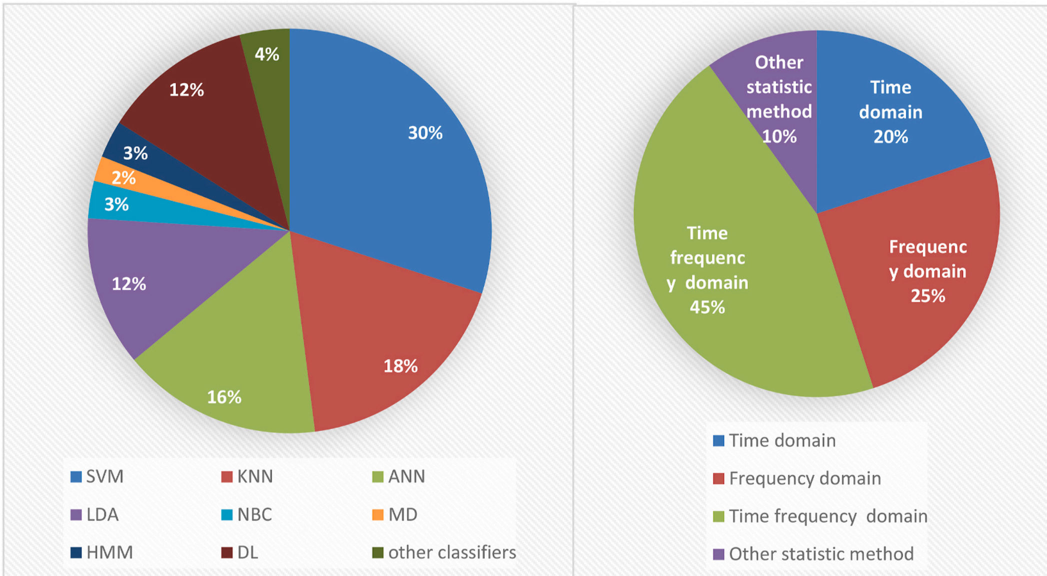

Fig. 7. Shows percentage-based feature extraction and classification methods in EEG MI-BCI systems.

Table 6
Advantages and disadvantages of the classification algorithm.

Classifiers	Type	Advantages	Disadvantages
SVM [178]	Linear classifiers	It is more effective, and faster with a smaller number of samples. It is used for regression analysis and classification and can handle nonlinear data.	Selecting the appropriate kernel function can be quite challenging to achieve optimal results, and the algorithmic complexity of SVM is high.
ANN [179]		ANN can handle more tasks at the same time. Its structure flexible and appropriate accuracy	Large neural networks require a lot of processing time.
LDA [180]		It reduces the number of features in the dataset to reduce variance.	It needs to assume that features have a normal distribution.
k-NN [181]	Nonlinear classifiers	Effortless, easy to learn, and time-saving.	Number of neighbors 'k' must be separately selected.
MD [182]		A common use of MD is in classification as well as clustering algorithms	In presence of noise performance decrease dramatically
NBC [183]		Probabilistic method used to non-linear problems and free of outlier bias.	Based on the premise that statistical significance of each characteristic is the same.
HMM [184]		HMM is built on a solid statistical basis and fast learning methods that can be applied to raw sequence data without sacrificing accuracy.	It is simply dependent on each state and its associated observed object.
DL [185]		Features are deduced automatically and tuned for the expected result.	It needs a huge quantity of data in order to dominate other approaches.

will also help the researchers in future investigations, and the next section presents the challenges for EEG-MI-BCI systems.

5. Challenges for EEG MI- BCI systems

A number of challenges have been found in establishing an appropriate BCI system with MI brain signal, which can be identified as usability and technically. EEG signal-to-noise ratios are very low, particularly in real-world environments. Numerous signal processing techniques have been implemented effectively for EEG-based MI-BCI systems and achieved good outcomes; still, a few unexplained problems and challenges fascinate the attention of investigators are presented in this study.

5.1. Usability challenges

They express drawbacks facing subject approval of BCI technology utilization. Mostly time, user desires system to be effortlessly approachable. They involve the problems associated with the training process required for the discrimination between classes.

5.2. Artifact removal

The brain's electrical activity is measured using an EEG, a crucial part of most BCI technologies. These captured EEG signals mostly suffer from distortion from abnormalities, including cardiac, muscle movement, and eye blink artifacts. Artifact removal process focuses on recognizing and eliminating particular these artifacts. Commonly, "independent component analysis" (ICA) is employed to eliminate artifacts. Temporal and spatial filters are also feasible choices for removing noise from EEG data. Reference channels are utilized for efficient artifact removal, although specific BCI applications do not make this choice practical. The requirement for a reference signal is used to eliminate certain artifacts. Consequently, it is challenging to identify an artifact removal technique that can be used practically while meeting all of the application's requirements. Advanced artifact elimination techniques for various artifact types are still necessary.

5.3. Training process

The training process performed by user is a lengthy task for brain-computer interface systems. It includes training users & guiding them through the BCI system and controlling EEG electrical signals. One of the primary research answers to this time consumption question is using single trials rather than multi-trial testing [175].

5.4. Non-linearity

The human brain is the best example of a non-linear mechanism that generates chaotic biological electrical EEG signals. Training & building

Table 7
Comparison of various EEG MI-BCI applications using machine learning techniques.

Publication year	Dataset	Aim of the research work/ Motor imagery activities	Feature extraction technique	Classification	Accuracy
2022 [186]	Dataset I -BCI Competition IV	Right - left hand, or foot	WPD	k-NN	92.86% (Modified binary grey wolf optimization)
2022 [187]	Dataset I -BCI Competition IV	Right - left hand, or foot	WPD	SVM k-NN	91.66% 90.33%
2022 [188]	Data set IIa -BCI competition IV	Right-left hand, tongue, foot	CSP	SVM	82.39%,
2021 [189]	Author Prepared	Right-left hand and right- left leg	WPD	Subtractive clustering - adaptive neural fuzzy inferences system	68%
2021 [190]	Author Prepared	Lower body limb	DWT	SVM	88.43%
2020 [191]	BNCI Horizon 2020	Right hand and feet	Statistical DWT	k-NN	92.49%
2020 [44]	Dataset I -BCI Competition III	Little-finger, left-hand and tongue	BLDA used for both		Best classification accuracy is 97%
2020 [192]	Dataset-3a -BCI competition-III	Right-left hand, feet and tongue	Hilbert transform	SVM	86.11%
	Dataset-2b -BCI competition-IV	Right -left hand, feet and tongue			82.50%
2020 [193]	Dataset 2a -BCI Competition- IV	Right hand and left hand	CSP	LDA SVM	79.19% 80.22%
2019 [194]	Dataset BCI 2003	Right left-hand movement	DWT	SVM k-NN	Maxi. = 86.4% Maxi. = 84.3%
2018 [195]	Author Prepared	Facial expression	WT	SVM	90.698%
2018 [8]	BCI Competition IV -Dataset I	Right - left hand, or foot	WPD	SVM	Subject 'a' = 86.5 ± 4.6 Subject 'b' = 81.4 ± 3.9
2017 [196]	Dataset IVa-BCI Competition III	Right-left hand, feet and tongue	CSP & LDA	SVM	91.68 ± 4.48%
2017 [197]	BCI Competition 2003	Right-left hand movement	WPD	k-NN	92.7 ± 3.90%
2017 [49]	Physionet Dataset record	Rest state, both feet, both fists movement	DWT	NBC ANN	86.31%, 93.05%
2016 [198]	Dataset 2b -BCI Competition- IV	Right-left hand, feet and tongue	CSP	SVM	90.57 ±5.23%
2016 [199]	BCI competition 2003 dataset III	MI activities	STFT	k-NN	83.57%
2015 [200]	BCI Competition 2003	Right-left hand	EMD	SVM	100%
2015 [201]	Author Prepared	Right-left hand, both hands and Rest,	CSP	LDA	51.67%
2015 [202]	Dataset IVa -BCI competition III	Left and Right hand	SFBCSP	SVM	91.05 ±2.45%
2014 [203]	Dataset III -BCI Competition II	Right- and left-hand	DWT	SVM k-NN Back propagation neural network (BPNN)	78.57% 72% 80%
2014 [204]	BCI Competition 2008 -dataset IIa	Left -right hand, foot, tongue	CSP	LDA, Quadratic discriminant analysis, SVM	Maxi. 78.82% (LDA)
2014 [205]	BCI Competition III	Right -left hand	WT	NN SVM	82.43% 85.54%
2014 [206]	Dataset Iva-BCI Competition III	Right hand -right foot movement.	DWT	Least-squares support-vector machines (LS-SVM)	99.4%
2013 [207]	Author Prepared	Left - right hand, feet	CSP	SVM	84%
2012 [208]	Author Prepared	Left, right and forward wheelchair movements	PSD	NN	Max. 85%
2012 [47]	BCI competition III	Left hand and right foot	WT	LDA SVM	Error Rate: 0.1286% Error Rate 0.2335%

worthwhile classifiers based on non-linear signals needs research work.

5.5. Information transfer rate (ITR)

ITR is common method for monitoring communication performance in control systems, particularly in BCI systems. It is broadly employed metric for evaluating commands for BCI applications. It relies on number of options, precision of target recognition, and time required to select a task. As a result, compared to MI BCI, selective attention techniques have a higher ITR because the options available are greater [176]. A greater ITR is the primary need for any brain-computer interface technology.

6. Suggested solutions for MI- EEG-BCI systems

6.1. Feature extraction

EEG signals are chaotic and frequently time-varying. It's also difficult to extract necessary information from EEG data in a reasonable amount of time Even though the CSP technique and its variations are frequently used in MI-BCI systems, spatial filters are needed to maximize the discriminability of the two classes. EEG signals in the time domain suffer the loss of spectral information [177]. So, feature extraction in time domain analysis not always provides the best results for non-stationary EEG signals [178]. FFT is only applicable to stationary signals. EEG signals are non-stationary, and the Fourier transform would not provide the optimum results. Therefore, for such non-stationary signals, a time–frequency representation is necessary to extract significant features for improved performance in BCI systems. Wavelet transform (WT) and its variants are among the best options for processing

Table 8
Comparison of various EEG-MI-BCI applications using Deep learning techniques.

Publication year	Dataset	Aim of the research work/ Motor imagery activities	Feature extraction technique	Classification technique	Accuracy
2022 [209]	BCI Competition IV-Dataset 2b	Right and left hand	Time frequency Representations	CNN	93.74%
2022 [210]	BCI Competition III-Dataset IVa	Right hand- right foot	Morlet wavelet	CNN ResNet	97.86%
2022 [211]	BNCI Horizon 2020	Right hand and feet	CSP	CNN	Improved
2021 [212]	Dataset 2a -BCI Competition IV	Right-left hand, tongue and feet	Spatio-spectral feature representation	CNN	87.15%
	Dataset 2b -BCI competition IV	Left-right hand			75.85%
	Open BMI Data	Left-right hand			70.37%
2021 [213]	BCI Competition IV -Dataset 2a	Right-left hand, tongue and feet	DWT	Temporary constrained sparse group lasso (TCSGL)- EEGNet	78:96%
2020 [214]	BCI Competition VI - 2a	Left-right-hand, tongue and both feet	Time frequency representations	CNN	81.04%
2020 [215]	BCI Competition 2003-III Dataset	Left, and right-hand	CWT	Vgg19 Alexnet	95.71% 92.86%
2019 [216]	Dataset 2b- BCI Competition IV	Right -left hand movement	STFT	VGG-16	71.4%
2018 [217]	BCI III Competition	Right-left hand, tongue and right foot	WT	CNN	86.20%
2018 [217]	BCI Competition III	Left hand & right foot	CNN and DWT	CNN and LSTM	87.36%
2018 [218]	BCI Competition IV-2a	Right-left hand, both feet and tongue	Time frequency representations	CNN	74.46%
2018 [219]	BCI Competition IV-2a	Right-left hand, both feet and tongue	CWT	CNN	85.59%
2018 [220]	Author Prepared	Left hand and right foot imagery	CWT	CNN	86.20%
2018 [221]	Dataset 2b -BCI Competition-	Right and hand Left	CWT	CNN	Max. 78.93%
2018 [222]	Dataset2a- BCI Competition IV	Left-right hand, Tongue and feet	RCNN	RCNN	45%
2017 [223]	BCI Competition IV dataset 2a	Left-right hand, Tongue and feet	FBCSP	CNN	84%
2016 [224]	BCI Competition IV-2b data set	left and right hand	FFT and WPD	FDBN	84%
2015 [225]	Dataset 2a- BCI Competition IV	Left- right hand, tongue and both feet	CSP	CNN	Maxi. 69.27%
2015 [226]	Dataset 2a- BCI Competition IV	Left-right hand, Tongue and feet	FBCSP	CNN	70.60%
2014 [227]	Dataset III – BCI Competition II	Right- left hand	CSP	Convolutional deep belief net (CDBN)	88.25 ± 5.70%
2013 [228]	Deep data set	emotion analysis	DBN	DBN	Outperforms 5 baselines (11.5%–24.4%.)

EEG data types. WT is mostly used in EEG-BCI because it offers optimistic results for chaotic and non-stationary biological signals. Recently, the WPT feature extraction method has been widely used in EEG-BCI applications to conquer drawback of subject-specific frequency band.

6.2. *Separability of multiple classes*

Artificial intelligence approaches turn the user's intention into commands and discriminate the specific class. They often eliminate some drawbacks associated with limited training sets and even flexibility between sessions and individual sessions. They also try to attain the best possible results and accuracy. Next, demonstrate three techniques of ML, such as SVM, k-NN and ANN.

6.2.1. *Support vector machine (SVM)*

SVM is a benchmark ML method that falls into the classification process category that separates two distinct types of classes. These approaches choose the hyperplane that maximizes margin from closed training data points. This ideal hyperplane is well-defined by vectors on the margin known as support vectors. It has numerous advantages. SVM is considered to have sufficient generalization properties, to be indifferent to overtraining and "curse-of-dimensionality." SVM demonstrates classy outcomes in both ERS/ERD for EEG-based MI BCIs.

6.2.2. *k-Nearest neighbors (k-NN)*

The k-NN is a decent example of an unsupervised learning algorithm. In this method, the vector feature of any data is allocated to the closest class of k neighbors, and the key strength of k-NN algorithms is flexibility. However, their sensitivity to curse-of-dimensionality is a crucial disadvantage affecting their performance of BCI applications. However, it can produce respectable performance with efficient feature extraction algorithms for the BCI system.

6.2.3. *Artificial neural networks (ANNs)*

ANNs are a subset of machine-learning algorithms that mimics the human brain. ANNs are an enhanced approach used in various MI BCI applications for classification. It was observed that ANN produced more accurate classification results than competing approaches [179]. ANN and its variants can be used to identify motor imagery activities for BCI applications.

6.3. *Clinical applications of EEG MI-BCI systems*

Non-invasive EEG-based BCI is the youngest technology used to monitor brain activity, and various brain signals are converted into instructions that control artificial devices for paralyzed or disabled patients. BCI technology can be used in various simple to complex applications. Most BCI devices (such as BCI wheelchairs and BCI browsers) were previously built for healthy individuals. It must be extended to unhealthy patients and is worth expanding to clinical applications. Nowadays, many BCIs have been employed in clinical uses, including the rehabilitation and treatment of hemiplegic patients. During the construction of EEG-based MI BCI systems, distinctions between healthy people and disabled persons must be adequately recognized. In certain circumstances, just one patient design is used. The use of the BCI system for disabled people in wheelchairs has just recently started. BCI-based communication and rehabilitation will be a significant area of study in the future. BCI should be coupled with several advanced technologies, including intelligent robotics and autonomous navigation systems. This combination minimizes the user's burden and improves the BCI system's reliability flexibility, enabling the subject to concentrate on the objective while ignoring the low-level issues connected with action execution. This is encouraging for people who have limited recognition and control skills. As a result, future investigations should target such needful patients.

7. Conclusion

This study demonstrates a straightforward interpretation of each strategy i.e., EEG non-invasive signal acquisition, pre-processing, feature extraction, and classification of motor imagery in BCI systems. Presently WT, EMD, and CSP offer relevant results for feature extraction for classifying EEG signals. WPT is an updated version of WT that provides the optimal results that can enhance the classification accuracy for the MI-EEG-BCI system. WPD coefficients analysis provides better results in classifying non-stationary and time-varying MI-EEG signals. The authors examine machine learning and deep learning approaches for identifying EEG paradigm, such as motor imagery. For BCI systems, LDA is a suitable classifier, especially for limited training data sets. Three benchmark machine learning classifiers, SVM, k-NN, and ANN mostly used for MI-BCI systems. DL mostly uses convolutional neural networks (CNNs) to classify MI signals in BCI systems. In this work, authors review more than 220 research papers that apply ML and DL to EEG and spanning brain-computer interfacing and cognitive monitoring applications. ML and DL techniques used by investigators presented in tabulated form for MI-BCI applications offer additional knowledge to improve future EEG-MI-BCI applications. In recent investigations, various DL methods have been used as a classification approach for motor imagery activities and provided optimal accuracy than conventional classification methods and it delivers the best results with a large data set. There is a pressing demand for ML techniques that can be trained in a shorter time with less training data and without compromising classification accuracy. In addition, robust classifiers ought to be developed for EEG data which is chaotic and large dimensional data. There is a requirement to create new classification strategies that can take input from the subject and help improve the effectiveness and reliability of BCI applications. Despite the numerous remarkable advancements in BCI research, several issues still need to be solved. Nowadays, EEG-MI-BCI systems have low ITR for practical applications. It will be necessary to enhance the ITR for BCI systems in the future research. Additionally, significant work should be done to minimize training period so that BCIs can be applied in real-world situations for better results. The authors believe this review paper will help the brain-computer interface community in future research.

CRediT authorship contribution statement

Pawan: Conceptualization, Methodology, Software, Data curation, Writing – original draft, Visualization, Investigation. **Rohtash Dhiman:** Supervision, Software, Validation, Writing – review & editing, approval of the updated version of the manuscript to be published.

Declaration of competing interest

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

Data availability

This study uses freely available BCI Competition IV-dataset I for this research work

References

[1] S.R. Sreeja, et al., Motor imagery EEG signal processing and classification using machine learning approach, in: Proceedings - 2017 International Conference on New Trends in Computing Sciences, ICTCS 2017 2018-Janua, 2017, pp. 61–66, https://doi.org/10.1109/ICTCS.2017.15.

[2] A. Palumbo, V. Gramigna, B. Calabrese, N. Ielpo, Motor-imagery EEG-based BCIs in wheelchair movement and control: a systematic literature review, Sensors 21 (18) (2021) 1–29, https://doi.org/10.3390/s21186285.

[3] A. Bonci, S. Fiori, H. Higashi, T. Tanaka, F. Verdini, Electronics An Introductory Tutorial on Brain-Computer Interfaces and Their Applications, 2021, https://doi.org/10.3390/electronics.

[4] C.H. Han, K.R. Müller, H.J. Hwang, Brain-switches for asynchronous brain–computer interfaces: a systematic review, Electronics (Switzerland) 9 (3) (2020), https://doi.org/10.3390/electronics9030422. MDPI AG.

[5] R. Portillo-Lara, B. Tahirbegi, C.A.R. Chapman, J.A. Goding, R.A. Green, Mind the gap: state-of-the-art technologies and applications for EEG-based brain-computer interfaces, APL Bioeng. 5 (3) (2021), https://doi.org/10.1063/5.0047237. American Institute of Physics Inc.

[6] B. He, B. Baxter, B.J. Edelman, C.C. Cline, W.W. Ye, Noninvasive brain-computer interfaces based on sensorimotor rhythms, Proc. IEEE 103 (6) (2015) 907–925, https://doi.org/10.1109/JPROC.2015.2407272.

[7] K. Wang, F. Tian, M. Xu, S. Zhang, L. Xu, D. Ming, Resting-state EEG in alpha rhythm may Be indicative of the performance of motor imagery-based brain–computer interface, Entropy 24 (11) (2022), https://doi.org/10.3390/e24111556.

[8] R. Dhiman, Priyanka, J.S. Saini, Motor imagery classification from human EEG signatures, Int. J. Biomed. Eng. Technol. 26 (1) (2018) 101–110, https://doi.org/10.1504/IJBET.2018.089265.

[9] P.E. Roland, B. Larsen, N.A. Lassen, E. Skinhoj, Supplementary motor area and other cortical areas in organization of voluntary movements in man, J. Neurophysiol. 43 (1) (1980) 118–136, https://doi.org/10.1152/jn.1980.43.1.118.

[10] S.B. Lee, H.J. Kim, H. Kim, J.H. Jeong, S.W. Lee, D.J. Kim, Comparative analysis of features extracted from EEG spatial, spectral and temporal domains for binary and multiclass motor imagery classification, Inf. Sci. 502 (Oct. 2019) 190–200, https://doi.org/10.1016/j.ins.2019.06.008.

[11] M.H. Aslam, et al., Classification of EEG signals for prediction of epileptic seizures, Appl. Sci. 12 (14) (2022), https://doi.org/10.3390/app12147251.

[12] B. Xu, et al., Wavelet transform time-frequency image and convolutional network-based motor imagery EEG classification, IEEE Access 7 (2019) 6084–6093, https://doi.org/10.1109/ACCESS.2018.2889093. Mi.

[13] S. Sun, J. Zhou, A review of adaptive feature extraction and classification methods for EEG-based brain-computer interfaces, in: Proceedings of the International Joint Conference on Neural Networks, 2014, pp. 1746–1753, https://doi.org/10.1109/IJCNN.2014.6889525.

[14] E.H. Houssein, A. Hammad, A.A. Ali, Human emotion recognition from EEG-based brain–computer interface using machine learning: a comprehensive review, Neural Comput. Appl. 34 (15) (2022) 12527–12557, https://doi.org/10.1007/s00521-022-07292-4. Springer Science and Business Media Deutschland GmbH.

[15] X. Gu, et al., EEG-based brain-computer interfaces (BCIs): a survey of recent studies on signal sensing technologies and computational intelligence approaches and their applications, IEEE ACM Trans. Comput. Biol. Bioinf 18 (5) (2021) 1645–1666, https://doi.org/10.1109/TCBB.2021.3052811.

[16] M. Ahn, S.C. Jun, H.G. Yeom, H. Cho, Editorial: deep learning in brain-computer interface, Front. Hum. Neurosci. 16 (2022), https://doi.org/10.3389/fnhum.2022.927567. Frontiers Media S.A.

[17] R.D. Fields, The first annual meeting of the society for neuroscience, 1971: reflections approaching the 50th anniversary of the society's formation, J. Neurosci. 38 (44) (2018) 9311–9317, https://doi.org/10.1523/JNEUROSCI.3598-17.2018.

[18] N. Kosmyna, A. Lécuyer, A conceptual space for EEG-based brain-computer interfaces, PLoS One 14 (1) (2019), https://doi.org/10.1371/journal.pone.0210145.

[19] K. Sowndhararajan, M. Kim, P. Deepa, S.J. Park, S. Kim, Application of the p300 event-related potential in the diagnosis of epilepsy disorder: a review, Sci. Pharm. 86 (2) (2018), https://doi.org/10.3390/scipharm86020010. MDPI AG.

[20] N. Siribunyaphat, Y. Punsawad, Steady-state visual evoked potential-based brain–computer interface using a novel visual stimulus with quick response (QR) code pattern, Sensors 22 (4) (2022), https://doi.org/10.3390/s22041439.

[21] A. Moran, H. O'Shea, Motor imagery practice and cognitive processes, Front. Psychol. 11 (2020), https://doi.org/10.3389/fpsyg.2020.00394.
[22] M.H. Bhatti, et al., Soft computing-based EEG classification by optimal feature selection and neural networks, IEEE Trans. Ind. Inf. 15 (10) (2019) 5747–5754, https://doi.org/10.1109/TII.2019.2925624.
[23] S. K. Pahuja Pooja, K. Veer, Recent approaches on classification and feature extraction of EEG signal: a review, Robotica 40 (1) (2022) 77–101, https://doi.org/10.1017/S0263574721000382. Cambridge University Press.
[24] J. Wang, M. Wang, Review of the emotional feature extraction and classification using EEG signals, Cognitive Robotics 1 (2021) 29–40, https://doi.org/10.1016/j.cogr.2021.04.001. KeAi Communications Co.
[25] F. Wang, et al., Improved brain–computer interface signal recognition algorithm based on few-channel motor imagery, Front. Hum. Neurosci. 16 (2022), https://doi.org/10.3389/fnhum.2022.880304.
[26] X. Jiao, K. Ding, G. He, An algorithm for improving the coefficient accuracy of wavelet packet analysis, Measurement 47 (1) (2014) 207–220, https://doi.org/10.1016/j.measurement.2013.08.049.
[27] K. Vărbu, N. Muhammad, Y. Muhammad, Past, present, and future of EEG-based BCI applications, Sensors 22 (9) (2022), https://doi.org/10.3390/s22093331. MDPI.
[28] C.D. Virgilio G, J.H. Sossa A, J.M. Antelis, L.E. Falcón, Spiking Neural Networks applied to the classification of motor tasks in EEG signals, Neural Network. 122 (2020) 130–143, https://doi.org/10.1016/j.neunet.2019.09.037.
[29] J. Jiang, C. Wang, J. Wu, W. Qin, M. Xu, E. Yin, Temporal combination pattern optimization based on feature selection method for motor imagery BCIs, Front. Hum. Neurosci. 14 (2020), https://doi.org/10.3389/fnhum.2020.00231.
[30] M.Z. Baig, N. Aslam, H.P.H. Shum, L. Zhang, Differential evolution algorithm as a tool for optimal feature subset selection in motor imagery EEG, Expert Syst. Appl. 90 (2017) 184–195, https://doi.org/10.1016/j.eswa.2017.07.033.
[31] K. Belwafi, S. Gannouni, H. Aboalsamh, H. Mathkour, A. Belghith, A dynamic and self-adaptive classification algorithm for motor imagery EEG signals, J. Neurosci. Methods 327 (2019), https://doi.org/10.1016/j.jneumeth.2019.108346.
[32] A. Subasi, S. Mian Qaisar, The ensemble machine learning-based classification of motor imagery tasks in brain-computer interface, J Healthc Eng 2021 (2021), https://doi.org/10.1155/2021/1970769.
[33] N. Ji, L. Ma, H. Dong, X. Zhang, EEG signals feature extraction based on DWT and EMD combined with approximate entropy, Brain Sci. 9 (8) (2019), https://doi.org/10.3390/brainsci9080201.
[34] G. Rodŕiguez-Beŕmudez, P.J. Gárcia-Laencina, Automatic and adaptive classification of electroencephalographic signals for brain computer interfaces, J. Med. Syst. 36 (SUPPL.1) (2012), https://doi.org/10.1007/s10916-012-9893-4.
[35] X. Zhang, et al., The combination of brain-computer interfaces and artificial intelligence: applications and challenges, Ann. Transl. Med. 8 (11) (2020) 712, https://doi.org/10.21037/atm.2019.11.109, 712.
[36] X. Lun, Z. Yu, T. Chen, F. Wang, Y. Hou, A simplified CNN classification method for MI-EEG via the electrode pairs signals, Front. Hum. Neurosci. 14 (2020), https://doi.org/10.3389/fnhum.2020.00338.
[37] M.J. Antony, et al., Classification of EEG using adaptive SVM classifier with CSP and online recursive independent component analysis, Sensors 22 (19) (2022), https://doi.org/10.3390/s22197596.
[38] N. Naseer, N.K. Qureshi, F.M. Noori, K.S. Hong, Analysis of different classification techniques for two-class functional near-infrared spectroscopy-based brain-computer interface, Comput. Intell. Neurosci. 2016 (2016), https://doi.org/10.1155/2016/5480760.
[39] P. Khan, et al., Machine learning and deep learning approaches for brain disease diagnosis: principles and recent advances, IEEE Access 9 (2021) 37622–37655, https://doi.org/10.1109/ACCESS.2021.3062484.
[40] N. Ji, L. Ma, H. Dong, X. Zhang, EEG signals feature extraction based on DWT and EMD combined with approximate entropy, Brain Sci. 9 (8) (2019), https://doi.org/10.3390/brainsci9080201.
[41] O. Aydemir, T. Kayikcioglu, Decision tree structure based classification of EEG signals recorded during two dimensional cursor movement imagery, J. Neurosci. Methods 229 (2014) 68–75, https://doi.org/10.1016/j.jneumeth.2014.04.007.
[42] X. Yu, P. Chum, K.B. Sim, Analysis the effect of PCA for feature reduction in non-stationary EEG based motor imagery of BCI system, Optik 125 (3) (2014) 1498–1502, https://doi.org/10.1016/j.ijleo.2013.09.013.
[43] M.Z. Baig, N. Aslam, H.P.H. Shum, L. Zhang, Differential evolution algorithm as a tool for optimal feature subset selection in motor imagery EEG, Expert Syst. Appl. 90 (2017) 184–195, https://doi.org/10.1016/j.eswa.2017.07.033.
[44] Y. Qi, F. Ding, F. Xu, J. Yang, Channel and Feature Selection for a Motor Imagery-Based BCI System Using Multilevel Particle Swarm Optimization, 2020, 2020.
[45] R. Ghosh, N. Sinha, S.K. Biswas, S. Phadikar, A modified grey wolf optimization based feature selection method from EEG for silent speech classification, J. Inf. Optim. Sci. 40 (8) (2019) 1639–1652, https://doi.org/10.1080/02522667.2019.1703262.
[46] H. Chang, J. Yang, Genetic-based feature selection for efficient motion imaging of a brain-computer interface framework, J. Neural. Eng. 15 (5) (2018), https://doi.org/10.1088/1741-2552/aad567.
[47] O. Carrera-León, J.M. Ramirez, V. Alarcon-Aquino, M. Baker, D. D'Croz-Baron, P. Gomez-Gil, A Motor Imagery BCI Experiment Using Wavelet Analysis and Spatial Patterns Feature Extraction," *2012 Workshop On Engineering Applications*, WEA 2012, 2012, pp. 18–20, https://doi.org/10.1109/WEA.2012.6220084.
[48] E. Mohamed, Enhancing EEG signals in brain computer interface using wavelet transform, Int. J. Inform. Electronics Eng. 4 (3) (2014), https://doi.org/10.7763/ijiee.2014.v4.440.
[49] G.S. Sagee, S. Hema, EEG feature extraction and classification in multiclass multiuser motor imagery brain computer interface u sing Bayesian Network and ANN, in: 2017 International Conference on Intelligent Computing, Instrumentation and Control Technologies, ICICICT 2017 2018-Janua, 2018, pp. 938–943, https://doi.org/10.1109/ICICICT1.2017.8342691.
[50] X. Ma, D. Wang, D. Liu, J. Yang, DWT and CNN based multi-class motor imagery electroencephalographic signal recognition, J. Neural. Eng. 17 (1) (2020), https://doi.org/10.1088/1741-2552/ab6f15.
[51] J. Yang, S. Yao, J. Wang, Deep fusion feature learning network for MI-EEG classification, IEEE Access 6 (2018) 79050–79059, https://doi.org/10.1109/ACCESS.2018.2877452.
[52] J.J. Shih, D.J. Krusienski, J.R. Wolpaw, Brain-computer interfaces in medicine, Mayo Clin. Proc. 87 (3) (2012) 268–279, https://doi.org/10.1016/j.mayocp.2011.12.008. Elsevier Ltd.
[53] R. Dhiman, J.S. Saini, Priyanka, Genetic algorithms tuned expert model for detection of epileptic seizures from EEG signatures, Appl. Soft Computing J. 19 (2014) 8–17, https://doi.org/10.1016/j.asoc.2014.01.029.
[54] S. Waldert, Invasive vs. non-invasive neuronal signals for brain-machine interfaces: will one prevail? Front. Neurosci. 10 (2016) https://doi.org/10.3389/fnins.2016.00295. JUN. Frontiers Research Foundation.
[55] S.C. Williams, et al., Neurosurgical team acceptability of brain–computer interfaces: a two-stage international cross-sectional survey, World Neurosurg 164 (2022) e884–e898, https://doi.org/10.1016/j.wneu.2022.05.062.
[56] P.M.R. Reis, M. Lochmann, Using a motion capture system for spatial localization of EEG electrodes, Front. Neurosci. 9 (2015), https://doi.org/10.3389/fnins.2015.00130.
[57] C.M. Michel, D. Brunet, EEG source imaging: a practical review of the analysis steps, Front. Neurol. 10 (2019), https://doi.org/10.3389/fneur.2019.00325.
[58] P. Fiedler, C. Fonseca, E. Supriyanto, F. Zanow, J. Haueisen, A high-density 256-channel cap for dry electroencephalography, Hum. Brain Mapp. 43 (4) (2022) 1295–1308, https://doi.org/10.1002/hbm.25721.
[59] T.L. Rich, B.T. Gillick, Electrode placement in transcranial direct current stimulation—how reliable is the determination of C3/C4? Brain Sci. 9 (3) (2019) https://doi.org/10.3390/brainsci9030069.
[60] S.N. Abdulkader, A. Atia, M.S.M. Mostafa, Brain computer interfacing: applications and challenges, Egyptian Inform. J. 16 (2) (2015) 213–230, https://doi.org/10.1016/j.eij.2015.06.002. Elsevier B.V.
[61] R. Bhavsar, Y. Sun, N. Helian, N. Davey, D. Mayor, T. Steffert, The correlation between EEG signals as measured in different positions on scalp varying with distance, Procedia Comput. Sci. 123 (2018) 92–97, https://doi.org/10.1016/j.procs.2018.01.015.
[62] A. Suarez-Perez, et al., Quantification of signal-to-noise ratio in cerebral cortex recordings using flexible MEAs with co-localized platinum black, carbon nanotubes, and gold electrodes, Front. Neurosci. 12 (NOV) (2018), https://doi.org/10.3389/fnins.2018.00862.
[63] I.G. Campbell, "EEG Recording and Analysis for Sleep Research," Current Protocols in Neuroscience, Blackwell Publishing Inc., 2009, https://doi.org/10.1002/0471142301.ns1002s49 no. SUPPL.49.
[64] S. Leske, S.S. Dalal, Reducing power line noise in EEG and MEG data via spectrum interpolation, Neuroimage 189 (2019) 763–776, https://doi.org/10.1016/j.neuroimage.2019.01.026.
[65] M.A. Hassan, E.A. Mahmoud, A comparison between windowing FIR filters for extracting the EEG components, J. Biosens. Bioelectron. 6 (4) (2015), https://doi.org/10.4172/2155-6210.1000191.
[66] E.P. Torres P, E.A. Torres, M. Hernández-Álvarez, S.G. Yoo, EEG-based BCI emotion recognition: a survey, Sensors 20 (18) (2020) 1–36, https://doi.org/10.3390/s20185083.
[67] M. Orban, M. Elsamanty, K. Guo, S. Zhang, H. Yang, A review of brain activity and EEG-based brain–computer interfaces for rehabilitation application, Bioengineering 9 (12) (2022), https://doi.org/10.3390/bioengineering9120768. MDPI.
[68] S.H.F. Syam, H. Lakany, R.B. Ahmad, B.A. Conway, Comparing common average referencing to laplacian referencing in detecting imagination and intention of movement for brain computer interface, in: MATEC Web of Conferences 140, 2017, https://doi.org/10.1051/matecconf/201714001028.
[69] X. Wu, B. Zhou, Z. Lv, C. Zhang, To explore the potentials of independent component analysis in brain-computer interface of motor imagery, IEEE J Biomed Health Inform 24 (3) (2020) 775–787, https://doi.org/10.1109/JBHI.2019.2922976.
[70] C.E. Tenke, J. Kayser, Surface Laplacians (SL) and phase properties of EEG rhythms : simulated generators in a volume-conduction model, Int. J. Psychophysiol. (2015), https://doi.org/10.1016/j.ijpsycho.2015.05.008.
[71] S.S. Lekshmi, V. Se, M.P. Rajasekaran, EEG Signal Classification Using Principal Component Analysis and Wavelet Transform with Neural Network," No. C, 2014, pp. 687–690.
[72] J.B. Nitschke, G.A. Miller, E.W. Cook, Digital filtering in EEG/ERP analysis: some technical and empirical comparisons, Behav. Res. Methods Instrum. Comput. 30 (1998) 54–67, https://doi.org/10.3758/BF03209416.
[73] K.P. Thomas, C. Guan, L.C. Tong, V.A. Prasad, An Adaptive Filter Bank for Motor Imagery Based Brain Computer Interface, 2008, pp. 1104–1107.
[74] V.P. Oikonomou, K. Georgiadis, G. Liaros, S. Nikolopoulos, I. Kompatsiaris, A comparison study on EEG signal processing techniques using motor imagery EEG data, Proc IEEE Symp Comput Based Med Syst (1) (2017) 781–786, https://doi.org/10.1109/CBMS.2017.113, 2017.

[75] N.S. Bastos, D.F. Adamatti, C.Z. Billa, Discovering patterns in brain signals using decision trees, Comput. Intell. Neurosci. 2016 (2016), https://doi.org/10.1155/2016/6391807.

[76] A.S. Al-Fahoum, A.A. Al-Fraihat, Methods of EEG signal features extraction using linear analysis in frequency and time-frequency domains, ISRN Neurosci 2014 (2014) 1–7, https://doi.org/10.1155/2014/730218.

[77] R. Boostani, M.H. Moradi, A new approach in the BCI research based on fractal dimension as feature and Adaboost as classifier, J. Neural. Eng. 1 (4) (2004) 212–217, https://doi.org/10.1088/1741-2560/1/4/004.

[78] S. K. Pahuja Pooja, K. Veer, Recent approaches on classification and feature extraction of EEG signal: a review, Robotica 40 (1) (2022) 77–101, https://doi.org/10.1017/S0263574721000382. Cambridge University Press.

[79] V.v. Moca, H. Bârzan, A. Nagy-Dăbâcan, R.C. Mureşan, Time-frequency super-resolution with superlets, Nat. Commun. 12 (1) (2021), https://doi.org/10.1038/s41467-020-20539-9.

[80] I. Stancin, M. Cifrek, A. Jovic, A review of eeg signal features and their application in driver drowsiness detection systems, Sensors 21 (11) (2021), https://doi.org/10.3390/s21113786. MDPI AG.

[81] M.Á. Luján, M.V. Jimeno, J.M. Sotos, J.J. Ricarte, A.L. Borja, A survey on eeg signal processing techniques and machine learning: applications to the neurofeedback of autobiographical memory deficits in schizophrenia, Electronics (Switzerland) 10 (23) (2021), https://doi.org/10.3390/electronics10233037. MDPI.

[82] D. Ma, J. Zheng, L. Peng, Performance evaluation of epileptic seizure prediction using time, frequency, and time–frequency domain measures, Processes 9 (4) (2021), https://doi.org/10.3390/pr9040682.

[83] C. Vidaurre, N. Krämer, B. Blankertz, A. Schlögl, Time domain parameters as a feature for EEG-based brain-computer interfaces, Neural Network. 22 (9) (2009) 1313–1319, https://doi.org/10.1016/j.neunet.2009.07.020.

[84] A. Atyabi, F. Shic, A. Naples, Mixture of autoregressive modeling orders and its implication on single trial EEG classification, Expert Syst. Appl. 65 (2016) 164–180, https://doi.org/10.1016/j.eswa.2016.08.044.

[85] H.R. al Ghayab, Y. Li, S. Siuly, S. Abdulla, A feature extraction technique based on tunable Q-factor wavelet transform for brain signal classification, J. Neurosci. Methods 312 (2019) 43–52, https://doi.org/10.1016/j.jneumeth.2018.11.014.

[86] A. Singh, A.A. Hussain, S. Lal, H.W. Guesgen, A comprehensive review on critical issues and possible solutions of motor imagery based electroencephalography brain-computer interface, Sensors 21 (6) (2021) 1–35, https://doi.org/10.3390/s21062173. MDPI AG.

[87] O. Dressler, G. Schneider, G. Stockmanns, E.F. Kochs, Awareness and the EEG power spectrum: analysis of frequencies, Br. J. Anaesth. 93 (6) (2004) 806–809, https://doi.org/10.1093/bja/aeh270.

[88] U.R. Acharya, S. Vinitha Sree, G. Swapna, R.J. Martis, J.S. Suri, Automated EEG analysis of epilepsy: a review, Knowl. Base Syst. 45 (2013) 147–165, https://doi.org/10.1016/j.knosys.2013.02.014.

[89] R.U. Alam, H. Zhao, A. Goodwin, O. Kavehei, A. McEwan, Differences in power spectral densities and phase quantities due to processing of eeg signals, Sensors 20 (21) (2020) 1–20, https://doi.org/10.3390/s20216285.

[90] Q. Xiong, X. Zhang, W.F. Wang, Y. Gu, A parallel algorithm framework for feature extraction of EEG signals on MPI, Comput. Math. Methods Med. 2020 (2020), https://doi.org/10.1155/2020/9812019.

[91] Ş. Mustafa, T. Mahmut, M. Hakan, Examining EEG Signals with Spectral Analyses Methods in Migrain Patients during Pregnancy, 2013.

[92] A.P. Liavas, G. v Moustakides, G. Henning, E.Z. Psarakis, P. Husar, A Periodogram-Based Method for the Detection of Steady-State Visually Evoked Potentials, 1998.

[93] P. Herman, G. Prasad, T.M. McGinnity, D. Coyle, Comparative analysis of spectral approaches to feature extraction for EEG-based motor imagery classification, IEEE Trans. Neural Syst. Rehabil. Eng. 16 (4) (2008) 317–326, https://doi.org/10.1109/TNSRE.2008.926694.

[94] M. Taherisadr, O. Dehzangi, H. Parsaei, Single channel EEG artifact identification using two-dimensional multi-resolution analysis, Sensors 17 (12) (2017), https://doi.org/10.3390/s17122895.

[95] D.P. Allen, C.D. MacKinnon, Time-frequency analysis of movement-related spectral power in EEG during repetitive movements: a comparison of methods, J. Neurosci. Methods 186 (1) (2010) 107–115, https://doi.org/10.1016/j.jneumeth.2009.10.022.

[96] C. Chen, X. Chu, Two-dimensional Morlet wavelet transform and its application to wave recognition methodology of automatically extracting two-dimensional wave packets from lidar observations in Antarctica, J. Atmos. Sol. Terr. Phys. 162 (2017) 28–47, https://doi.org/10.1016/j.jastp.2016.10.016.

[97] A. Bhattacharyya, R.B. Pachori, A. Upadhyay, U.R. Acharya, Tunable-Q wavelet transform based multiscale entropy measure for automated classification of epileptic EEG signals, Appl. Sci. 7 (4) (2017), https://doi.org/10.3390/app7040385.

[98] Y. Zhang, Z. Guo, W. Wang, S. He, T. Lee, M. Loew, A comparison of the wavelet and short-time fourier transforms for Doppler spectral analysis, Med. Eng. Phys. 25 (7) (2003) 547–557, https://doi.org/10.1016/S1350-4533(03)00052-3.

[99] L.P.A. Arts, E.L. van den Broek, The fast continuous wavelet transformation (fCWT) for real-time, high-quality, noise-resistant time–frequency analysis, Nat Comput Sci 2 (1) (2022) 47–58, https://doi.org/10.1038/s43588-021-00183-z.

[100] W. Ting, Y. Guo-zheng, Y. Bang-hua, S. Hong, EEG feature extraction based on wavelet packet decomposition for brain computer interface, Measurement 41 (6) (2008) 618–625, https://doi.org/10.1016/j.measurement.2007.07.007.

[101] B.H. Yang, G.Z. Yan, R.G. Yan, T. Wu, Feature extraction for EEG-based brain-computer interfaces by wavelet packet best basis decomposition, J. Neural. Eng. 3 (4) (2006), https://doi.org/10.1088/1741-2560/3/4/001.

[102] M. Rhif, A. ben Abbes, I.R. Farah, B. Martínez, Y. Sang, Wavelet transform application for/in non-stationary time-series analysis: a review, Appl. Sci. 9 (7) (2019), https://doi.org/10.3390/app9071345. MDPI AG.

[103] M. Tangermann, et al., "Review of the BCI Competition IV," Frontiers in Neuroscience, 2012, https://doi.org/10.3389/fnins.2012.00055.

[104] C. Park, D. Looney, P. Kidmose, M. Ungstrup, D.P. Mandic, Time-frequency analysis of EEG asymmetry using bivariate empirical mode decomposition, IEEE Trans. Neural Syst. Rehabil. Eng. 19 (4) (2011) 366–373, https://doi.org/10.1109/TNSRE.2011.2116805.

[105] A. Kawala-Sterniuk, et al., "brain Sciences Summary of over Fifty Years with Brain-Computer Interfaces-A Review,", 2021, https://doi.org/10.3390/brainsci.

[106] S. Sadeghi, A. Maleki, The empirical mode decomposition-decision tree method to recognize the steady-state visual evoked potentials with wide frequency range, J. Med. Signals Sens. 8 (4) (2018) 225–230, https://doi.org/10.4103/jmss.JMSS_20_18.

[107] X. Tang, W. Li, X. Li, W. Ma, X. Dang, Motor imagery EEG recognition based on conditional optimization empirical mode decomposition and multi-scale convolutional neural network, Expert Syst. Appl. 149 (2020), https://doi.org/10.1016/j.eswa.2020.113285.

[108] L. Wu, T. Wang, Q. Wang, Q. Zhu, J. Chen, EEG signal processing based on multivariate empirical mode decomposition and common spatial pattern hybrid algorithm, Int. J. Pattern Recogn. Artif. Intell. 33 (9) (2019), https://doi.org/10.1142/S0218001419590304.

[109] H. Ramoser, J. Müller-Gerking, G. Pfurtscheller, Optimal Spatial Filtering of Single Trial EEG during Imagined Hand Movement, 2000.

[110] F. Wang, et al., Improved brain–computer interface signal recognition algorithm based on few-channel motor imagery, Front. Hum. Neurosci. 16 (2022), https://doi.org/10.3389/fnhum.2022.880304.

[111] M. Norizadeh Cherloo, H. Kashefi Amiri, M.R. Daliri, Ensemble Regularized Common Spatio-Spectral Pattern (ensemble RCSSP) model for motor imagery-based EEG signal classification, Comput. Biol. Med. 135 (2021), https://doi.org/10.1016/j.compbiomed.2021.104546.

[112] S.H. Park, S.G. Lee, Small sample setting and frequency band selection problem solving using subband regularized common spatial pattern, IEEE Sensor. J. 17 (10) (2017) 2977–2983, https://doi.org/10.1109/JSEN.2017.2671842.

[113] J.K. Feng, et al., An optimized channel selection method based on multifrequency CSP-rank for motor imagery-based BCI system, Comput. Intell. Neurosci. (2019) 2019, https://doi.org/10.1155/2019/8068357.

[114] Q. Zhao, T.M. Rutkowski, L. Zhang, A. Cichocki, Generalized optimal spatial filtering using a kernel approach with application to EEG classification, Cogn Neurodyn 4 (4) (2010) 355–358, https://doi.org/10.1007/s11571-010-9125-x.

[115] N. Yahya, H. Musa, Z.Y. Ong, I. Elamvazuthi, Classification of motor functions from electroencephalogram (EEG) signals based on an integrated method comprised of common spatial pattern and wavelet transform framework, Sensors 19 (22) (2019), https://doi.org/10.3390/s19224878.

[116] A.S. Aghaei, M.S. Mahanta, K.N. Plataniotis, Separable common spatio-spectral patterns for motor imagery BCI systems, IEEE Trans. Biomed. Eng. 63 (1) (2016) 15–29, https://doi.org/10.1109/TBME.2015.2487738.

[117] K.K. Ang, Z.Y. Chin, C. Wang, C. Guan, H. Zhang, Filter bank common spatial pattern algorithm on BCI competition IV datasets 2a and 2b, Front. Neurosci. (2012), https://doi.org/10.3389/fnins.2012.00039.

[118] W. Abbas, N.A. Khan, FBCSP-Based Multi-Class Motor Imagery Classification Using BP and TDP Features, 2018, 10.0/Linux-x86_64.

[119] A.S. Al-Fahoum, A.A. Al-Fraihat, Methods of EEG signal features extraction using linear analysis in frequency and time-frequency domains, ISRN Neurosci 2014 (2014) 1–7, https://doi.org/10.1155/2014/730218.

[120] M.K. Delimayanti, et al., Classification of brainwaves for sleep stages by high-dimensional FFT features from EEG signals, Appl. Sci. 10 (5) (2020), https://doi.org/10.3390/app10051797.

[121] Z. chuan Tang, C. Li, J. feng Wu, P. cheng Liu, S. wei Cheng, Classification of EEG-based single-trial motor imagery tasks using a B-CSP method for BCI, Frontiers of Information Technology and Electronic Engineering 20 (8) (2019) 1087–1098, https://doi.org/10.1631/FITEE.1800083.

[122] S.S. Hussin, R. Sudirman, EEG interpretation through short time fourier transform for sensory response among children, Australian Journal of Basic and Applied Sciences Aust. J. Basic & Appl. Sci 8 (85) (2014) 417–422.

[123] A.S. Al-Fahoum, A.A. Al-Fraihat, Methods of EEG signal features extraction using linear analysis in frequency and time-frequency domains, ISRN Neurosci 2014 (2014) 1–7, https://doi.org/10.1155/2014/730218.

[124] C. Engineering, et al., "Performance Comparison of PF, WT and EMD Algorithms in De-noising of ECG Signal,", 3, 2014, pp. 8142–8147, 10.

[125] S. Huang, C.A.I. Nianguang, P. Penzuti Pacheco, S. Narandes, Y. Wang, X. U. Wayne, Applications of support vector machine (SVM) learning in cancer genomics, Cancer Genomics Proteomics 15 (1) (2018) 41–51, https://doi.org/10.21873/cgp.20063. International Institute of Anticancer Research.

[126] B. Gaye, D. Zhang, A. Wulamu, Improvement of support vector machine algorithm in big data background, Math. Probl Eng. 2021 (2021), https://doi.org/10.1155/2021/5594899.

[127] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, B. Arnaldi, A review of classification algorithms for EEG-based brain-computer interfaces, J. Neural. Eng. 4 (2) (2007), https://doi.org/10.1088/1741-2560/4/2/R01.

[128] K. Mebarkia, A. Reffad, Multi optimized SVM classifiers for motor imagery left and right hand movement identification, Australas. Phys. Eng. Sci. Med. 42 (4) (2019) 949–958, https://doi.org/10.1007/s13246-019-00793-y.
[129] L.I. Kuncheva, J.J. Rodríguez, Interval feature extraction for classification of event-related potentials (ERP) in EEG data analysis, Progress in Artificial Intelligence 2 (1) (2013) 65–72, https://doi.org/10.1007/s13748-012-0037-3.
[130] X. Li, X. Chen, Y. Yan, W. Wei, Z.J. Wang, Classification of EEG signals using a multiple kernel learning support vector machine, Sensors 14 (7) (2014) 12784–12802, https://doi.org/10.3390/s140712784.
[131] B. Szuflitowska, P. Orłowski, Comparison of the EEG signal classifiers LDA, NBC and GNBC based on time-frequency features, Pomiary Automatyka Robotyka 21 (2) (2017) 39–45, https://doi.org/10.14313/par_224/39.
[132] S.S. Abdulwahab, H.K. Khleaf, M.H. Jassim, EEG motor-imagery BCI system based on maximum overlap discrete wavelet transform (MODWT) and cubic SVM, in: Journal of Physics: Conference Series 1973, 2021, https://doi.org/10.1088/1742-6596/1973/1/012056, 1.
[133] M.J. Antony, et al., Classification of EEG using adaptive SVM classifier with CSP and online recursive independent component analysis, Sensors 22 (19) (Oct. 2022), https://doi.org/10.3390/s22197596.
[134] E.K. Laitinen, Classification accuracy and correlation: LDA in failure prediction, Eur. J. Oper. Res. 183 (1) (2007) 210–225, https://doi.org/10.1016/j.ejor.2006.09.054.
[135] C. Vidaurre, M. Kawanabe, P. von Bünau, B. Blankertz, K.R. Müller, Toward unsupervised adaptation of LDA for brain-computer interfaces, IEEE Trans. Biomed. Eng. 58 (3) (2011) 587–597, https://doi.org/10.1109/TBME.2010.2093133. PART 1.
[136] R. Zhang, P. Xu, L. Guo, Y. Zhang, P. Li, D. Yao, Z-score linear discriminant analysis for EEG based brain-computer interfaces, PLoS One 8 (9) (2013), https://doi.org/10.1371/journal.pone.0074433.
[137] D.H. Krishna, I.A. Pasha, T.S. Savithri, Classification of EEG motor imagery multi class signals based on cross correlation, Procedia Comput. Sci. 85 (2016) 490–495, https://doi.org/10.1016/j.procs.2016.05.198.
[138] W.Y. Hsu, EEG-based motor imagery classification using enhanced active segment selection and adaptive classifier, Comput. Biol. Med. 41 (8) (2011) 633–639, https://doi.org/10.1016/j.compbiomed.2011.05.014.
[139] J. Yang, Z. Ma, T. Shen, Multi-time and multi-band csp motor imagery eeg feature classification algorithm, Appl. Sci. 11 (21) (2021), https://doi.org/10.3390/app112110294.
[140] J.V. Riquelme-Ros, G. Rodríguez-Bermúdez, I. Rodríguez-Rodríguez, J. V. Rodríguez, J.M. Molina-García-pardo, On the better performance of pianists with motor imagery-based brain-computer interface systems, Sensors 20 (16) (2020) 1–17, https://doi.org/10.3390/s20164452.
[141] J.F. Hu, Comparison of different classifiers for biometric system based on EEG signals, in: Proceedings - 2nd International Conference on Information Technology and Computer Science, ITCS 2010, 2010, pp. 288–291, https://doi.org/10.1109/ITCS.2010.77.
[142] J. Shin, C.H. Im, Performance improvement of near-infrared spectroscopy-based brain-computer interface using regularized linear discriminant analysis ensemble classifier based on bootstrap aggregating, Front. Neurosci. 14 (2020), https://doi.org/10.3389/fnins.2020.00168.
[143] A. Subasi, E. Erçelebi, Classification of EEG signals using neural network and logistic regression, Comput. Methods Progr. Biomed. 78 (2) (2005) 87–99, https://doi.org/10.1016/j.cmpb.2004.10.009.
[144] T. Rajendran, K.P. Sridhar, Epileptic seizure classification using feed forward neural network based on parametric features, Int. J. Pharmaceut. Res. 10 (4) (2018) 189–196, https://doi.org/10.31838/ijpr/2018.10.04.046. Advanced Scientific Research.
[145] J. Liu, et al., EEG-based emotion classification using a deep neural network and sparse autoencoder, Front. Syst. Neurosci. 14 (2020), https://doi.org/10.3389/fnsys.2020.00043.
[146] Institute of Electrical and Electronics Engineers, ICET 2013, IEEE 9th International Conference on Emerging Technologies : December 09-10, 2013.
[147] SCAD Institute of Technology and Institute of Electrical and Electronics Engineers, in: Proceedings of the International Conference on Intelligent Sustainable Systems (ICISS 2017) 7–8, 2017.
[148] A. Bablani, D.R. Edla, S. Dodia, Classification of EEG data using k-nearest neighbor approach for concealed information test, Procedia Comput. Sci. 143 (2018) 242–249, https://doi.org/10.1016/j.procs.2018.10.392.
[149] Karachi, "Effective Classification of EEG Signals Using K-Nearest Neighbor Algorithm,", 2016, https://doi.org/10.1109/FIT.2016.28.
[150] A. Franklin Alex Joseph, C. Govindaraju, Minimizing electrodes for effective brain computer interface, Biomed. Signal Process Control 63 (2021), https://doi.org/10.1016/j.bspc.2020.102201.
[151] A. Alhudhaif, An effective classification framework for brain-computer interface system design based on combining of fNIRS and EEG signals, PeerJ Comput Sci 7 (2021) 1–24, https://doi.org/10.7717/PEERJ-CS.537.
[152] S. Chaudhary, S. Taran, V. Bajaj, S. Siuly, A flexible analytic wavelet transform based approach for motor-imagery tasks classification in BCI applications, Comput. Methods Progr. Biomed. 187 (Apr) (2020), https://doi.org/10.1016/j.cmpb.2020.105325.
[153] R. Alhalaseh, S. Alasasfeh, Machine-learning-based emotion recognition system using EEG signals, Computers 9 (4) (2020) 1–15, https://doi.org/10.3390/computers9040095.
[154] Bhattacharyya, A. Khasnobish, S. Chatterjee, A. Konar, D.N. Tibarewala, Performance analysis of LDA, QDA and KNN algorithms in left-right limb movement classification from EEG data, in: 2010 International Conference on Systems in Medicine and Biology, Kharagpur, India, 2010, pp. 126–131, https://doi.org/10.1109/ICSMB.2010.5735358.
[155] S.R. Mishra, P.S.B. Somani, P. Deshmukh, D. Soni, EEG Signal Processing and Classification of Sensorimoter Rhythm-Based BCI, 1, 2012, pp. 3–6, 4.
[156] F. Babiloni, et al., Mahalanobis distance-based classifiers are able to recognize EEG patterns by using few EEG electrodes, Annu. Rep. Res. React. Inst. Kyoto Univ. 1 (2001) 651–654, https://doi.org/10.1109/iembs.2001.1019019. February.
[157] F. Babiloni', et al., Mahalanobis Distance-Based Classifiers Are Able to Recognize EEG Patterns by Using Few EEG Electrodes, 2001.
[158] H.U. Amin, W. Mumtaz, A.R. Subhani, M.N.M. Saad, A.S. Malik, Classification of EEG signals based on pattern recognition approach, Front. Comput. Neurosci. 11 (2017), https://doi.org/10.3389/fncom.2017.00103.
[159] H. Wang Siuly, Y. Zhang, Detection of motor imagery EEG signals employing Naïve Bayes based learning process, Measurement 86 (2016) 148–158, https://doi.org/10.1016/j.measurement.2016.02.059.
[160] J. Machado, A. Balbinot, and A. Schuck, "A Study of the Naive Bayes Classifier for Analyzing Imaginary Movement EEG Signals Using the Periodogram as Spectral Estimator.".
[161] Annual IEEE Computer Conference, IEEE International Symposium on Circuits and Systems 2014.06.01-05 Melbourne, and ISCAS 2014.06.01-05 Melbourne, *IEEE International Symposium On Circuits And Systems (ISCAS), 2014 1-5*, 2014 *(Melbourne, Australia*.
[162] E.M. Thomas, A. Temko, G. Lightbody, W.P. Marnane, G.B. Boylan, Gaussian mixture models for classification of neonatal seizures using EEG, Physiol. Meas. 31 (7) (2010) 1047–1064, https://doi.org/10.1088/0967-3334/31/7/013.
[163] B. Obermaier, C. Guger, C. Neuper, G. Pfurtscheller, Hidden Markov models for online classi®cation of single trial EEG data [Online]. Available: www.elsevier.com/locate/patrec.
[164] I.H. Sarker, Deep learning: a comprehensive overview on techniques, taxonomy, applications and research directions, SN Computer Science 2 (6) (2021), https://doi.org/10.1007/s42979-021-00815-1. Springer.
[165] L. Alzubaidi, et al., Review of deep learning: concepts, CNN architectures, challenges, applications, future directions, J Big Data 8 (1) (Dec. 2021), https://doi.org/10.1186/s40537-021-00444-8.
[166] C. Su, Z. Xu, J. Pathak, F. Wang, Deep Learning in Mental Health Outcome Research: a Scoping Review," ***Translational Psychiatry***, 10, Springer Nature, 2020, https://doi.org/10.1038/s41398-020-0780-3, 1.
[167] P. Kant, S.H. Laskar, J. Hazarika, R. Mahamune, CWT based transfer learning for motor imagery classification for brain computer interfaces, J. Neurosci. Methods 345 (2020), https://doi.org/10.1016/j.jneumeth.2020.108886.
[168] N.E. Elsayed, A.S. Tolba, M.Z. Rashad, T. Belal, S. Sarhan, A deep learning approach for brain computer interaction-motor execution EEG signal classification, IEEE Access 9 (2021) 101513–101529, https://doi.org/10.1109/ACCESS.2021.3097797.
[169] K.W. Ha, J.W. Jeong, Temporal pyramid pooling for decoding motor-imagery EEG signals, IEEE Access 9 (2021) 3112–3125, https://doi.org/10.1109/ACCESS.2020.3047678.
[170] N.A. Alzahab, et al., Hybrid deep learning (Hdl)-based brain-computer interface (bci) systems: a systematic review, Brain Sci. 11 (1) (2021) 1–37, https://doi.org/10.3390/brainsci11010075. MDPI AG.
[171] G. Xu, et al., A deep transfer convolutional neural network framework for EEG signal classification, IEEE Access 7 (2019) 112767–112776, https://doi.org/10.1109/ACCESS.2019.2930958.
[172] H.K. Lee, Y.-S. Choi, A convolution neural networks scheme for classification of motor imagery EEG based on wavelet time-frequecy image, in: 2018 International Conference on Information Networking (ICOIN), Chiang Mai, Thailand, 2018, pp. 906–909, https://doi.org/10.1109/ICOIN.2018.8343254.
[173] J. Chai, H. Zeng, A. Li, E.W.T. Ngai, Deep learning in computer vision: a critical review of emerging techniques and application scenarios, Mach. Learn. Applicat. 6 (2021), 100134, https://doi.org/10.24433/CO.0411648.v1.
[174] P. Xiong, S.M.Y. Lee, G. Chan, Deep learning for detecting and locating myocardial infarction by electrocardiogram: a literature review, Front. Cardiovascular Med. 9 (2022), https://doi.org/10.3389/fcvm.2022.860032. Frontiers Media S.A.
[175] N. Lu, T. Li, X. Ren, H. Miao, A deep learning scheme for motor imagery classification based on restricted Boltzmann machines, IEEE Trans. Neural Syst. Rehabil. Eng. 25 (6) (2017) 566–576, https://doi.org/10.1109/TNSRE.2016.2601240.
[176] N.E. Elsayed, A.S. Tolba, M.Z. Rashad, T. Belal, S. Sarhan, A deep learning approach for brain computer interaction-motor execution EEG signal classification, IEEE Access 9 (2021) 101513–101529, https://doi.org/10.1109/ACCESS.2021.3097797.
[177] Y. Fujiwara, J. Ushiba, Deep residual convolutional neural networks for brain–computer interface to visualize neural processing of hand movements in the human brain, Front. Comput. Neurosci. 16 (2022), https://doi.org/10.3389/fncom.2022.882290.
[178] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, B. Arnaldi, A review of classification algorithms for EEG-based brain-computer interfaces, J. Neural. Eng. 4 (2) (2007), https://doi.org/10.1088/1741-2560/4/2/R01.
[179] N.T.H. Anh, T.H. Hoang, D.T. Dung, V.T. Thang, T.T.Q. Bui, An Artificial Neural Network approach for electroencephalographic signal classification towards brain-computer interface implementation, in: 2016 IEEE RIVF International Conference on Computing and Communication Technologies: Research, Innovation, and Vision for the Future, RIVF 2016 - Proceedings, 2016, pp. 205–210, https://doi.org/10.1109/RIVF.2016.7800295.

[180] J.F. Hu, Comparison of different classifiers for biometric system based on EEG signals, in: Proceedings - 2nd International Conference on Information Technology and Computer Science, ITCS 2010, 2010, pp. 288–291, https://doi.org/10.1109/ITCS.2010.77, 2.
[181] N. Tiwari, D.R. Edla, S. Dodia, A. Bablani, Brain computer interface: a comprehensive survey, Biolog. Inspired Cognitive Architectures 26 (October) (2018) 118–129, https://doi.org/10.1016/j.bica.2018.10.005.
[182] M. Wölfel, H.K. Ekenel, in: Feature Weighted Mahalanobis Distance: Improved Robustness for Gaussian Classifiers," *13th European Signal Processing Conference*, EUSIPCO 2005, 2005, pp. 2018–2021.
[183] A. Rakshit, A. Khasnobish, D.N. Tibarewala, A Naïve Bayesian Approach to Lower Limb Classification from EEG Signals," *2016 2nd International Conference On Control, Instrumentation, Energy And Communication*, CIEC 2016, 2016, pp. 140–144, https://doi.org/10.1109/CIEC.2016.7513812.
[184] B.-J. Yoon, Hidden Markov models and their applications in biological sequence analysis, Curr. Genom. 10 (6) (2009) 402–415, https://doi.org/10.2174/138920209789177575.
[185] I.H. Sarker, Deep learning: a comprehensive overview on techniques, taxonomy, applications and research directions, SN Comput Sci 2 (6) (2021) 1–20, https://doi.org/10.1007/s42979-021-00815-1.
[186] Pawan, R. Dhiman, Motor Imagery Signal Classification Using Wavelet Packet Decomposition and Modified Binary Grey Wolf Optimization," Measurement: Sensors, Dec. 2022, p. 100553, https://doi.org/10.1016/j.measen.2022.100553.
[187] Pawan, R. Dhiman, Electroencephalogram channel selection based on pearson correlation coefficient for motor imagery-brain-computer interface, Measurement: Sensors 25 (Feb. 2023) 100616, https://doi.org/10.1016/j.measen.2022.100616.
[188] Y. Tang, Z. Zhao, S. Zhang, Z. Li, Y. Mo, Y. Guo, Motor imagery EEG decoding based on new spatial-frequency feature and hybrid feature selection method, Math. Probl Eng. 2022 (2022), https://doi.org/10.1155/2022/2856818.
[189] M.A. Riyadi, I. Setiawan, A. Amir, EEG multiclass signal classification based on subtractive clustering-ANFIS and wavelet packet decomposition, in: Proceedings - IEIT 2021: 1st International Conference on Electrical and Information Technology, 2021, pp. 81–86, https://doi.org/10.1109/IEIT53149.2021.9587407.
[190] X. Peng, J. Liu, Y. Huang, Y. Mao, D. Li, Classification of lower limb motor imagery based on iterative EEG source localization and feature fusion, Neural Comput. Appl. 6 (2022), https://doi.org/10.1007/s00521-021-06761-6.
[191] S. Mohdiwale, M. Sahu, G.R. Sinha, V. Bhateja, Statistical wavelets with harmony search- based optimal feature selection of EEG signals for motor imagery classification, IEEE Sensor. J. 21 (13) (2021) 14263–14271, https://doi.org/10.1109/JSEN.2020.3026172.
[192] N. Bagh, M.R. Reddy, Biomedical Signal Processing and Control Hilbert Transform-Based Event-Related Patterns for Motor Imagery Brain Computer Interface, 62, 2020.
[193] P. Gaur, R.B. Pachori, H. Wang, S. Member, An automatic subject specific intrinsic mode function selection for enhancing two-class EEG based motor imagery-brain computer interface, IEEE Sensor. J. 19 (2019) 1, https://doi.org/10.1109/JSEN.2019.2912790.
[194] P. Kant, J. Hazarika, S.H. Laskar, Wavelet transform based approach for EEG feature selection of motor imagery data for braincomputer interfaces, in: Proceedings of the 3rd International Conference on Inventive Systems and Control, ICISC 2019, Icisc, 2019, pp. 101–105, https://doi.org/10.1109/ICISC44355.2019.9036445.
[195] D.R. Edla, F. Ansari, N. Chaudhary, S. Dodia, ScienceDirect classification of facial expressions from EEG signals using wavelet packet transform and SVM for wheelchair control operations, Procedia Comput. Sci. 132 (2018) 1467–1476, https://doi.org/10.1016/j.procs.2018.05.081. Iccids.
[196] S. Kumar, A. Sharma, T. Tsunoda, An Improved Discriminative Filter Bank Selection Approach for Motor Imagery EEG Signal Classification Using Mutual Information, 18, 2017, https://doi.org/10.1186/s12859-017-1964-6. Suppl 16.
[197] M.A. Li, W. Zhu, H.N. Liu, J.F. Yang, Adaptive feature extraction of motor imagery EEG with optimalwavelet packets and SE-isomap, Appl. Sci. 7 (4) (2017), https://doi.org/10.3390/app7040390.
[198] M.H. Bhatti, et al., Soft computing-based EEG classification by optimal feature selection and neural networks, IEEE Trans. Ind. Inf. 15 (10) (2019) 5747–5754, https://doi.org/10.1109/TII.2019.2925624.
[199] T.U. Jang, B.M. Kim, Y.M. Yang, W. Lim, D.H. Oh, Motor-imagery EEG signal classification using position matching and vector quantisation, International Journal of Telemedicine and Clinical Practices 1 (4) (2016) 306, https://doi.org/10.1504/ijtmcp.2016.078426.
[200] B. Medina Salgado, L. Duque Muñoz, Fuzzy entropy relevance analysis in DWT and EMD for BCI motor imagery applications, Ingenieria 20 (1) (2015) 9–19, https://doi.org/10.14483/udistrital.jour.reving.2015.1.a01.
[201] C. Lindig-Leon, L. Bougrain, A multi-label classification method for detection of combined motor imageries, in: Proceedings - 2015 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2015, 2016, pp. 3128–3133, https://doi.org/10.1109/SMC.2015.543.
[202] Y. Zhang, G. Zhou, J. Jin, X. Wang, A. Cichocki, Optimizing spatial patterns with sparse filter bands for motor-imagery based brain-computer interface, J. Neurosci. Methods 255 (2015) 85–91, https://doi.org/10.1016/j.jneumeth.2015.08.004.
[203] I. Dokare, N. Kant, Performance analysis of SVM, k-NN and BPNN classifiers for motor imagery, Int. J. Eng. Trends Technol. 10 (1) (2014) 19–23, https://doi.org/10.14445/22315381/ijett-v10p205.
[204] L.Q. Thang, C. Temiyasathit, Increase performance of four-class classification for motor-imagery based brain-computer interface, in: 2014 International Conference on Computer, Information and Telecommunication Systems, CITS 2014, 2014, pp. 0–4, https://doi.org/10.1109/CITS.2014.6878959.
[205] E. Mohamed, Enhancing EEG signals in brain computer interface using wavelet transform, Int. J. Inform. Electronics Eng. 4 (3) (2014), https://doi.org/10.7763/ijiee.2014.v4.440.
[206] N.K. Verma, L.S.V.S. Rao, S.K. Sharma, Motor imagery EEG signal classification on DWT and crosscorrelated signal features, 9th Int. Conf. Indust. Inform. Syst., ICIIS (2014) 2015, https://doi.org/10.1109/ICIINFS.2014.7036473.
[207] W. Yi, S. Qiu, H. Qi, L. Zhang, B. Wan, D. Ming, EEG feature comparison and classification of simple and compound limb motor imagery, J. NeuroEng. Rehabil. 10 (1) (2013) 1–12, https://doi.org/10.1186/1743-0003-10-106.
[208] R. Chai, S.H. Ling, G.P. Hunter, H.T. Nguyen, Mental non-motor imagery tasks classifications of brain computer interface for wheelchair commands using genetic algorithm-based neural network, Proc. Int. Joint Conf. Neural Networks (2012) 10–15, https://doi.org/10.1109/IJCNN.2012.6252499.
[209] A.M. Roy, A CNN Model with Feature Integration for MI EEG Subject Classification in BMI, 2022, pp. 1–37, https://doi.org/10.1101/2022.01.05.475058, bioRxiv 2022.
[210] W. Liu, Y. Zeng, Motor imagery tasks EEG signals classification using ResNet with multi-time-frequency representation, in: 2022 7th International Conference on Intelligent Computing and Signal Processing (ICSP), Xi'an, China, 2022, pp. 2026–2029, https://doi.org/10.1109/ICSP54964.2022.9778786.
[211] X. Wang, R. Yang, M. Huang, An unsupervised deep-transfer-learning-based motor imagery EEG classification scheme for brain–computer interface, Sensors 22 (6) (2022), https://doi.org/10.3390/s22062241.
[212] J.S. Bang, M.H. Lee, S. Fazli, C. Guan, S.W. Lee, Spatio-spectral feature representation for motor imagery classification using convolutional neural networks, IEEE Transact. Neural Networks Learn. Syst. (2021) 1–12, https://doi.org/10.1109/TNNLS.2020.3048385.
[213] X. Deng, B. Zhang, N. Yu, K. Liu, K. Sun, Advanced TSGL-EEGNet for motor imagery EEG-based brain-computer interfaces, IEEE Access 9 (2021) 25118–25130, https://doi.org/10.1109/ACCESS.2021.3056088.
[214] B. Abibullaev, I. Dolzhikova, A. Zollanvari, S. Member, A Brute-Force CNN Model Selection for Accurate Classification of Sensorimotor Rhythms in BCIs, 2020, pp. 1–10, https://doi.org/10.1109/ACCESS.2020.2997681.
[215] P. Kant, S.H. Laskar, J. Hazarika, R. Mahamune, CWT based transfer learning for motor imagery classification for brain computer interfaces, J. Neurosci. Methods 345 (2020), 108886, https://doi.org/10.1016/j.jneumeth.2020.108886. February.
[216] G. Xu, et al., A deep transfer convolutional neural network framework for EEG signal classification, IEEE Access 7 (2019) 112767–112776, https://doi.org/10.1109/ACCESS.2019.2930958.
[217] J. Yang, S. Yao, J. Wang, Deep fusion feature learning network for MI-EEG classification, IEEE Access 6 (c) (2018) 79050–79059, https://doi.org/10.1109/ACCESS.2018.2877452.
[218] S. Sakhavi, C. Guan, S. Yan, Learning temporal information for brain-computer interface using convolutional neural networks, IEEE Transact. Neural Networks Learn. Syst. 29 (11) (2018) 5619–5629, https://doi.org/10.1109/TNNLS.2018.2789927.
[219] B. Xu, et al., Wavelet transform time-frequency image and convolutional network-based motor imagery EEG classification, IEEE Access 7 (2019) 6084–6093, https://doi.org/10.1109/ACCESS.2018.2889093. MI.
[220] J. Yang, S. Yao, J. Wang, Deep fusion feature learning network for MI-EEG classification, IEEE Access 6 (2018) 79050–79059, https://doi.org/10.1109/ACCESS.2018.2877452.
[221] H.K. Lee, Y.S. Choi, A convolution neural networks scheme for classification of motor imagery EEG based on wavelet time-frequecy image, Int. Conf. Inform. Network. 2018-Janua (2018) 906–909, https://doi.org/10.1109/ICOIN.2018.8343254.
[222] W. Ko, J. Yoon, E. Kang, E. Jun, J.S. Choi, H. Il Suk, Deep recurrent spatioooral neural network for motor imagery based BCI, in: 2018 6th International Conference on Brain-Computer Interface, BCI 2018 2018-Janua, 2018, pp. 1–3, https://doi.org/10.1109/IWW-BCI.2018.8311535.
[223] R.T. Schirrmeister, et al., Deep learning with convolutional neural networks for EEG decoding and visualization, Hum. Brain Mapp. 38 (11) (2017) 5391–5420, https://doi.org/10.1002/hbm.23730.
[224] N. Lu, T. Li, X. Ren, H. Miao, A deep learning scheme for motor imagery classification based on restricted Boltzmann machines, IEEE Trans. Neural Syst. Rehabil. Eng. 25 (6) (2017) 566–576, https://doi.org/10.1109/TNSRE.2016.2601240.
[225] H. Yang, S. Sakhavi, K.K. Ang, C. Guan, On the use of convolutional neural networks and augmented CSP features for multi-class motor imagery of EEG signals classification, in: Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society 2015-Novem, EMBS, 2015, pp. 2620–2623, https://doi.org/10.1109/EMBC.2015.7318929.
[226] S. Sakhavi, C. Guan, S. Yan, Parallel convolutional-linear neural network for motor imagery classification, in: 2015 *23rd* European Signal Processing Conference, EUSIPCO 2015, 2015, pp. 2736–2740, https://doi.org/10.1109/EUSIPCO.2015.7362882.
[227] Y. Ren, Y. Wu, Convolutional deep belief networks for feature extraction of EEG signal, in: Proceedings of the International Joint Conference on Neural Networks, 2014, pp. 2850–2853, https://doi.org/10.1109/IJCNN.2014.6889383.
[228] K. Li, X. Li, Y. Zhang, A. Zhang, Affective state recognition from EEG with deep belief networks, in: Proceedings - 2013 IEEE International Conference on Bioinformatics and Biomedicine, IEEE BIBM 2013, 2013, pp. 305–310, https://doi.org/10.1109/BIBM.2013.6732507.

Pawan received his Bachelor of Engineering from Maharshi Dayanand University, Rohtak, India, in 2010. He received his Master of Engineering in Electrical Engineering from Deenbandhu Chhotu Ram University of Science and Technology, Murthal, Haryana (India), in 2013. He is pursuing his Ph.D. in Electrical Engineering from the Deenbandhu Chhotu Ram University of Science and Technology, Murthal, Sonipat, Haryana, India, in 2018-2023. He is the topper of Ph.D. coursework in the academic session 2018-2019 and availed the university research scholarship. He has extensive academic experience as well as research experience. His current areas of interest include MATLAB Simulink, biomedical signal processing, especially brain-computer interface with an electroencephalogram, bio-inspired optimization techniques, Machine learning, and Deep learning. He has published his research work in various reputed journals, including Elsevier, Inderscience and international conferences.

Rohtash Dhiman completed his schooling from Government High School, Mohana, and Senior Secondary Certificate Examination from Hindu College, Sonipat, Haryana, India. He completed his Bachelor of Engineering (1998) and Master of Engg. (2008) degrees from C.R. State College of Engineering (Now D.C.R. University of Science and Technology) Murthal, Sonipat, India). He is an Assistant Professor in the Electrical Engineering Department at Deenbandhu Chhotu Ram University of Science and Technology, Murthal, Sonipat, India, and completed his Ph.D. in 2017 from the same university. His current areas of interest include computational intelligence, autonomous robots, biomedical signal processing, intelligent techniques, brain-computer interface, genetic algorithms, bio-inspired optimization techniques, machine vision, and image processing. He has the extensive academic experience and has published his research work in various reputed journals, including Elsevier and international conferences. He has been awarded a Certificate of appreciation for Quality Enhancement in Engineering Education for the January-April 2017 session by the Indian Institute of Technology Madras (India). He has been awarded the AICTE-ECI Vishwakarma Chhatra Mentor award on 19th September 2017 by the All-India Council for Technical Education (AICTE) New Delhi.