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REVIEW ARTICLE

Review of Machine Learning Techniques for EEG Based Brain Computer Interface

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Abstract

A brain computer interface (BCI) framework uses computer algorithms to detect mental activity patterns and manipulate external devices. Because of its simplicity and non-invasiveness, one of the most commonly used imaging technologies is electroencephalography (EEG). The evaluative method used in assessing the output of an EEG-based BCI system is classifying EEG signals for particular applications. The growth of artificial intelligence technology inspired researchers to use machine learning (ML) techniques and deep learning (DL) approaches to classify EEG-based BCI. Machine learning techniques enable the brain computer interface to learn from the subject's brain with each new session, adapting the generated rules for classifying thoughts and thus improving the system's efficiency. The authors present a concentrated survey on the use of various ML/DL techniques in EEG-based BCI. Three EEG paradigms for classification are used: motor imagery, p300, and steady state evoked potential. In addition, the challenges that recent EEG-based BCI systems face are addressed based on ideal signal processing methods, BCI functioning, performance assessment and commercialization. The authors hope that the information gathered would aid in application of suitable machine learning techniques, as well as provide a foundation for BCI researchers to enhance future BCI system.

1 Introduction

The basic concept of human society is communication or social contact. This quality allows people to exchange feelings, desires, and innovative ideas with one another. Human communication becomes simpler and less constrained if this communication is formed by voice, gesture, or writing. People with locked-in syndrome, on the other hand, may not have the above opportunities for contact. Since it's almost impossible for someone suffering from paralysis to communicate with others, the BCI enables communication with the environment for such people. BCI is a device that makes humans bind their brains to computers, allowing people to generate brain waves that are converted into commands for the applications they are designed for [1].

Many noninvasive BCIs use electroencephalography (EEG) signals to precisely quantify cortical electrical processes with high resolution in the time domain [2, 3]. An external device will rebuild the neuromuscular bypass using an EEG-based BCI system. The brain potentials captured by a scalp electrode are translated into commands for controlling a robotic arm, exoskeleton, wheelchair, or another robot. Mu rhythm [4], slow cortical potential [5], event-related p300 [6], and steady-state visual evoked potential [7] are several of the electrical brain processes that have been used to differentiate EEG-based BCI.

Controlling a wheelchair [8], speller [9], and neurorehabilitation [10] are only a few of the applications for EEG-based BCI. The overarching goal of these studies is to gain a more comprehensive interpretation of the brain's behavior by correctly interpreting EEG signal patterns. The accuracy and efficiency of BCIs are determined by the feature extraction methods and classifiers used in signal processing. For performing the classification of EEG signals, various machine learning methods such as linear discriminant analysis, support vector machine, K-nearest neighbor, and deep learning architecture have been used.

As a result, the study's goal is to examine EEG-based BCI systems in terms of various brain control signals and machine learning techniques. Furthermore, a short description of EEG paradigms is provided to aid in the selection

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of the best paradigm for a given application. Furthermore, pertinent challenges that need to be resolved for developing brain computer interfaces to be used in a patient's environment are reported.

1.1 Brain Computer Interfaces (BCI)

BCI is a "system that measures central nervous system (CNS) activity and converts it into artificial output that replaces, restores, enhances, supplements, [informs],or improves natural CNS output and thereby changes the ongoing interactions between the CNS and its external or internal environment"[11].

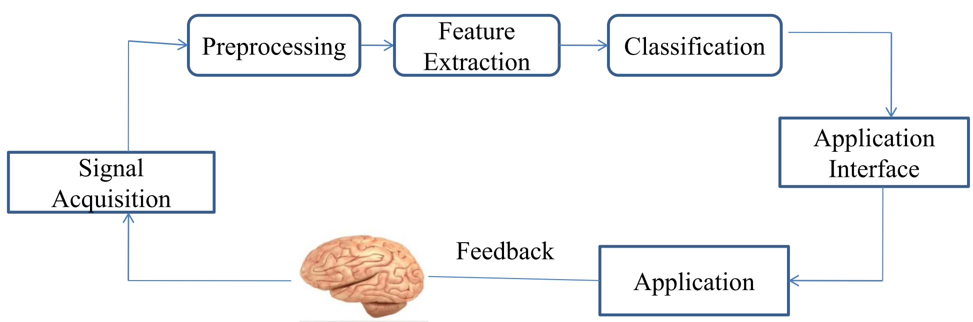
BCIs, as we know them today, are brain-imaging devices that use invasive and non-invasive techniques for input, starting with electroencephalography (EEG) and moving on to magnetoencephalography (MEG), electrocorticography (ECoG), and others. Despite the imaging technique used for data acquisition, BCI is used to represent instances of the functions of an individual's brain, allowing the brain and the machine to interface digitally. BCIs are applied across a range of applications by tracking and evoking complex signal activity through the presentation of stimuli. The recognized activity issue commands to the system, allowing an individual to operate the wheelchair, perform spell check through speller, control cursor, and play games, and more.

Vidal first coined the term brain computer interfaces in 197 3[12], while it was previously researched [13, 14]. Originally, BCIs were developed for persons with disabilities [15], but the prevailing spectrum of use has been expanded to competent users [16], neuro-rehabilitation [10], etc.

The components of the BCI system include signal acquisition, preprocessing, feature extraction, classification, and an application interface, shown in Fig. 1. Using feature extraction techniques from the EEG signal acquired by BCI, task-specific characteristics in the frequency and time domain are extracted [17]. The purpose of the classification process is to convert the extracted characteristics output based on the application to carry the intent of the user [18].

BCI systems are generally classified into a variety of categories. The three classification systems, namely dependability, imaging technique, and mode of operation, are illustrated in Fig. 2 [19]. BCI may be categorized as dependent and independent BCI concerning dependability. Dependent BCIs are those that enable individuals to use some form of motor control, such as gaze. BCIs based on motor imagery are examples of commonly used dependent BCIs. In contrast, independent BCIs do not need any motor control and are ideal for people who have had a stroke or who have the locked-in syndrome. Given imaging techniques, BCIs are invasive or non-invasive. Electrocardiograms (ECoG) and single-neuron recordings are invasive techniques, whereas electroencephalography (EEG), magnetoencephalography (MEG), positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and near-infrared spectroscopy (NIRs) are non-invasive techniques. Finally, BCI

Fig. 1 Components of BCI



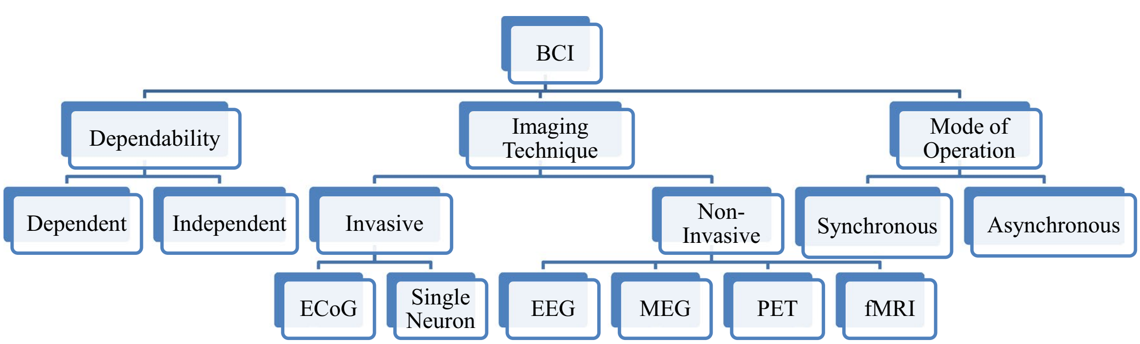


Fig. 2 Classification of types of BCI

operates in either a synchronous mode or an asynchronous one. In a synchronous BCI, the subject communicates with the system in response to a cue imposed by the system over a set period. Asynchronous BCI, on the other hand, enables the subject to communicate with the application at any time. Synchronous BCIs are less usability than asynchronous BCIs, but they are simpler and easier to build [20].

EEG is a widely used non-invasive method with BCIs nowadays. Guger et al. (2015) [21], in a report that provided a yearly analysis of participants in the Annual BCI Study Awards, justifies their findings. Another research [22] found that the number of EEG-based BCI studies has been gradually rising. This review, therefore, concentrates on non-invasive BCIs, especially EEG-based BCIs, because of their simplicity, low cost, and convenience.

1.2 EEG Paradigms used in BCI

To allow the BCI to understand the person's notion, certain neurophysiological signals have been decoded, referred to as EEG control signals. Although there are various EEG control signals such as slow cortical potential (SCP), P300 event-related potential, motor imagery (MI), error-related potential (ErrP), steady-state visually evoked potentials (SSVEP) steady-state auditory evoked potentials (SSAEP), and steady-state somatosensory evoked potentials (SSSEP), MI, P300, and SSVEP are most widely used and thus discussed by the authors in this paper.

1.2.1 Motor Imagery (MI)

Motor Imagery [23] is the cognitive process of imagining your part of the body's motion without actually moving that part of the body. It is capable of altering neurological pattern in dominant sensorimotor regions, is close to actual motion execution. A BCI will decipher motor imagery task from the EEG, aligning it to a particular scalp's area. The alpha and beta frequency of EEG are the most impactful for motor imagery. Action conjure by the MI of the left hand is generated from C3 region and right hand is created from C4 region of brain, while imagery of foot movement originates from Cz. The action of these motor parts can therefore be regulated by BCI system through imagination [24].

1.2.2 Event-Related Potential (ERP)

Event-related potential [25], which are all stereotyped visual, audio, or tactile stimulus EEG responses. The P300 wave is the most commonly used ERP that occurs as a positive EEG deflection in the Pz portion of the human brain that develops approximately 300 ms after the stimulus [26]. The P300 variable can be induced in an oddball model that includes two types of stimuli, target, and non-target stimuli, with the target stimulus appearing less frequently than the non-target stimulus. The P300 variable can be induced in an oddball model that includes two types of stimuli, target, and non-target stimuli, with the target stimulus appearing less frequently than the non-target stimulus. The convenience of using P300 based BCI is that it requires little or no training. However, it should be remembered that the amplitude of P300 decreases in the event of a rare stimulus, obstructing the system's performance.

Recently, researchers have explored another ERP component, the error-related potential (ErrP) used to rectify the errors of BCI. ErrP is triggered by a misalignment between the patient's target and the BCI response [27]. The frontal and central lobes have the most pronounced ErrP. The delay and non-stationary features of ERP is an open problem for real-time BCI implementation [27].

1.2.3 Steady-State Evoked Potentials (SSEP)

Steady-state evoked potentials (SSEP) are induced by stable frequency oscillatory stimuli. SSEP is categorized into Steady-State Visually Evoked Potentials (SSVEP) Steady-State Auditory Evoked Potentials (SSAEP) and SteadyState Somatosensory Evoked Potentials (SSSEP) based on visual, auditory, and somatosensory stimulation.

SSVEP based BCI is triggered by constant-frequency visual stimuli, usually between 3.5 and 75 Hz [26]. When a particular flickering stimulus is focused, an SSVEP with the same frequency as the target flicker is generated. Therefore, the subject visually focuses on the target, and by evaluating the SSVEP features, the BCI decides the target. Due to its high information transmission rate compared to other paradigms, BCI spellers are one of the most widely used applications using this paradigm.

SSAEP are commonly extracted by trains of click stimuli, tone pulses, or amplitude-modulated tones, with a repetition or modulation rate between 20 and 100 Hz.

Vibrotactile sensors are mounted on predetermined parts of the body in the SSSEP paradigm, and these sensors produce stimulation at distant frequencies [28]. The lack of a standardized tactile stimulator limits research in this field, and only a few SSSEP studies in with elation to visual-based BCI studies have been published.

The authors have considered three classic classification paradigms i.e. motor imagery, P300, and SSVEP based BCI in this paper.

1.3 Machine Learning

Machine Learning (ML) algorithms use the labeled data to learn brain signal characteristics from specific subjects. These are used to predict the intentions of users on unseen and new data. Machine learning algorithms are divided into three groups based on their outcomes: supervised learning, unsupervised learning, and reinforcement learning. The categories of machine learning algorithms are shown in Fig. 3.

1.3.1 Supervised Learning

Supervised Learning algorithms draw predictions of unavailable data from labeled data. The labeled training data is used in supervised learning to enable the machine to learn. Using machine learning techniques, the training data is used to decide about the unknown patterns present in the labeled data, resulting in a successful prediction or classification for the testing data.

Classification: Classification is a method by which a group of groups, multi-label, are classified into one class. It can be achieved on data that is either structured or unstructured. Classification aims to decide which class or group the newly added data belongs to. Classifying motor imagery tasks is an example of a classification problem; the problem can be binary classification in the case of two classes. i.e. classifying movement as the left or right hand, and multi-classification in case of more than two classes, e.g. classifying movement as left hand, right hand, feet, and others.

Regression: Regression is a standard statistical technique for determining the functional accord among variables and is generally used for time series modeling. The regression analysis produces univariate or multivariate; simple or multiple responses to predict variables; linear and non-linear response is generated for linearly transformable data and nonlinearly transformable data respectively [29]. Regression analysis is the paramount instrument for data modeling and analysis.

1.3.2 Unsupervised Learning

Unsupervised learning techniques use knowledge, unlike supervised learning algorithms, that is unlabeled or categorized in the training data. The references are taken from datasets consisting of input data with no responses being named. Without any guidance, given the similarities and differences between these data, the algorithms can group unsorted information. Unsupervised learning is often used for clustering and feature reduction. As a kind of learning, it takes people to understand certain items or events from a comparative class after the technique's use, for example, by analyzing the degree of similarity between objects. It is mostly used for finding a meaningful framework inherent in a collection of examples as a tool.

Clustering: clustering separates data into groups in such a way that data points in the same group are identical to each other but differ from data points in other groups. To put it another way, it's a list of data that's been separated into identical and dissimilar features. It is simply a list of entities based on their similarity and dissimilarity. Clustering is a useful tool for identifying the peculiar organization of labeled data. For a successful clustering, there are no conditions. It depends on the customer, what are the specifications they should use that meet their needs.

Association: Association rule learning is a rule-based machine learning approach to discover to find any interesting relationships or correlations between the dataset variables. Discovering the fascinating relationships between variables in the database is based on various laws. In other words, learning the association rule is a type of unsupervised learning technique that checks for one data item's dependence on another data item and maps it accordingly so that it can be more profitable.

Dimensionality reduction: Dimensionality reduction is a technique for reducing the number of features in a big corpus with a significant count of random variables to curtail the data's dimensional space and processing time. It is important to investigate methods for selecting suitable features from data for successful BCI applications. To obtain accurate results, it may be possible that the signal obtained is skewed by noise interference and needs to be effectively segregated. The dimensionality reduction approaches are used to scale down the dataset and separate the unwanted features from the selected features.

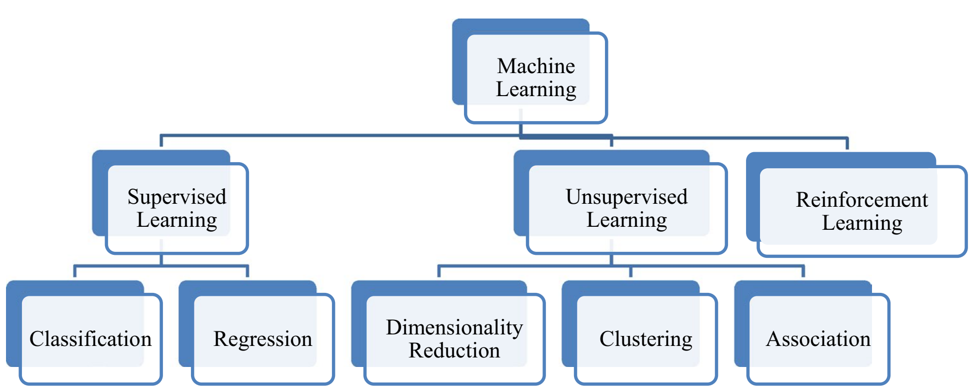


Fig. 3 Categorization of Machine learning techniques

1.3.3 Reinforcement Learning

Reinforcement learning allows the machine to learn the right actions based on the reward at the end of a series of actions. This learning is different from the other algorithms where the task has not been instructed to complete; it does it on its own and learns from previous experience. In the human world, learning by experimentation is a lot like that. Reinforcement learning focuses more on results than the knowledge provided.

1.4 Machine Learning in EEG Based BCI

Figure 4 depicts the steps taken to apply machine learning to achieve the desired results in EEG-based BCI. The method of classification is divided into the training and testing phase. To draw generalized rules, the machine learning model is fed with a lot of data during training. The classification model is created to access the final performance of the qualified classifier. New data is added in the testing process to envision a new input class using the classification model as a guide to the classifier. To monitor the application, the expected outcomes are then used. The performance of the BCI classification is measured in terms of accuracy and transmission of information rate.

The major limitation for EEG-based BCI is the nature of EEG signals, which is easily contaminated for the same subject by interference and noise, non-stationary, and vary across various subjects and sessions. The process of collecting data from subjects during training, known as a calibration session, is usually tedious and inconvenient for the user. It is therefore important for the market success of EEG-based BCIs to reduce this subject-specific calibration. Using Machine Learning, the BCI receives input from the user's brain for each new session by adjusting to it to better identify its thoughts, reducing the basic calibration time of the subject. Whatever the BCI procedure used, the human brain and the system can operate with each other in a symbiotic way. To try to minimize the number of errors, an AI layer based on machine learning mechanisms might lie on it, thus connecting us to a new world with the possibility of being at the same IA robot level [30].

Brain-computer interfaces (BCIs), is one of the medical application that use neural signals to control wheelchair, control cursor movement. Several researchers have been exploring various machine learning techniques to increase the effectiveness of BCI using EEG recordings [31]. ML algorithms help in identifying the variables used for predicting behavior, irrespective of the relationship form between variables. The gaze control BCI, for example, has been used to determine the visual characteristics that predict the neural basis of focused attention [32]. Thus, Machine learning plays a major role in BCI research and produces a more accurate model that provides a better understanding of relations between neural activity and machine interface.

1.5 Contribution and Organization of the Paper

A summary of machine learning in the EEG-dependent BCI is discussed here in this paper. The authors have addressed machine learning techniques and deep neural networks proposed by various researchers for different EEG-based BCI paradigms in depth. In addition, the study also discussed different research questions concerning machine learning. Furthermore, the authors identified and categorized the challenges existing in this area.

The remaining part of the paper is formatted as follows: The research methodology is addressed in Sect. 2. The methods for selecting literature are listed in this section. A correlative overview of this study with existing relevant surveys is provided in Sect. 3. A comprehensive discussion on applications of Machine Learning techniques in EEG-based BCI is given in Sect. 4. Section 5 describes publically available

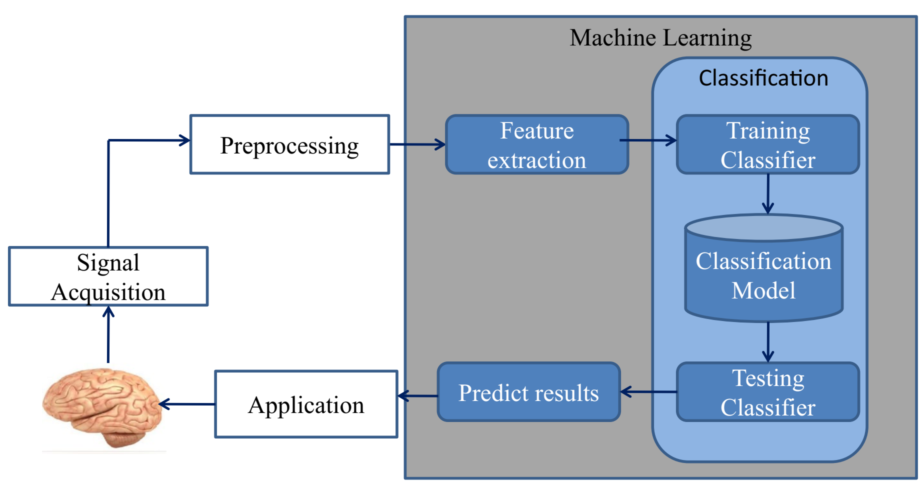


Fig. 4 Application of Machine Learning process in EEG based BCI

datasets. Section 6 categorizes and addresses the challenges for EEG-based BCI. Finally, Sect. 7 concludes the study.

2 Review Planning

This section gives an overview of the methodology adopted by the authors for conducting an extensive survey.

2.1 Research Questions

The main reason for the analysis of this study is to assist emergent researchers in the relevant area. This analysis paper answers several research issues. This study will assist them to figure out the underlying glossary of machine learning techniques used for EEG-based BCI paradigms and to define the main research issues in this field. In Table 1, these research issues are addressed.

2.2 Exclusion Criteria

The authors analyzed the collected articles for inclusion and exclusion from the review. The exclusion criteria used are as follows:

EC1: Paper not related to EEG based BCI and machine learning.
EC2: Paper that does not provide any experimental results.
EC3: Paper that talks about theoretical considerations of EEG based BCI.
EC4: Publication before 2009.

2.3 Article Acquisition

The papers were gathered by searching for them using keywords related to EEG-based BCI. "EEG-based BCI," "Motor Imagery classification using machine learning," "P300-based BCI," "SSVEP-based BCI," "EEG-based BCI and machine learning" are the keywords used to scan for related articles. The authors performed a search on Science direct and IEEE Explore. Initially, the authors selected 105 papers based on the keywords and importance of this analysis. After that, to get insights from the most appropriate articles, more filtering was performed and 37 papers were rejected based on the above-mentioned exclusion criteria. Thus, in total 68 papers from reputable journals and conferences were included in this review. Figure 5 presents the number of papers for each paradigm searched and selected.

3 Related Work

Various works relating to the literature on EEG-based brain computer interfaces have been discovered. However, the majority of previous reviews concentrate on only one paradigm of EEG-based BCI. Furthermore, these are not covering the answer to all the review questions quoted in Table 1. The authors compare all previous studies to the current research based on review questions cited in Table 1. Table 2 summarizes the research questions addressed by

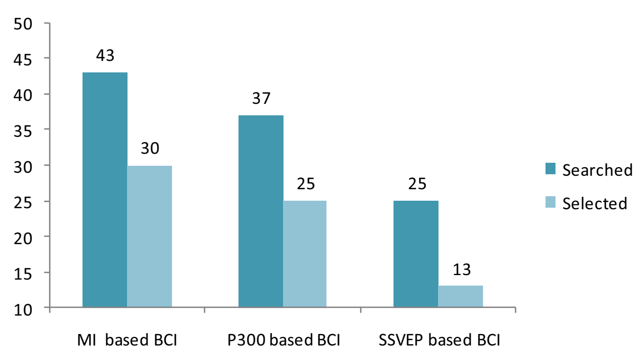


Fig. 5 Number of papers analyzed for the review

Table 1 Research questions related to machine learning in EEG based BCI

S. no	Research questions
Q1	What kind of study is conducted for BCI
Q2	What are the different paradigms of EEG used for BCI
Q3	What are the machine learning techniques used for MI based BCI
Q4	What are the machine learning techniques used for P300 based BCI
Q5	What are the machine learning techniques used for SSVEP based BCI
Q6	What are the challenges for EEG based BCI
Q7	What is the future direction in BCI using ML
Q8	Role of Deep Learning in BCI
Q9	What type of limitations are associated with the latest machine learning strategies for BCI's
Q10	What are the methods used for the specific application of a particular paradigm
Q11	What datasets are publically available for EEG based BCI

Table 2 Research questions addressed by related work

Related work	Research questions										
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11
Abiri et al. [27]	✓	✓	✓								
Wu et al. [33]	✓	✓	✓	✓	✓						
Al-Saegh et al. [34]	✓	✓	✓					✓	✓		
Cao et al. [35]	✓		✓	✓	✓		✓		✓		
Lotte et al. [36]	✓		✓	✓	✓		✓	✓	✓		
This study	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

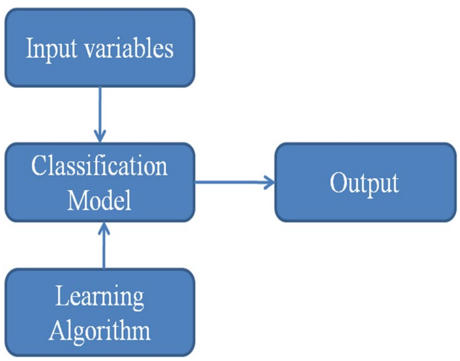


Fig. 6 Classification process using machine learning techniques [37]

existing surveys on EEG-based BCI concerning this study and presents the primary core disparity between them.

The authors of this paper have pursued to discuss all the questions addressed in Table 1. Furthermore, this paper gives a multidimensional exploration of various machine learning techniques used for different paradigms of EEG-based BCI.

4 Machine Learning Techniques

The authors find evidence in the literature for various computational methods that use machine learning techniques for the classification of motor imagery, P300, and SSVEP signals. In the training process, a learning algorithm is used to learn the rules, which is then fed into a classification model, as depicted in Fig. 6. The performance is evaluated using the same model in the testing process. All of these analytical methods aid in the development of BCI for communication.

4.1 Machine Learning in MI Based BCI

In motor imagery brain computer interfaces, classification algorithms are used to convert extracted features into distinct motor tasks such as hand gestures, foot movements, word generation, and so on. BCI researchers have experimented with a variety of machine learning methods for two and multi-class classification of motor imagery. Linear Discriminant Analysis (LDA) [38–40] and Support Vector Machine (SVM) are two popular methods in BCI research (SVM) [39, 41–43], with the SVM classifier outperforming other classifiers such as LDA, and K-Nearest Neighbor (K-NN) [39, 44].

K-Nearest Neighbor [49] is memory-based approach, in which all data in memory is processed at the same time, have also been found to be popular in the implementation of MI BCI. When opposed to kernel-based approaches like SVM, this invariably raises computational costs. Overfitting can occur in both the LDA and SVM approaches; however, in the case of LDA, this can be mitigated by using regularization, which was suggested by Friedman, J. H [45] to solve the singularity issue. Regularized LDA (RLDA) has been successfully implemented for classifying right hand and right foot motor imagery [46] and also used in [47], suggesting high classification accuracy compared to LDA.

Overfitting was minimized in SVMs by selecting the appropriate training scheme. Due to the non-stationary existence of EEG, selecting the SVM kernel function becomes difficult. The optimal kernel and penalty parameters were chosen using the particle swarm optimization (PSO) algorithm, which improved classification accuracy over traditional SVM [43].

Bayesian analysis is commonly used in BCI systems, according to the authors, and it typically produces good results [39, 48–50]. Robust classifiers perform better but take longer; therefore, there is a tradeoff between accuracy and speed. Researchers used an artificial neural network to provide a rational tradeoff. A Gaussian discriminant function represents a class prototype in-unit of this NN. This classifier has been successfully used to classify motor imagery [51]. Several techniques, such as LDA, artificial neural networks (ANN) [51], and neural networks based on radial basis function (RBF) [52], have been well used for BCI throughout the classification level. The time-consuming and repetitive calibration sessions for users, on the other hand, make BCI impossible to use in real-time. During classification, this necessitates the use of a small training dataset Spiking neural network [53] and sparse group representation model [54] have been used to alleviate this problem, indicating that it is a good choice for avoiding long calibration sessions and has improved efficiency.

The majority of these classifiers are designed to solve binary classification problems. These classifiers use a one-vs-one or one-vs-all technique to break down multiple MI tasks into a sequence of binary classifiers. However, when there are a lot of MI tasks, it takes a long time to train multiple binary classifiers. Researchers have recently used deep neural network (DNN), in which features are automatically extracted and the classifier learns directly from data. DNN has a high descriptive ability, which increases the system's accuracy.

Initially, Na Lu et al. [55] suggested using manually extracted FFT-based features from the channels which are then fed into a Deep Belief Network (DBN). Convolutional Neural Network (CNN) is effective for the classification of motor imagery tasks due to its pattern and degree of translation invariance [56–61]. Amin et al. (2019) [58] proposed a convolutional neural network (CNN) that performs feature fusion for MI-based EEG classification. However, when target data is corrupted, CNN classification accuracy is harmed. Even from the same individual, the measured signals for motor imagery electroencephalogram (EEG) are not stable and can be significantly distorted. Thus, the author in [62] proposed a capsule network (CapsNet) to learn unique and relevant features of EEG, improving the results compared to the state-of art CNN approach.

In [63] Luo, Zhou, and Chao, a deep recurrent neural network (RNN) with a sliding window cropping strategy (SWCS) was used to classify the EEG MI signal. In Nair, Kumar, and Mathew(2018) [64], five classes of EEG MI data were categorized using a stack auto encoder (SAE) and softmax layer for generating features and for classification respectively.

Besides the above-mentioned deep learning architectures, researchers solicited to enhance classification accuracy by developing hybrid deep learning architectures in EEG-based BCI research. Uyulan [65] proposed a hybrid DL model for EEG MI classification combining long short-term memory (LSTM) with CNN. Kumar et al. [66] proposed the OPTICAL predictor, a novel method for improving MI EEG signal classification that combines CSP and LSTM networks.

The combination of multiple classifiers, rather than one classifier, is considered a better option for classifying motor imagery signals. Since it was discovered that the multi-class classification of MI BCI has lower accuracies, the authors in [67, 68] proposed LDA ensemble and extra tree, respectively, to improve multi-class classification of motor imagery tasks. In [69], the author demonstrated that the random subspace k-NN ensemble method significantly improved classification accuracy as compared to conventional models tested.

When comparing supervised learning techniques to unsupervised learning techniques for the classification of motor tasks, it is clear that supervised learning was largely preferred. Some of the unsupervised methods, like the Gaussian method, may be used for classifying motor tasks in the future. Table 3 contains a summary of studies for motor imagery classification.

4.2 Machine Learning in P300 Based BCI

The P300 signal is a part of the electroencephalogram elicited about 300 ms after the experience of significant auditory, and visual stimulus [70]. When compared to motor imagery interfaces, P300-based BCIs generally have a higher information transfer rate. Spellers [71–73], smart home environments [74–76], and wheelchairs [77] are only some of the examples of P300 based BCI. P300-based BCIs are useful in the treatment of certain diseases such as ALS [73], spinocerebellar ataxia [71], and post-stroke paralysis [72, 74].

A realistic BCI device should be capable of producing reliable results with a high rate of data transfer. Various studies on classification methods occur in the literature to obtain higher performance. For the classification of P300 signals, traditional machine learning techniques such as Linear Discriminant Analysis (LDA) [71, 73, 75, 78] and support vector machine (SVM) [77, 79] are commonly used. However, for efficient classification model training, the simple LDA classifier normally takes prolonged calibration time and suffers from an under-sampling problem [35]. The undersampling problem in ERP classification has been solved using a variety of algorithms. Stepwise linear discriminant analysis (SWLDA) [80], an adjunct of LDA that produces higher output while using fewer training samples than simple LDA, is one of the methods used for treating an under-sampling problem. Regularized discriminant analysis often outperforms the classic LDA model in terms of classification accuracy [81]. Other classifiers used in P300 detection include random forest [76, 82], Quadratic Discriminant Analysis (QDA) [83], logistic regression [84] and neural network [83]. Non-linear methods, on the other hand, are less potent than linear techniques in P300-based BCI systems.

Deep learning methods have ushered in a new era of study in the area of P300 BCI systems because of recent developments in the field. Due to the amalgamation of pre-training and successive hyper-parameters tuning, deep neural networks have been successfully implemented as precise classification methods for P300 detection. Convolutional neural networks (CNN), one of the commonly used deep neural architectures, have been used by many researchers for P300 based BCI. Although the convolutional neural network is effective, it is prone to overfitting, which lowers recognition efficiency [85]. Lawhern Vernon classified four varieties of EEG signals, including P300 EEG signals, applying

Table 3 Machine learning techniques used for MI based BCI

References	Machine learning techniques	Dataset	Performance
Aler et al. [41]	SVM	BCI-III competition	Accuracy: Evolved Filters- Subject1- 77.96%, Subject2-75.11%, Subject-3 57.76%
Temiyasathit [38]	LDA	BCI competition 2008	Accuracy: LDA- 78.82%
Baig [39]	LDA, SVM, K-NN, Naïve Bayes	BCI competition III Dataset IVa	Accuracy: 90.4% (PSO), 87.44% (simulated annealing), 94.48% (ABC optimization), 84.54% (ACO)
Kumar [40]	LDA	BCI Competition III Dataset IVa, BCI Competition IV Dataset I and BCI Competition IV Dataset IIb	Misclassification Rate: Dataset 1: 8.32 ± 4.48, Dataset 2: 17.66 ± 8.01, Dataset 3: 18.98 ± 8.48
Fu et al. [47]	RLDA, LDA	BCI Competition IV	Accuracy: 93.04%
Kim et al. [46]	RLDA	BCI Competition III Dataset IVa	Accuracy: 74.28%
Islam et al. [42]	SVM	BCI competition III Dataset IIIa, and IIIb, BCI competition IV Dataset IIa	Avg recognition accuracy: Dataset IIIa: 71.85% Dataset IIIb: 76.85% Dataset 2a: 83.82%
Ma et al. [43]	SVM with PSO	BCI Competition III Data Iva	Accuracy: 91.60%
Vangelis [44]	LDA, SVM	Graz B	Mean Accuracy: LDA: 70.90% SVM: 79.33%
Wang and Zhang [48]	Naïve Bayes	BCI Competition III datasets, IVa and IVb	Overall Performance: Dataset IVa: 96.36 ± 2.32 Dataset IVb: 91.97 ± 7.02
Zhang et al. [49]	Sparse Bayesian Learning	BCI Competition IV dataset IIb	Accuracy: 81.7 ± 15.1
Miao et al. [50]	Weighted Naïve Bayes	BCI competition III Dataset IVa, BCI competition IV Dataset IIa	BCI competition III dataset IVa: 86.38%,
Salazar-Varas and Vazquez [53]	Spiking Neural Network	BCI Competition Dataset IIIa, IVa, V	Average area under ROC: Data set IVa: 81.1 3.1, Data set V: 71.9 2.8, Data set IIIa: 77.0 4.5
Hamedi et al. [52]	Radial basis function Neural network	Author prepared	
Jiao et al. [54]	Sparse group Representation	BCI Competition IV dataset IIb	Averaged accuracy = 78.2%, Kappa = 0.57
Amin et al. [58]	Multi layer CNN fusion	BCI Competition IV-2a dataset and the High Gamma Dataset	Accuracy: BCI Competition IV 2a Dataset: 75.7% and High Gamma Dataset: 95.4%
Nu et al. [55]	Deep neural network with RBM	BCI competition IV data set 2B	
Lee and Choi [56]	CNN	BCI competition IV dataset 2B	Accuracy: Morlet- 78.93%, Bump-77.25%
Zhang et al. [57]	CNN	Author prepared	Accuracy: CNN(RELU)- 86.74%, CNN(ELU) – 88.92, CNN(SELU)- 92.73%
Sakhavi et al. [59]	CNN	BCI competition IV dataset 2A	Accuracy: 70.60%
Ko et al. [60]	Recurrent CNN	BCI Competition IV dataset 2A	Accuracy: 45%

Table 3 (continued)

References	Machine learning techniques	Dataset	Performance
Sakhavi et al. [61]	CNN	BCI Competition III dataset 4A BCI competition IV dataset 2A	Accuracy: 74.46%
Ha and Jeong [62]	Capsule network	BCI competition IV 2b	Accuracy: 78.44%
Luo and Chao [63]	Deep RNN in combination with a sliding window cropping strategy (SWCS)	BCI Competition IV 2a and 2b	Misclassification rate: Dataset 2a: 26.44 ± 4.38, Dataset 2b:17.25 ± 3.84
Nair et al. [64]	Autoencoders	Author prepared	Accuracy: 82.21%
Uyulan [65]	1D CNN and LSTM	BCI Competition IV dataset A	Accuracy: 95.62% (± 1.2290742), Kappa Value: 0.9462 (± 0.01216265)
Kumar et al. [66]	Long short-term memory (LSTM) network	BCI Competition IV Dataset I and GigaDB dataset	Misclassification rate: BCI Competition IV Dataset I:3.09%, GigaDB: 2.07%
Nicolas-Alonso et al. [67]	Stacked LDA	BCI Competition IV dataset 2a	Kappa Value: 0.66 + 0.19
Bera et al. [68]	Extra-Trees algorithm	BCI Competition IV dataset 2a	Accuracy: Binary Class: 98%, Multiclass: 84%
Rashid et al. [69]	Ensemble k-nearest neighbor (k-NN)	BCI Competition III dataset 1 (data-1), dataset IIIA (data-2), dataset IVA (data-3) and BCI Competition IV dataset II (data-4))	Accuracy: (data-1): 99.21%, (data-2): 93.19%, (data-3):93.57% and (data-4):90.32%

a compact convolutional neural network (CNN), and demonstrated the effectiveness of CNN on P300 signal. [86]. In [87], the author suggested using deep belief networks (DBNs) with healthy subjects and stroke patients to distinguish P300 single trials. To distinguish P300 EEG signals, a 3D recurrent convolution neural network (3DRCNN) was suggested and was converted to three dimensional signals, which were then fed into the RCNN for accurate classification [88]. Feng Li [89] explored a new CNN architecture, which was combined with principal component analysis (PCA) to classify P300 signals. Even after implementing deep learning techniques, the ITR remains low, owing to a large number of trials as well as classification issues such as overfitting and trial-to-trial variability. Furthermore, maximizing the accuracy-to-ITR trade-off for few trials is vital for the clinical implementation of the P300 spellers.

Ensemble learning, an amalgamation of machine learning methods, was investigated to overcome the constraints of deep learning architecture. Researchers have used an ensemble of LDAs and ensemble of support vector machine (EWSVM) as a classifier in P300-based BCI applications [91–94] Other ensemble techniques used in the literature for P300-based BCI include a fuzzy combination of classifiers[74] and group-sparse Bayesian linear discriminant analysis (gsBLDA) [95]. Although existing ensemble learning methods were well implemented, they do have some limitations. One limitation is that the output is dependent on the number of ensembles selected, while another is the partition size generated during model training [96]. Kshirsagar et al. [97] proposed a weighted ensemble of deep convolution neural networks (DCNN) to address these limitations and classifier instability, extending the principle of ensemble learning to deep ensemble learning. Furthermore, a new channel dropout-based character detection method is imported for real-time adaptation of the P300 speller and to deal with the false detection rate.

To boost real-time efficiency, unsupervised machine learning techniques have been tested for P300-BCI. Wei Gao [98] proposed the multi-ganglion artificial neural network-based feature learning (ANNFL) approach that extracts the deep features from single-trial multi-channel ERP signals, which outperformed PCA. Researchers have suggested autoencoder [99] and sparse coding models [100] as examples of traditional neural networks for unsupervised learning. The automated methods of feature extraction based on deep learning have been proposed to resolve the limitations of hand-crafted features by extracting topic and class-dependent features. For small training data, Sourav Kundu [92] explored a novel multiscale convolutional neural network (MsCNN) with transfer learning. Another study [93] implemented a stack encoder to automatically extract deep features from the data. The problem of over-fitting is resolved using a sparse regularization method applied to the Autoencoder

(AE), and the changed AE are stacked together. Table 4 contains a summary of BCI studies that uses machine learning techniques for P300 detection.

4.3 Machine Learning in SSVEP Based BCI

SSVEPs are a form of brain response that is described by a frequency pattern at the stimulus frequency as well as its harmonic frequencies. SSVEP-based BCIs perform better than p300 and motor imagery BCI in terms of signal stability and signal processing complexity, making them ideal for use in subjects with serious disabilities. SSVEPs are broadly used in numerous applications, including speller [101–104], smart home [105], game [106, 107], robot control [108, 109], and exoskeleton control [10, 110] because of their high information transmission rate and low or no training stipulation.

In SSVEP-based BCI, machine learning techniques are used to produce discrete observations, such as estimating the frequency of an SSVEP. The various classification algorithms used for SSVEP analysis are described in this subsection. The supervised learning techniques such as the Linear Discriminant Analysis (LDA) [107] Support Vector Machine (SVM) [107, 111, 112], and k-nearest neighbors (KNN) [10] are used. Support vector machine is the most used machine learning algorithm in the SSVEP community. Furthermore, as artificial intelligence has progressed, numerous researchers have used artificial neural networks to detect SSVEP [111, 112].

Recently, researchers have explored deep learning architectures to investigate the viability of implementing an SSVEP-based BCI. Deep neural networks, unlike conventional machine learning methods, do not require feature extraction and are capable of performing on their own. The earliest deep neural architecture for the classification in offline mode was proposed by Hubert Cecotti [113]. The architecture designed performs spatial filtering and time filtering, followed by frequency signal transformation and classification is carried out in the last layer. In another study, the CNN was applied in an ambulatory environment to perform robust SSVEP frequency classification [110]. The author uses a multi-channel headset to create a two-dimensional SSVEP map to distinguish SSVEP frequencies that are accurate even under challenging conditions. In [103], the author proposed a novel 1-D CNN-based architecture to minimize computational time and increase machine accuracy.

Previous CNN architectures used domain-specific knowledge for SSVEP classification to reduce the amount of training data available. The methods use an FFT-based approach, which might not be able to collect all of the information and therefore hinder deep learning on SSVEP datasets. Nicholas Waytowich et al. [114] use a recently built compact convolutional neural network (Compact-CNN) that can operate on small data and extract task-related information automatically. Furthermore, the Compact-CNN performs temporal convolutions to efficiently represent signals. Podmore et al. [104] use publically available 40 stimuli SSVEP data to examine the feasibility of deep convolutional neural networks (DCNNs) architecture for a speller task for simulating in real scenarios. Furthermore, pure deep learning models suffer from overfitting, which was addressed by Yao Li et al. [115], who suggested a new deep learning model known as convolution correlation analysis (Conv-CA). The obtained structure is a combination of CNN structure having signal-CNN and reference-CNN as two divisions and conventional correlation analysis. Conv-CA has good accountability, according to the report, and outperforms the task-related component analysis (TRCA) process.

In light of CNN's success in classifying scalp-EEG signals, the author of a recent study [116] attempted to use CNN to decipher low SNR SSVEP in ear-EEG signals. To boost the classification accuracy of ear-EEG signals, the ensemble learning technique was used in conjunction with divergent kernels EEGNet For implementing SSVEP-based BCI, a new framework called broad learning has recently been implemented [117]. Frequency sequences are obtained by performing FFT on EEG signals. The frequency-related features are then extracted using a limited penetrable visibility graph (LPVG) and corresponding degree series. The extracted features are classified using a broad learning system. These new approaches open up new locale for analyzing EEG-based BCI systems to improve the accuracy and be used for practical applications. The summary of machine learning techniques for classifying SSVEP signals is shown in Table 5.

5 Public Datasets

This segment examines the publicly accessible datasets that are most commonly used for EEG-based BCI. The mapping of different EEG-based BCI paradigms with the available datasets is shown in Fig. 7. BCI competitions are among the datasets available, which also provide datasets for EEG modalities. GigaDB is another dataset that can be used to analyze motor imagery signals. The following subsection describes the BCI datasets that are available publically.

5.1 BCI Competition II

The BCI Competition II is made up of many datasets, each of which contains single-trials of random EEG operation. The goal is to assess the efficacy of different classification methods used in brain machine interfaces. Dataset IIb, for example, is a log of P300 evoked potentials reported with BCI20001 in the oddball paradigm. A user concentrated on

Table 4 Machine learning techniques used for signal processing in P300 based BCI

References	Machine learning techniques	Dataset	Accuracy	Application
Achanccaray et al. [74]	Combination of fuzzy classifiers by voting	Author prepared	> 80%	Smart Home Interaction
Aydin et al. [75]	Linear discriminant analysis	Author prepared	Correct region selection: 96.63%	Environment control system
De Venuto et al. [77]	Support vector machine	Author prepared	84.28 ± 0.87%	Wheelchair
Guy et al. [73]	Linear discriminant analysis	Author prepared	Correct symbol > 95%	Spelling
Masud et al. [76]	Random forest	Author prepared	Avg accuracy: 87.5%	Intelligent home control
Nurseitov et al. [84]	Regularized logistic regression	Author prepared	Mean real time accuracy: 67%	Mobile robot
Okahara et al. [71]	Linear discriminant analysis	Author prepared	Mean online accuracy: patients: 82.9%, healthy controls: 83.2%	Spinocerebellar Ataxia
Stan et al. [78]	Linear discriminant analysis	Author prepared		Hand orthosis
Zhumadilova et al. [81]	Regularized Linear Discriminant Analysis (rLDA)	Author prepared	Mean real time accuracy: 71%	Speller
Oralhan [90]	Convolutional neural network	Author prepared	Avg class cation accuracy: 94.22%, Avg information transfer rate: 5.53 bit/min	Region based Speller
Li et al. [89]	Convolutional neural network	Author prepared	Avg recognition accuracy: 97%	Not mention
Hashmi et al. [79]	Support vector machine	Author prepared	Accuracy: S1: 98.53%, S2: 99.25%	Speller
Akram et al. [82]	Random forest	Author prepared	Avg time: 1.67minperword	Speller
Chaurasiya et al. [96]	Weighted Ensemble of Support Vector Machines (WESVM)	Author prepared	Avg accuracy: 94.2%	Speller
Kundu and Ari [92]	Multiscale convolutional neural network (MsCNN) and ensemble of support vector machines (ESVMs)	BCI competition II Dataset IIb and BCI competition III Dataset II	Correctly recognized characters: 31	Speller
Gao et al. [97]	Multi-ganglion artificial neural network and Support vector machine	Author prepared	Mean accuracy: 88.1%	Not mention
Kundu and Ari [94]	CNN and ensemble of support vector machine (ESVM)	Author prepared	Avg Character recognition: 99%	Speller
Kundu and Ari [93]	Stacked sparse autoencoder (SSAE) and ensemble of support vector machine (ESVM)	BCI Competition II Dataset IIb, BCI Competition III dataset II	BCI Competition III dataset: SSAE-ESVM: 98.5%	Speller
Arican and Polat [91]	Ensemble of Least squares support vector machine (LS-SVM) and ensemble of LDAs	BCI Competition III Challenge 2004 Dataset II	Accuracy: 94.166%	Speller
Wu et al. [100]	Regularized Group Sparse Discriminant Analysis	BCI Competition III, EPFL BCI dataset	*p*-value < 0.01	
Cortez et al. [87]	Deep belief networks (DBNs)	Author prepared	Highest accuracy: Healthy subject: 91.6%, post-stroke victim: 88.1%	Speller
Sharma [83]	LDA, QDA and Neural network	BCI laboratory at Computer Science department at Colorado State University, BCI competition III dataset II	13% accuracy gain	Speller
Vařeka and Mautner [99]	Stacked autoencoder	Author prepared	Accuracy: 69.2%, recall: 58.8%	Not mention

Table 4 (continued)

References	Machine learning techniques	Dataset	Accuracy	Application
Kshirsagar and Londhe [96]	Weighted ensemble of deep convolution neural network	Author prepared	ITR: 55.45 bits/min., accuracy: 92.64%	Speller
Yu et al. [95]	Group-sparse Bayesian linear discriminant analysis	Author prepared	Accuracy: 97%	Speller

one of 36 different characters in these experiments. This competition aims to predict the characters in one of the three sessions available.

5.2 BCI Competition III

BCI competition III consists of various distinct datasets, contributed by a collaboration of a group of universities and laboratories. The EEG recordings from five subjects while performing various tasks generate one of the datasets, known as dataset IIIa. For example, EEG recordings of five subjects performing various tasks are included in dataset IIIa. Three subjects' data were collected at a sampling rate of 250 Hz utilizing 62 channels Neuroscan amplifier. In the experiments, the participants imagined the movement of four body parts that are left hand, right hand, foot, and tongue in response to a cue.

The IIIb dataset consists of three subjects recorded over three sessions having a 125 Hz sampling rate. This dataset is used to identify motor imagery signals using time-varying binary classification with feedback. Using a 118-channel EEG headset, dataset IVa was registered for five healthy subjects. The subjects were given 280 trials of the imagination to switch three body parts in response to a cue, including the left hand, right hand, and right foot.

5.3 BCI Competition IV

BCI competition IV, with five separate datasets, was held in 2008 to continue the BCI competitions. More subjects and activities are included in these datasets. The EEG recordings collected from nine subjects using a 22-channel device mounted on the scalp with a sampling frequency of 250 Hz while performing the task of imagining the gestures of their left hand, right hand, left and right legs, and tongue contributed to form dataset 2a.

EEG data from 9 subjects were collected at a sampling rate of 250 Hz in Dataset 2b. The motor imagery (MI) of the left hand and right hands was divided into two classes in the cue-based screening paradigm. Within two weeks, each subject had two screening sessions with no input reported on two separate days.

5.4 Giga DB

The dataset includes 52 healthy subjects who participated in MI EEG recordings and were divided into two classes to perform the motor task of the left and right hands. For each subject, the EEG and EMG recordings for real hand movement were also recorded in 20 trials along with non-task and motor imagery task-related states. The EEG signals were captured with 512 Hz sampling rates using a 64 channel Biosemi ActiveTwo system.

Table 5 Machine learning techniques used for SSVEP based BCI

References	Machine learning techniques	Accuracy	Application
Singla and Haseena [111]	Support vector machine (SVM) and Artificial neural network (ANN)	Accuracy: 88.55%	Not mention
Martišius and Damaševičius [107]	Linear Discriminant Analysis (LDA), Support vector machine (SVM) with linear kernel and radial basis function	Accuracy: LDA: 78.2%, SVM with linear kernel: 79.3%, SVM with radial basis function: 80.5%	Game
Singla and Haseena [112]	Artificial neural network and support vector machine	Range of accuracy: 70.83–100	Wheelchair
Kwak et al. [10]	K-Nearest Neighbor (KNN)	Accuracy: 91.3 ± 5.73%, Response Time: 3.28 ± 1.82 s, ITR: 32.9 ± 9.13 bits/min	Lower limb exoskeleton control
Cecotti [113]	Convolutional neural network (CNN)	Mean recognition rate: 95.61%	Not mention
Kwak et al. [110]	Convolutional neural network (CNN)	Classification rate: static condition: 99.28%, ambulatory condition: 94.03%	Exoskeleton control
Nguyen et al. [102]	Support vector machine	Overall accuracy: 93.8%	Speller
Nguyen and Chung [103]	1-D Convolutional neural network (CNN)	Avg accuracy: 97.4%, Information transfer rate: 49 ± 7.7 bits per min	Speller
Waytowich et al. [114]	Compact convolutional neural network (Compact-CNN)	Mean accuracy: approximately 80%,	Not mention
Podmore et al. [104]	Deep convolutional neural networks (DCNN)	Accuracy: 86%	Speller
Li et al. [115]	Convolutional correlation analysis (Conv-CA)	ITR: 226.19 bits/min	Not mention
Zhu et al. [116]	CNN with ensemble learning	Avg accuracy: from session 1 to session 2: 81.12%, from session 1 to session 3: 81.74%	Not mention
Gao et al. [117]	Broad learning	Avg classification accuracy: 96.22%	Not mention

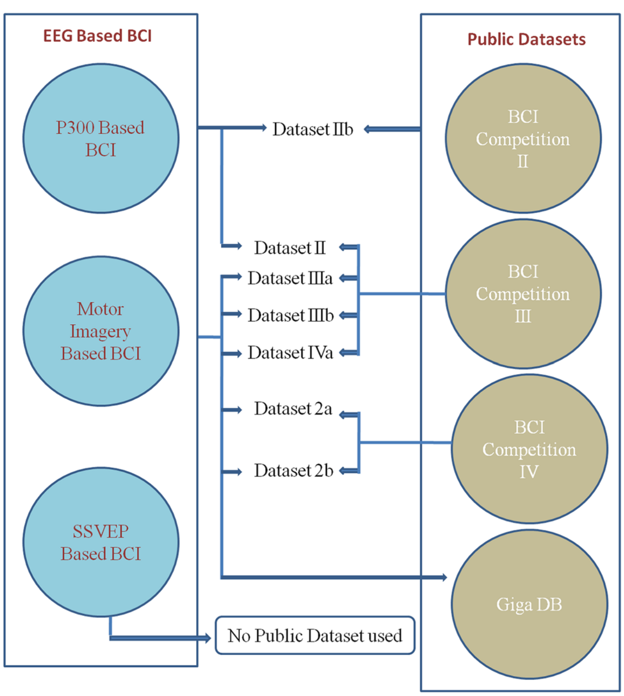


Fig. 7 Mapping of EEG modality with publically available datasets

6 Challenges

Although various EEG-related data has been successfully analyzed using machine learning techniques with good accuracy performance, but there are still some unanswered problems and concerns. However, for BCIs to progress further, the BCI group must resolve these concerns. The authors have classified the challenges based on signal processing methods, BCI functioning, performance assessment, and commercialization as depicted in Fig. 8.

6.1 Ideal Signal Processing Methods

Artifact removal, feature extraction, and classification of EEG signals are all part of signal processing. Even though most signal processing methods perform well when used for EEG-based BCI, they have several drawbacks.

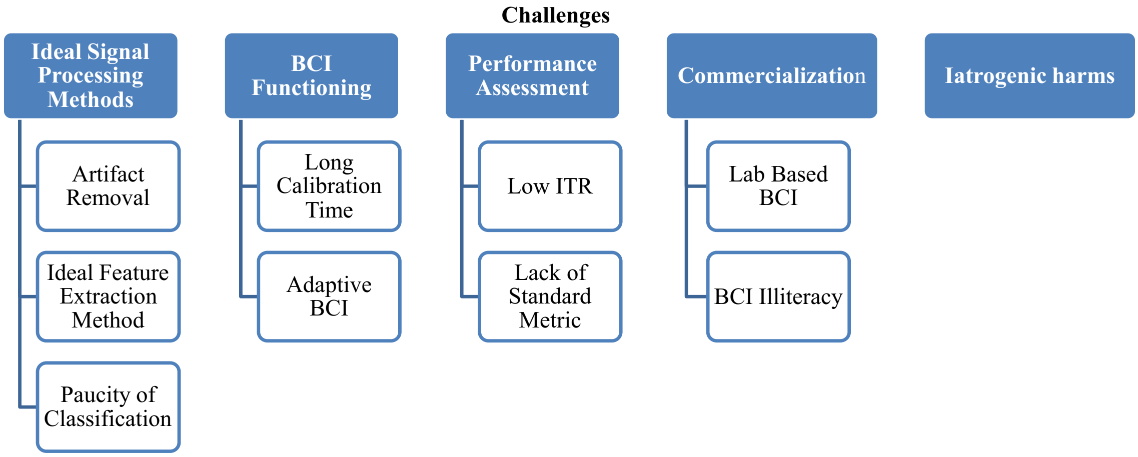


Fig. 8 Categorization of identified challenges

6.1.1 Artifact Removal

The artifact removal process concentrated on detecting and removing specific artifacts. Independent component analysis is the common method applied for removing artifacts. For eliminating noise from EEG signals, spatial and temporal filters are also viable options. For effective artifact removal, reference channels are used but this option is not feasible for some of the applications of BCI.

The need for a reference signal restricts the available filters and the techniques used for the elimination of specific artifacts. As a result, it is difficult to find a process that is effective and reliable for artifact removal, satisfying all the restrictions required for the application. Thus, the creation of a time-efficient and reliable application-specific approach will be the next step. Apart from this, advanced artifact removal algorithms for a variety of artifact types are still required.

6.1.2 Ideal Feature Extraction Method

Since EEG signals are typically noisy and time-varying, the extraction of specific features from signals having a short time window may be difficult. In motor imagery-based BCI, the Common Spatial Pattern (CSP) and its variants are widely used. Canonical correlation analysis is generally used to detect SSVEP frequency in SSVEP-based BCI, suggesting that frequency features for SSVEP perform better.

The performance of CSP and its variants in multiclass classification remains an open question, however, due to the substantial increase in the number of feature subsets in MI tasks. Researchers have also been working on improving the performance of CCA for BCI based on SSVEP. It is, indeed, difficult to judge the best technique for a particular EEG signal modality.

6.1.3 Paucity of Ideal Classification Methods

For the classification of motor imagery, P300, and SSVEP, several deep learning approaches have been used. Deep network architecture is entirely determined by network structure and input formalization. It has been observed that CNN has optimal performance with time-series data and spectral images. As a result, a thorough analysis is required considering the layer structure and number of network architectures to have a better understanding and comparison. Aside from network structure, further research is needed to determine how raw signals can be interpreted using deep learning architectures as these types of studies are limited.

In the reviewed papers, the majority of machine learning methods were applied for offline classification. As a result, online testing and validation of classification algorithms are necessary to ensure that they are easy to compute and can be used and calibrated for real-time applications. Furthermore, robust classifiers that can be used online and operate with non-stationary data must be built to have a fair tradeoff between accuracy and performance.

6.2 BCI Functioning

The issue with BCI functioning is long calibration times make BCI operation a time-consuming process, in addition to the training requirements, as stated in the papers reviewed.

6.2.1 Long Calibration Time

For the motor imagery BCI to be used clinically, the targeted user must complete oodles of training trials, making the calibration time unacceptably long for a practical model. As a result, research should focus on reducing the calibration time as well as successful training strategies.

Although the nature and variety of the disease can have a huge effect on the results of the P300 modality, it has higher average ITRs and does not require training. Nonetheless, many reviews have shown that even people with locked-in syndrome can tolerate a P300-based BCI for long periods. Furthermore, for P300 based applications the number of trials increases with an increase in instructions, resulting in reduced overall efficiency. The calibration time could be reduced by the amalgamation of basic architecture with online training that could improve the efficiency of P300-based BCI systems and even customer satisfaction [118].

6.2.2 Adaptive BCI

The other issue related to the functioning of BCI on which researchers are being worked is the steadiness of the classifier's accuracy over long sessions. This occurs because EEG is a non-stationary signal and changes over time as well as when the recording context and state of mind alters. This issue may be resolved by the adoption of the adaptive methods and modifying the training protocol to make it adaptive for the user. Faller et al. [119] have proposed an adaptive classifier that performs calibration automatically. Their system learns to remove outliers when discriminating features for classifier retraining at regular intervals.

6.3 Performance Assessment

Information transmission rate, accuracy, Kappa value, confusion matrix, precision, sensitivity, ROC curve, and other performance metrics are used to evaluate the brain machine interface. It is important to determine the efficiency of the BCI framework to ensure its efficient implementation. The lack of a common metric and BCI's low ITR are problems pertaining to performance assessment.

6.3.1 Lack of Common Metric

Task-specific metrics, such as task completion time and number of active trials, number of collisions, and so on, were used in many papers. It's nearly impossible to compare BCI systems of the same kind that are measured using different performance metrics. As a result, the BCI research group should propose clear performance indicators for each BCI application. The common performance matrices for BCI applications are required to have a clear and direct comparison among varied BCI studies.

6.3.2 BCI's Low ITR

The major stipulation of any successful brain computer interface system is a higher ITR. ITR is the most widely used metric for evaluating the output of BCI. A BCI system's ITR is calculated by three factors: the number of groups, precision for target disclosure, and time to detect target [2]. One of the most significant aspects of BCIs is reducing the target recognition time, which helps to increase the ITR. Adopting machine learning techniques for single-trial classification and the manifestation of proper stimulus can help shorten the time it takes to identify the target.

6.4 Commercialization

Three major issues hamper the commercialization of BCIs: the first is the adaptation of lab-based BCI, the second is BCI illiteracy, and the third is usability. This segment goes through these topics in detail.

6.4.1 Lab-Based BCI

The considerable problems with BCIs are that most of the BCI studies have been carried out in a controlled lab, disregarding the practical surroundings in which the intended individuals operate. As a result, it is critical to thoroughly review the system's basic requirements, environmental factors, circumstances, and target users during the system design phase.

6.4.2 BCI Illiteracy

The fact that 10–30% of users never gain mastery over BCI, a condition known as BCI illiteracy, is due to a large difference in user capacity for motor imagery [120, 121]. Some of the researchers are interested in determining whether or not a person falls into the BCI illiterate group. This could aid in the creation of a better algorithm for classifying motor imagery tasks and in a better training protocol that can enhance an individual's skills.

The issue of BCI illiteracy can be solved by employing a multimodal approach that can boost efficiency even when the user is illiterate. External variables, such as assistive peripheral electrical stimulation, may enhance BCI precision. Vidaurre et al. [122] suggested using it to improve illiteracy among subjects.

6.5 Iatrogenic Harms

Even if the aforementioned issues are resolved, the intelligent BCI device may encounter problems with unintended consequences that make patients more vulnerable and susceptible to iatrogenic harms. The findings of a semi-structured interview conducted by Gilbert et al. in a study [123] on self-change perception confirm this. BCIs can boost a patient's sense of self and control, but they can also cause extreme discomfort, feelings of loss of control, and a rupture of patient identity, according to the study. Daniel John et al. [124] evaluated a possible technique for building an implanted EEG-based brain monitoring and seizure prediction system in another study. The algorithm was examined in a First-In-Man trial with 15 patients who were implanted and followed for two years. The system was shown to be extremely sensitive for only two patients, with a warning duration of 114 min. This type of technology might increase patients' confidence in engaging in activities such as walking, but it could also harm those who are less sensitive to algorithm. Brown et al. [125] conducted an open-ended and semi-structured interview with essential tremor patients who took part in a trial of a BCI-controlled DBS device implanted. BCI has been found to provide patients with a powerful form of control over their neurostimulators, albeit this control may come with extra obstacles. Users of the BCI-DBS will need to figure out how to use their neurostimulator in a way that allows them to maintain their identity and feeling of agency. As a result, physicians must consider what their patients desire from BCI control, how they integrate BCI-DBS into their daily life, and how their values may hinder or assist them along the process.

Due to paucity of practical data, the authors analyzed that the exploration of user experiences and iatrogenic harms of BCI technology is currently unfilled. Researchers working in this domain have thus sufficient reasons to explore this dimension of BCI technology.

7 Conclusion

Machine learning approaches are developed on the human brain's ability to learn from prior experience in real-time. Various fields of study have commonly used these methods to find solutions to their problems. The author presents a comprehensive analysis of machine learning methods for classifying popular EEG paradigms such as motor imagery, P300, and SSVEP, as well as the important contributions required in this field of research. The challenges pertaining to EEG-based BCI were identified and categorized according to signal processing, BCI functioning, performance assessment, and commercialization.

Despite the many outstanding breakthroughs in BCI study, there are still some problems that need to be addressed. The current BCIs have a relatively low ITR for any form of successful BCI use. As a result, it is needed to improve the ITR of BCI in the future. Another significant problem in EEG-based BCI research is commercialization, which is hampered by long calibration times and BCI usage by disabled patients. This may be overcome by using multi-stage and multimodal approaches.

BCI community has started to progress from traditional machine learning algorithms to deep learning architectures due to the current availability of computing resources. The classification of non-stationary EEG is now possible thanks to the use of such cutting-edge techniques. In addition, major efforts have been made to reduce the training time so that BCI can be used in real-world scenarios. Researchers' ongoing attempts to find new solutions will pave the way for brain computer interfaces to turn into a feasible approach to human machine interaction in the not-too-distant future.

Declaration

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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