Multimedia Tools and Applications (2023) 82:47003–47047
https://doi.org/10.1007/s11042-023-15653-x

Electroencephalogram based brain-computer interface: Applications, challenges, and opportunities

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Received: 25 October 2021 / Revised: 17 July 2022 / Accepted: 22 April 2023 /
Published online: 4 May 2023

Abstract
Brain-Computer Interfaces (BCI) is an exciting and emerging research area for researchers and scientists. It is a suitable combination of software and hardware to operate any device mentally. This review emphasizes the significant stages in the BCI domain, current problems, and state-of-the-art findings. This article also covers how current results can contribute to new knowledge about BCI, an overview of BCI from its early developments to recent advancements, BCI applications, challenges, and future directions. The authors pointed to unresolved issues and expressed how BCI is valuable for analyzing the human brain. Humans' dependence on machines has led humankind into a new future where BCI can play an essential role in improving this modern world.

Keywords Brain-computer interface (BCI) · BCI advancements · EEG feature extraction · BCI future · BCI challenges · BCI tools

1 Introduction

Brain-computer interface (BCI) is an interesting topic for researchers, as evidenced by extensive research and study material. Interacting with any device or PC using brain signals is the central idea behind the BCI. The BCI encompasses a thought signal that drives hardware with software applications. According to this definition, BCI aims to capture the brain signal with the help of sensors, process the captured signal, extract features from these signals and then send that desired output to control any device. It's a relay between the brain and the device. The possibility of a BCI began in 1929 when Hans Berger [180] explained the electroencephalogram (EEG). He recorded the brain waves and identified the oscillations with every brain activity. Such brain waves are also known as Berger waves. In 1973, J.J.Vidal [295] tried to implement an EEG-based BCI, which recorded the evoked electrical activity of the brain using EEG. Farwell and Don Chin [89] used P300 to link the brain and the machine. U. Hoffman [126] also proposed a P300-based BCI to re-establish

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the link between the brain and the affected body part. According to J.P. Donoghue et al. [82], "a BCI in which the major goal is to provide an instruction signal from the cortex that may control any paralyzed body part or any actual device." According to J.R. Wolpaw et al. [312], "a BCI is a device that connects the brain to a non-physical channel of communication and command."

Humans' ability to communicate with each other is one of the fundamental principles of human civilization because they cannot fully understand others' perspectives without communication. The field of communication is very diverse, i.e., speech, conversation, visual communication, gesture, or writing. With the help of communication, one can share emotions, expectations, and creative thoughts among human beings. BCI is a boon for those where communication is not possible, i.e., locked-in syndrome, spinal cord injury, brain stroke, cerebral palsy, etc. Due to these disabilities, one cannot communicate with others while they are well aware of things around them [23, 127]. BCI provides basic communication abilities by interfacing the human brain and the device. The user generates various brain waves that are converted into commands for the device [215].

BCI was originally developed for biomedical applications to allow physically disabled users to move around, replace the disappeared motor functions and develop assistive devices for medical purposes. But after a long time, this technology has expanded and found its way into various non-medical applications. The extension of BCI is very vast in non-medical applications [86, 266] such as lie detection [171, 302], drowsiness detection [69, 101, 175], virtual reality [46, 50, 259, 276, 285], video games [161, 209], drivers fatigue detection [131, 191, 206, 304, 327], stress detection [329, 337], brain to brain interface [19, 110, 221, 249], driving humanoid robots [53, 278], wheelchair control [94], BCI mobile robot [34], emotion recognition [11, 133], biometrics [9, 240], upper limb rehabilitation after stroke [55, 97, 313] etc. In the last decade, many research and review articles have been published, as shown in Fig. 1. The number of published articles increased continuously, but a decline can be seen due to the COVID-19 pandemic. To write a specialized review article on BCI, the authors referred to some important BCI review articles in Table 1. Wolpaw et al. [311] summarised the first international meeting on the

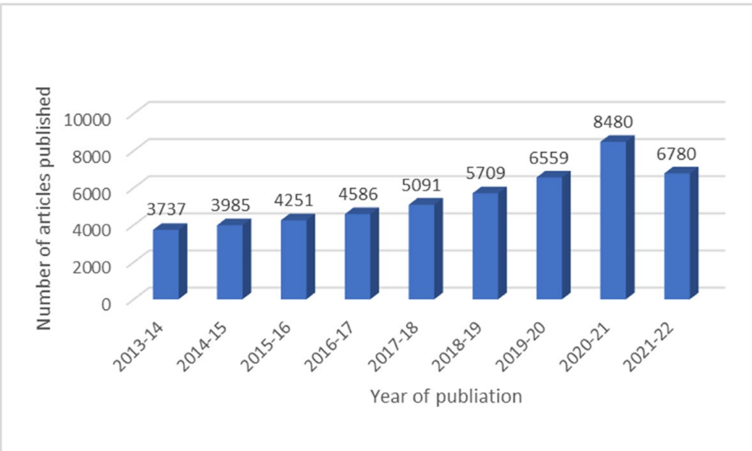

Fig. 1 Brain-Computer Interface research and review articles published by reputed publication houses such as Springer, Nature, Elsevier, IEEE, Taylor and Francis, Wiley

Table 1 Some Important BCI review Articles

Reference	Summary
Wolpaw et al. [311]	• The article summarized the first international meeting on the research and development of BCI • The article explained the BCI definition, essential features, invasive data acquisition methods, signal analysis, translational algorithms, BCI applications, and the future
Hwang et al. [134]	• The article summarized EEG-based BCI articles from 2007 to 2011 • It also discussed different BCI paradigms, classification algorithms, BCI applications, and feature types
Ramadan et al. [247]	• The article explained various brain control signals, characteristics, and differences. The current hardware and software of BCI technology are well explained • Various neuroimaging methods, BCI challenges, and future directions are excellently explained
Ahn et al. [4]	• Performance-based motor imagery BCI studies and their results have been discussed • Physiological conditions affected the BCI performance
Nicolas et al. [217]	• The article excellently discussed the various neuroimaging modalities, EEG control signals, and different artifacts removing techniques • Various algorithms have been described in the feature extraction and classification section
Abdulkader et al. [1]	• This article discussed various applications of BCI • Critical technical problems and their solutions have been discussed in this article
Choi et al. [60]	• The current state-of-the-art hybrid BCIs have been reviewed in this article • The article focused extensively on the task and measurement characteristics of hybrid BCIs
Amiri et al. [14]	• The article reviewed various hybrid BCIs, their multiple combinations, benefits, and drawbacks
Papanastasiou et al. [229]	• The article described how BCI devices impacted the subject's attention and working memory and how proper training enhanced cognitive skills • The authors discussed the rehabilitation of neuro-developmental diseases for multiple population groups and provided future instructions for application-based BCIs
Van et al. [87]	• The article characterized the brain connectivity and functions in 1200 healthy subjects using multiple imaging modalities
Saha et al. [261]	• The article explained BCI challenges and applications excellently
Chaudhari et al. [54]	• BCI applications in communication and rehabilitation have been explained very well
Lotte et al. [185]	• The article discussed different machine learning classification algorithms used in EEG-based BCIs from 2007 to 2017
Abiri et al. [2]	• A comprehensive review of EEG-based brain-computer interface paradigms
Banville et al. [30]	• A review article on non-invasive modalities such as EEG, fTCD, NIRS, and hybrid BCIs • Different EEG control signals, experimental protocols, and signal processing methods have been discussed
Rezeika et al. [254]	• The article summarised different BCI spelling models, their categorization and methodologies, and the current system's limitations
Rashid et al. [250]	• The article described essential components of BCI, different EEG data acquisition frameworks, data processing strategies, feature extraction, classification methods, etc • The Application-based approach, current challenges, and future directions have also been provided in this article

Table 1 (continued)

Reference	Summary
Zhang et al. [331]	• The article explained BCI architecture and invasive and non-invasive data acquisition techniques • The article also covered different EEG paradigms, deep learning approaches in BCI, hybrid BCIs, and future directions
Islam et al. [141]	• The article summarized various features, features extraction techniques, system performance, and algorithms used in emotion recognition • It also excellently described the deep learning and shallow learning techniques used in emotion recognition
Zhang et al. [330]	• Applications of transfer learning on the brain-computer interface were explained well

developments of BCI. The article explained the BCI's basic developments and future possibilities, while the paper lags from the feature extraction and processing point of view. Hwang et al. [134] summarized EEG-based BCI articles from 2007 to 2011. The article discussed different BCI paradigms, classification algorithms, BCI applications, and feature types, but the future directions and current state of the art were missing. Ramadan et al. [247] discussed EEG control signals and their classifications excellently. The authors described BCI very well from the software and hardware perspective, but the signal processing and application parts were not appropriately explained. Ahn et al. [4] provided various performance-based motor imagery BCI studies. The article explained how physiological factors affect the performance of a BCI and how BCI reliability can be improved to deal with these fluctuations. The feature extraction and the application-based approaches were not adequately considered. Nicolas et al. [217] proposed an excellent review article considering every aspect of BCI.

Abdulkader et al. [1] discussed the fundamental aspects and covered a broad spectrum of EEG-based BCI. The article also discussed BCI applications, essential usability issues, and solutions. However, the articles reviewed were fewer. Choi et al. [60] proposed an excellent article on hybrid BCIs. A systematic methodology has been adopted for the classification of hybrid BCIs. The article focused extensively on the task and measurement characteristics of hybrid BCIs. Ameri et al. [14] also discussed hybrid BCIs and their multiple combinations, benefits, and drawbacks. Papanastasiou et al. [229] described how BCI devices impacted the subject's attention skills and working memory. BCI-based applications enhance persons' cognitive skills with proper training and rehabilitation. The article also discussed the rehabilitation of neuro-developmental diseases for multiple population groups and provided future instructions for application-based BCIs. Van et al. [87] characterized the brain connectivity and functions in 1200 healthy subjects using multiple imaging modalities. Saha et al. [261] explained the BCI challenges and applications excellently. Chaudhari et al. [54] explained the BCI contributions to communication and rehabilitation. Lotte et al. reviewed [185] different EEG-based BCI classification algorithms from 2007 to 2017. The article also provided the guidelines for selecting the appropriate machine learning technique, and their pros and cons, while the evaluation performance matrix was missing. Abiri et al. [2] proposed a comprehensive review of EEG-based brain-computer interface paradigms. Different EEG external stimulation paradigms have been explained in this article. Banville and Falk [30] reviewed various non-invasive data acquisition modalities, i.e., EEG, functional translational Doppler (fTCD), near-infrared spectroscopy (NIRS), and hybrid BCIs based on these techniques. The authors summarised the fifty-five BCI studies from 2008 to 2014. EEG control signals, experimental protocols, and signal processing methods with future directions were explained well in this article. Rezika et al. [254] reviewed different BCI spelling models, their categorization, and the current system's limitations in a specific manner. Rashid et al. [250] proposed a very informative article including every aspect of BCI, i.e., essential components, control signals, data acquisition methods, data processing, feature extraction, and classification methods with popular BCI applications. Zhang et al. [331] proposed an excellent BCI article that explained various aspects of BCI and the deep learning approaches used in BCI. Islam et al. [141] reviewed different feature extraction techniques used in emotion recognition and provided observations and recommendations for future research. The article excellently explained the usability of deep learning and shallow learning techniques. Zhang et al. [330] proposed an article on the applications of transfer learning in the BCI. The article focused on all non-invasive methods, EEG signals, experimental design protocols, signal processing methods, and future directions of EEG-based BCI research. However, the experimental results between BCI applications for EEG modulation were missing.

After a deep investigation, the authors found that most of the published articles were application-specific. Some BCI-related information was missing or not accurately described, including methodology descriptions, recent advancements, future research directions, etc. The authors focused on a review article that provides the basic BCI information and effectively covers the application, recent advancements, and challenges of the BCI. The basic structure of this study is shown in Fig. 2. The authors also compared some recently published BCI reviews with this article, as shown in Table 2. Covering all the BCI aspects in a single article is really challenging. The authors are already working on one more BCI article based on BCI feature extraction and processing techniques.

The inclusion criteria for the articles were that they covered various aspects of BCI, including applications, recent advancements, challenges, and future directions. As described in Fig. 3, the PRISMA method has been adopted to search these articles.

This review article will be helpful to the research community for the following points:

(1) Introductory information about BCI and its components will be helpful for novice researchers.

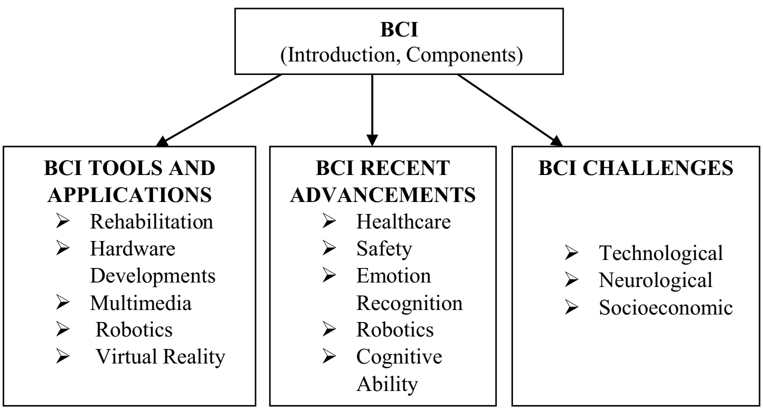

Fig. 2 Study diagram

Table 2 Comparison of the proposed article with some already published BCI articles

Reference	BCI Components	BCI Applications	BCI Challenges	BCI Tools	BCI Future Directions	BCI Recent Advancements
[247]	✓	✓	✓	✓	✓	✗
[1]	✓	✓	✓	✗	✗	✗
[261]	✗	✓	✓	✗	✓	✓
[250]	✓	✓	✓	✗	✓	✓
[331]	✓	✓	✗	✗	✓	✗
This Study	✓	✓	✓	✓	✓	✓

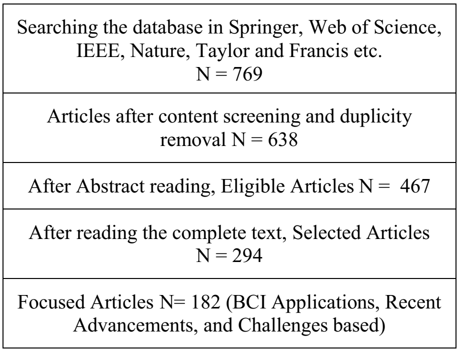

Fig. 3 PRISMA technique adopted to search the database

(2) The article provides knowledge about the Software/tools and BCI Applications, providing insights and interest for researchers in this field.
(3) The article contains the recent advancements and challenges of the BCI that will be helpful for the developers and expert-level researchers to think of solutions to these challenges.
(4) The discussion and future possibilities will be helpful in developing new thinking and possibilities in this field.

The paper is organized as follows. The second section of the article contains BCI components, i.e., the signal acquisition, why the EEG is better than other signal acquisition techniques, and the comparison between the EEG and other data acquisition modalities. This section also contains pre-processing, feature extraction, and classification. Different BCI software and the BCI applications are described in the third section. The fourth section contains the BCI's recent advancements. Section five explains the challenges in BCI. The sixth and seventh sections are the discussion, conclusion, and future scope.

2 BCI Components

The brain-computer interface is an effective and powerful tool for user system communication without muscle intervention [130]. Every BCI system consists of these essential components; signal acquisition, pre-processing, feature extraction, classification, and applications [121]. Figure 4 illustrates a typical BCI system that indicates the different stages of the BCI. In the signal acquisition stage, brain activity is captured by different types of sensors and different data acquisition modalities (EEG/fMRI/NIRS/MEG) [234]. This captured raw signal has various artifacts removed in the pre-processing stage [85]. Then in the feature extraction stage, a few relevant signal values are extracted, called features [24]. These extracted features are then classified using different techniques in the classification stage [277].

2.1 Signal Acquisition

The two major parts of the human brain are the cerebral cortex and subcortical regions. Subcortical regions are essential to control various activities such as body temperature, heart rate, reflexes, learning, respiration, etc. The cerebral cortex or cerebrum is responsible to controls sensory and motor functions and various activities like language refinement, planning, thinking, pattern identification, etc.

The cerebral cortex is divided into two hemispheres, each of which is divided into four lobes: frontal, parietal, temporal and occipital, as shown in Fig. 5. The frontal lobe is associated with planning, thinking, problem-solving and emotional control. The parietal lobe is associated with Sleeping, manipulation, awareness, and perception [250]. Memory, emotion generation, and language processing are associated with the temporal lobes. The occipital lobe is responsible for all visual activities.

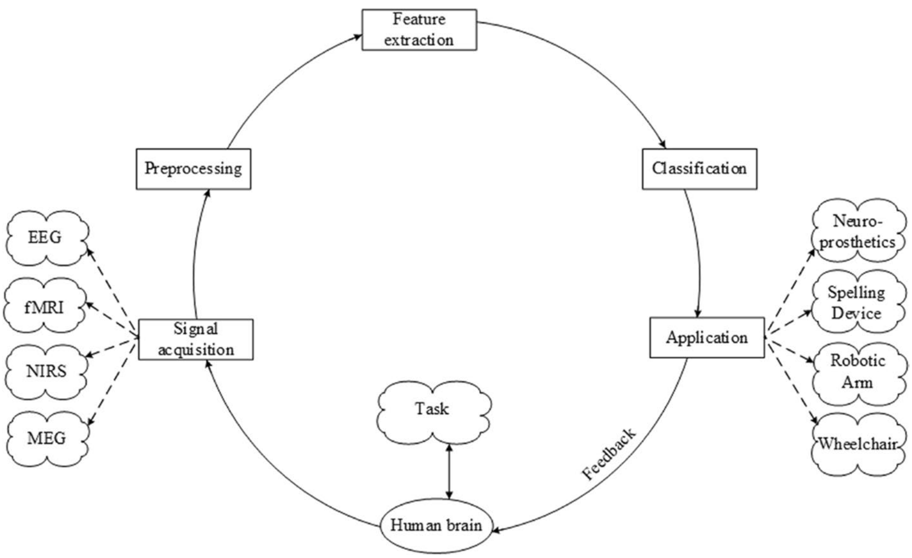

Fig.4 Typical BCI components

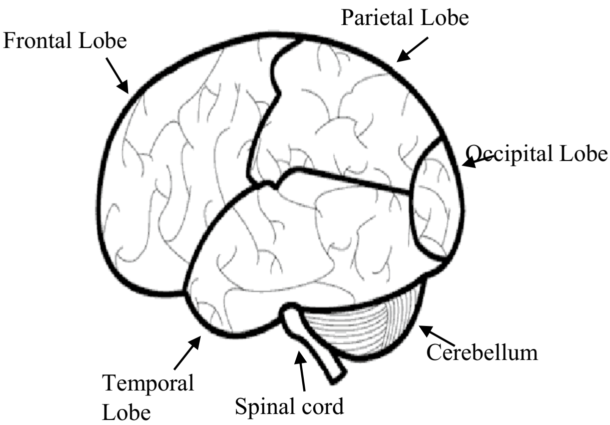

Fig. 5 Different parts of the human brain

The nervous system is another essential human body system. It is divided into two parts: the central and peripheral systems. The central nervous system comprises the spinal cord and the brain. The autonomic nervous system is part of the peripheral nervous system. It is responsible for regulating digestion, hormone secretion, and breathing. Acquiring the raw signal is a crucial step for a typical BCI system. Different types of electrodes have been used for signal acquisition, as shown in Table 3. Some of them are injected inside the scalp by the surgery, and others are placed on the scalp. These electrodes are application-specific and selected based on their availability and ergonomics. Based on the signal acquisition techniques, BCIs are divided into two types: either invasive (surgical) [16, 292] or non-invasive (nonsurgical) [62, 336]. Neurosurgery introduced microelectrodes into the brain [264]. A high-quality signal can be picked up with this technique, but there is a possibility of tissue damage during such surgery that could result in signal loss. A disadvantage of such an electrode is that it is impossible to pick up signals from any part of the brain other than the implantation site [336]. The brain signals can be picked up by the scalp in non-invasive BCI [172, 301]. The signal quality is not as effective as with the invasive BCI, but it is preferred since surgery is avoided. Numerous non-invasive devices are available today and can easily be used for signal acquisition without any special training or medical supervision. Emotive, Open BCI and National Instruments are some companies that provide easy-to-use electrodes and electrode caps [115, 183]. The semi-invasive is another type of BCI where the electrodes are placed on the exposed part of the brain. The strip or grid electrodes cover a vast cortex space (up to 256 electrodes), enabling many cognitive studies [52]. In [247, 250], different EEG electrode has been discussed.

2.1.1 EEG instead of other signal acquisition techniques

EEG is a non-invasive technique. Using EEG, we can extract signals from the brain and use them for further pre-processing. In the EEG, we can quantify the electrical signal generated by the physio-electrical activity of the brain. The EEG waveform varies with the position of the electrodes. It is a complex pattern compared to Electrocardiography (ECG). EEG is an inexpensive, affordable, safe, and readily available technology [116, 163]. There are two classes of EEG electrodes, one is active, and the other is passive. The active electrodes have an amplifier circuitry, but the passive electrode necessitates an external amplifier circuit to amplify the diagnosed brain signal [198]. The saline solution minimizes the

Table 3 Available EEG devices and their basic descriptions

Device	Description
Brain Products	Wireless communication, Channels available (8/16/32), Sampling frequency (250/ 500/1000)Hz
NeuroScan	Wired communication, Channels available (32/40/64), Sampling frequency (20 kHz) and (1000 /1024 /4096) Hz
OpenBCI	Wireless communication, Channels available 16, Sampling rate 256 Hz
Muse	Wireless communication, Channels available 4, Sampling rate 256 Hz
Bio semi	Wired communication, Channels available (16/32/64), Sampling frequency (2/4 /8/16) KHz
mBrain Train	Wireless communication, Channels available 24, Sampling rate 250–500 Hz
Neuroelectrics Enobio 32	Wireless communication, Channels available 32, Sampling rate 500 Hz
Emotive	Wireless communication, Channels available (5/14/32), Sampling frequency 128 Hz
Melon EEG head	Wireless communication, channels available 3, sampling rate 20 Hz
NeuroSky	Wireless communication, Channels available 1, Sampling rate 512 Hz
PLX Xwave	Wireless communication, Channels available 1, Sampling rate 250 Hz
Advanced brain monitoring	Wireless communication, Channels available 24, Sampling rate 256 Hz
AntNeuro eego	Wireless communication, Channels available 64, Sampling rate 2084 Hz
MyndBand	Wireless communication, Channels available 3, Sampling rate 512 Hz
Enobio	Wireless communication, Channels available (8/20/32), Sampling rate 500 Hz
Quasar	Wireless communication, channels available 8, Sampling rate 400 Hz
Cognionics Mobile	Wireless communication, Channels available 72, Sampling rate 500–1000 Hz
OxyMon	Wireless communication, Channels available 1 to 112, Sampling rate 32.64 Hz
g.tech nautilus	Wireless communication, Channels available 64, Sampling rate 500 Hz

impedance between the body and the electrode interface. This gel dries over time, so we adopt the dry electrodes instead [177, 203]. Advantages of using EEG are a low signal-to-noise ratio (SNR), a high resolution, and a rapid response (0.5-130 ms) [100]. Different standards are available globally for using EEG electrodes. As shown in Fig. 6, the 10–20

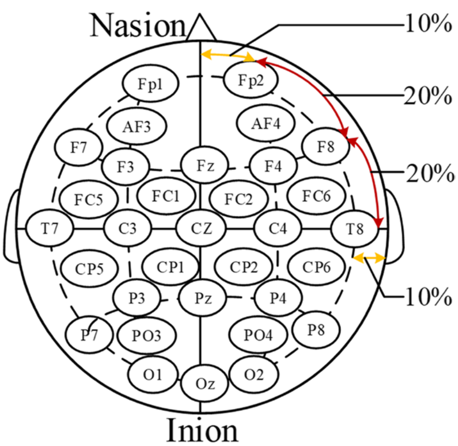

Fig. 6 EEG electrode placement 10–20 system

system is one of the configurations accepted globally for data acquisition [44, 331]. The system relies on the connection between the electrode location and the cerebral cortex's underlying area. The numerals 10 and 20 indicate that the distance between adjacent electrodes is 10% or 20% of the skull's total front-back or right-left distance, respectively. The lobe on either side is represented by a letter, while a number represents the hemisphere location. The frontal, parietal, occipital, and temporal lobes are denoted by F, P, O, and T in this system. The electrode placements of the right hemispheres are indicated by the even digits 2,4,6,8. The electrode placements in the left hemisphere are represented by odd numbers 1,3,5,7. Table 4 shows different EEG bands with different frequency ranges, amplitudes and characteristics [196, 212, 334].

Except EEG, Electrocorticography (ECoG) is a semi-invasive technology where electrodes are placed inside the skull to improve spatial resolution [244]. This technique cannot be adopted outside the hospital room [315]. The non-invasive Magnetoencephalography (MEG) uses the brain's magnetic field to record the brain's neural activity [201, 263]. Positron Emission Tomography (PET) refers to the metabolic process. It is used to test how our organs and tissues work [138]. It is also a non-invasive technique, but the operating cost is high, and portability is another issue with this technique [29]. Functional magnetic resonance imaging (fMRI) is based on the principle that there is a variation in the oxygen content in the blood to receive the signals from active brain regions [37, 274]. Table 5 shows various signal acquisition techniques' advantages and drawbacks.

2.2 Pre-Processing

Pre-processing is required to extract the noise from the recorded EEG signal. The analog-to-digital (A/D) conversion, amplification, and filtering are performed in the pre-processing stage [36, 143]. When we record the electrical neural activity of the brain, some electrical and muscular activities can also be recorded. These undesired signals are known as artifacts [265]. The removal of artifacts is necessary before further signal processing [291]. Endogenous and exogenous are the two broad categories of artifacts. Electromyography (EMG) is the artifact usually due to muscle activity such as muscle contractions. In addition, cardiac activity also introduces a rhythmic disturbance into the brain waves. Some undesired signals are generated by blinking and other eye movements and develop a low-frequency pattern with the brain signal. These all are endogenous artifacts [147].

Table 4 Different EEG bands and their characteristics

EEG Bands	Frequency Range (Hz)	Characteristics	Location on Brain
Delta	0.5–4	Deep sleep, Unconscious	Frontal
Theta	4–7	Drowsiness, Imaginary, Enthusiastic	Midline, Temporal
Alpha	7–12	Relaxation, calm, eyes closed	Frontal, Occipital
Mu	8–13	Motor neurons activated	Sensory-motor cortex
Beta	12–30	Alertness, aware of surroundings, Thinking	Frontal, Symmetrically distributed on both sides
Gamma	Above 30	Abnormality, Agitation, Short term memory for matching objects	Frontal, central, somatosensory cortex

Table 5 Comparison between various data acquisition techniques

The technique (s)	Advantage (s)	Drawback (s)
EEG	• Can get mainly all the brain information such as any disease, disorder, coma, brain death, etc • Non-invasive in nature • No harmful side effects	• Not suitable for the images of the brain cross-section • Unable to find the location of the injury
ECoG	• Direct measurement • Lower signal-to-noise ratio (SNR) • Resolution is better than EEG	• The placement of the electrode is only for a limited time
MEG	• Excellent resolution to EEG • The magnetic field is less influenced than the current	• Very expensive • Noise interruption
PET	• Almost all brain activity can be sensed • Inexpensive and non-injected	• The brain cross-section cannot retrieve • Unable to get the exact location of the injury
fMRI	• Better temporal resolution • Very much sensitive to motion • Relatively inexpensive than PET as well as EEG	• Very expensive • Non-user friendly
Optical imaging	• Easy to use • Radioactive	• Time-taking process

Exogenous artifacts may be due to the 50/60 Hz mains disturbance from AC sources [142]. After identification, artifact removal is the next step [139, 219]. The brain signals can be removed from the EMG and ECG signals [166, 310]. The EEG signal is usually between 0.2 and 40 Hz. So we can apply filters to eliminate artifacts above and below this range, such as discrete Fourier transform (DFT), finite impulse response (FIR filters), and infinite impulse response filters (IIR). Some standard methods for removing artifacts are linear filtering, principal component analysis [22], independent component analysis [262], etc. A good pre-processing increases signal quality, which results in better feature extraction and classification performance.

2.3 Feature Extraction

The activity of finding secret facts and the behavior of the captured signal is called feature extraction [145]. The behavior of a signal set can be represented by its characteristics [128, 186, 326]. Various techniques are now available for the feature extraction process, viz. principal component analysis, independent component analysis, autoregressive (AR) modeling [328], genetic algorithm [273], and sequential selection [106]. The principal component analysis is preferred to extract the activities and obtain the signal information [320]. AR modeling and genetic algorithms are used for pattern recognition and feature extraction in patients with epilepsy [3, 6, 25, 78]. Table 6 shows the different feature extraction techniques and their applications.

In time-domain analysis, the signal amplitudes vary with time. When extracting features in the time domain, we take a specific time window of the signal and extract characteristic properties. Statistical data properties can remove the most valuable elements from the signal [293]. In addition, various application-oriented techniques such as AR, LPC, and KB modeling are also available. The signal characteristics depend on the signal's present and past values in AR and LPC models. The advantages of these techniques are signal compression, noise reduction, resolution enhancements, biometric modeling, EOG, EMG analysis, cancer cell analysis, speech recognition, coding, etc.

ERS and ERD are the types of Event-Related Potential (ERP). When the signal power increases in a specific EEG band, it is called ERS. The ERD indicates a decrease in signal power in the same way. Different brain activities are recorded in various frequency bands like delta, alpha, or gamma. These variations in the activities are recorded and referred to as the ERS and ERD patterns. Evoked potentials are the electrical responses in a specific pattern recorded from a particular part of the nervous system, such as the brain [84, 169, 188]. In steady-state evoked potentials (SSEPs), the person receives a periodic stimulus, i.e., an image flicker, a sound wave, or vibration. After receiving such a stimulus, our brain reacts accordingly. These SSEP signals can be steady-state visual potentials (SSVEP), auditory SSEP, or somatosensory SSEP. SSVEPs are the oscillations of the brain response in the visual cortex by repetitive visual stimuli. There are many studies in which the successful outcome of BCI was integrated with SSVEP or VEP [51]. SSVEP is used when the user's eye movements are perfect; it does not apply to uncontrolled eye and neck movements [193].

P300 also belongs to the ERP types [90]. In P300, the person is exposed to a surprising task that fluctuates in the EEG pattern after every 300 ms. It deals with the processing of memory variation and allows its users to spell 26 letters and numbers (0 to 9) on a computer screen [155]. The rhythms associated with motor actions are sensorimotor (beta = 12–30 Hz) and sensory signals. The subject can control the amplitude of such

Table 6 Different feature extraction techniques and their applications

Feature Extraction Domain	The technique (s)	Application(s)
Time	AR modeling, LPC, Kernel-Based modeling	EOG & EMG investigation, audio signal and cancer signal investigation, speech recognition, time series analysis, etc
Frequency	DFT/FFT, Spectral estimation, Hilbert transform	EEG & ECG investigation, audio signal investigation, speaker recognition, filter designing, etc
Time–Frequency	STFT, CWT/DWT	Speech, music, medical image, EEG, EMG, and ECG analysis. Fingerprinting applications, magnetic resonance imaging, etc

signals. If the signal frequency is below 1 Hz, it belongs to slow cortical potentials (SCP) [124]. These are very sluggish variations that can end within a few milliseconds to seconds.

The time-domain representation is often used in BCIs. Due to very low amplitudes (mv), detecting neural activity is sometimes challenging and provides only temporal information. All of these difficulties can be eliminated by frequency domain analysis. The Fourier transform (FT) is a dominant and joint transform used to analyze biomedical signals. With the help of FT, the EEG waveforms are displayed in the frequency domain. The Fourier transformation tells us which frequencies are present in the signal and their proportion. The Fourier transformation can be used in both continuous and discrete signals; the neural signal is represented in the frequency domain to characterize its properties [233]. A band power characteristic representation is averaging of instance values over a specific frequency class. The band performance function illustrated the performance details in each specified frequency band. The power spectrum is often applied to ascertain brain operations [83]. It explains the distribution of the power of EEG curves over a specific frequency range. Combined time–frequency domain analysis is the combined method of extracting features in both times and the frequency domain. The neurotic waveforms contain the attributes of both the time and frequency domains. Both temporal and spectral variations can be analyzed using this technique. FFT is used to determine the signal power at any time and explore the signal [8]. Wavelet transformation is also helpful for quickly analyzing the brain's spectral patterns [13]. The various wavelets were effectively implemented for the execution of the BCI mechanism, such as Morlet wavelets [66], Daubechies wavelets [66], Mexican hat wavelets [232], etc.

2.4 Classification

It is essential to convert the feature into the required command and get the desired action by an effective classifier. Various classification algorithms are available to extract the desired feature. Broadly the classifiers can be divided into two categories, linear and non-linear. A direct relationship exists between the network's input and output patterns in linear classifiers. Linear discriminant analysis LDA [317] and support vector machine SVM [309] are the two types of such classifiers. Fisher formulated the LDA method in 1936. It is an elementary classifier with reasonable reliability and low mathematical requirements [296]. Usually, a two-class classifier can be expanded into multiple classes. Bayesian linear discriminant analysis (BLDA) and Fisher linear discriminant analysis (FLDA) are the improved LDA versions [202]. The non-linear classifiers are used when there is no association between input and output patterns. Examples of such classifiers are artificial neural networks (ANN) [192], k-nearest neighbor classifiers [178], and SVMs [316]. ANN is a very flexible multiclass classifier that classifies the input signal by the training process. Developing a training algorithm is essential to the ANN; Multilayer perceptron (MLP) is frequently used to solve various classification-related problems.

3 BCI Tools and BCI Applications

BCI tools are the general-purpose systems used for BCI research. These tools are used to collect data, Process raw data, extract unwanted signals, and monitor different brain parts depending on the specific application. Some of these tools are available online for free, while others are paid. EEGLAB is a toolbox in MATLAB for handling EEG and other electrophysiological signals. After loading the data into the EEGLAB Toolbox, various data operations such as pre-processing, removal of artifacts, time/frequency analysis, Independent Component Analysis (ICA), plotting the data functions for visualization, data scrolling, event, and channel location handling can be performed. It's a free, multi-purpose toolbox developed by the Swartz Center of Computational Neuroscience (SCCN) at the Wadsworth Centre in 2000. Another tool called BCI2000 contains four components, i.e., Source, signal translation, client application, and operator component. The signal detection is carried out in the source component. The received signal is processed in the signal processing component. The client application part provides a feedback signal to the person. It runs on Windows, Linux, and OS X and is written in C + +. Several filters such as Fourier Transform, Random Filter, Spatial Filter, Normalizer, and simple low pass filters are compatible with BCI2000. Open Vibe is another software platform for BCI. It supports various data acquisition systems and includes many signal processing algorithms. It is an openly accessible software package for planning and experimenting with BCI. Real-time signal processing of the brain signal is one of the functions of Open Vibe. It can be used for signal acquisition, filtering, processing, and projecting brain signals in real-time. It is unpaid software that is compatible with Windows and Linux operating systems. It offers real-time biofeedback and diagnostics. Open Vibe can use a wide range of hardware EEG devices. It has various capabilities, such as signal processing algorithms, machine learning functions, and a better graphical user interface. TOBI is a Common Implementation Platform (CPI) developed for BCI in 2008. TiA, TiB, and TiC are the interfaces in TOBI. TiA sends different signals, TiB is responsible for transmitting signal properties, and TiC is accountable for recognizing classes and labels in BCI. Besides these tools, we have various other widely used tools like BCILAB (an open-source MATLAB tool for BCI), BCI + +, OPEN BCI, etc.

As shown in Fig. 7, BCI is used in various fields i.e. medicine [272], games and entertainment [195], advertising [231], education [269], robotic control [257], self-regulation and meditation [283], smart homes [47] and safety [207]. BCI can prevent, detect and diagnose various diseases. AD Instruments, Advanced Brain Monitoring, ANT Neuro, BEE Medic, Biopac Systems Inc, Biosemi, Blackrock Microsystems, Brain Homecare, Brain Products, Brain Rhythms Inc, Brain Gate, Brain Master Technologies Inc, Brain Science

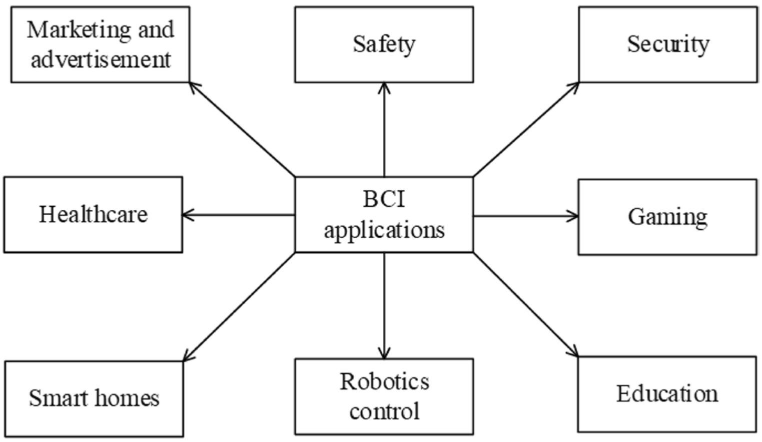

Fig. 7 BCI applications

Technology are some of the international companies that are active in the BCI research. Table 7 shows some important application-related findings of BCI in recent years.

4 BCI Recent Advancements

Human psychology is an exciting topic for researchers and medical professionals. Lim et al. [179] proposed a comparative study that differentiates the concentration and immersion state of the human brain. Thirty-two college students participated in this study, and the Absolute Power Analysis shows the difference between the two states. The concept can be used in future studies with more number of candidates. In many countries, the death toll in car accidents increases every day due to driver's drowsiness. Nguyen et al. [216] proposed a method to detect drowsiness while driving using EEG and NIRF (near-infrared signals). The author measured the subject's vital body parameters in wakefulness and drowsiness conditions and found that the oxygen concentration and power densities differed. The classification accuracy can be increased in the future with actual driving tasks. It will be good if the automobile industry adopts such innovative approaches to prevent road crashes due to sluggishness. Further, Gao et al. [104] also proposed an EEG-based system to detect driver fatigue while driving. The performance of this proposed method was compared to eight competing methods, where this method provides better classification accuracy than the others. From a future perspective, the method can be more reliable using deep learning approaches. One step ahead, a classification model for the neurological operations of successful stopping and failed stopping trials in the reaction of the right hand was developed by Chikara et al. [58]. It has been observed that the quadratic discriminant analysis (QDA) has an accuracy of 94.94%. Catrambone et al. [49] proposed an EEG-based classification method to predict mechanically transient, non-transitive and device-arbitrated upper limb movements. The authors found a remarkable difference in the accuracy of the male and female data in predicting movement. The authors also achieved an accuracy of 78.55% in distinguishing the movements above when using EEG data extracted only from the female subjects. This EEG model of gender difference can also predict gender in other activities. Qu et al. [243] proposed a study in which the sensitive bands of EEG data were analyzed due to different physiological brain loads. ICA has been proposed for data processing. A comparison of the power spectral density was carried out. The SVM classifier shows that the beta band is more sensitive than other bands under different brain loads. Other classification methods can be adopted in the future to get better accuracy.

Today stress has become one of the main complications in our society, affecting a person's mental and cognitive abilities. Mental stress can cause serious problems such as depression, high blood pressure, abnormal sugar levels, anxiety, etc. At the same time, in some extreme cases, a nervous system breakdown can also occur due to unnecessary mental stress. Baik et al. [28] investigated how heart rate variability (HRV) affects the association between frontal and partial inequality and depression. The authors found that HRV balanced the association between depression and parietal alpha symmetry in the case of major depressive disorder (MDD) patients. Medical professionals can use this innovative approach in the future. Ofner et al. [222] examined arm and hand variations in patients with paraplegia. Innovative approaches to the epileptic brain are also increased in the last decades. Fan et al. [88] analyzed different abnormal patterns of epileptic seizures via temporal synchronization of EEG signals. The authors examined Spatio-temporal synchronization patterns by graph theory. This approach can also be helpful for real-time anomaly detection

Table 7 Different BCI applications and their finding (s)

Application (s)	Finding (s)
Rehabilitation and Cognitive Training	• The dependence of neurorehabilitation on neuroplasticity is due to cognitive and perceptual learning [43, 65, 271] • The effectiveness of neurofeedback relies on the plasticity of the particular part of the brain [184] • Alpha activities are linked to visually evoked potentials and motor skills [26] • Neurofeedback-based training units induce the plastic nature of the brain and enable the rehabilitation of attention deficits [39, 80, 108, 184, 256] • Movement-related tasks improved motor learning for the skilled control of neuroprosthetics [117, 299] • BCI can increase motor skills through training-induced plasticity and stimulate neuronal substrates to regain control [225, 282] • BCI can help in training-induced plasticity and neurological rehabilitation to regain the lost control [63, 80, 81, 129] • BCI-induced plasticity depends on the signal acquisition technique, feedback modality, and classification accuracy [114, 218] • Rehabilitation through BCI needs the re-stimulation of the damaged synaptic network or by the attachment of neural prostheses to the impaired body part [226, 248, 303, 307, 333] • BCI-controlled orthotics increased neuromuscular coherence to restore movement [35, 237] • BCI can be used in cerebral palsy [57, 137, 239], brain stroke [79, 95, 107, 149], spinal cord injuries [132, 160, 223, 288], amyotrophic lateral sclerosis [270], chronic peripheral neuropathies [40], etc • The extent of neuroplasticity achieved after rehabilitation varies from person to person, and consequently, an individual training session is necessitated [38, 173] • BCI offers a further degree of freedom that substantially enhances the quality of life of physically disabled users [102, 182, 255] • Neurofeedback generates sturdy somatosensory oscillations associated with the brain [224] • BCI-based rehabilitation differentiates the task-induced and resting-state activities [290] • Controlling the feedback of rehabilitation training can promote the motivation of participants to stimulate and enhance the rehabilitation treatment effect [93] • Optimized deep brain stimulation parameters can be used to treat depressive disorders [74]

Table 7 (continued)

Application (s)	Finding (s)
Hardware Developments	• Development of custom neuro sensors of multiple forms, i.e., electrical, chemical, or biological [112, 165] • Development of electrodes with wireless approaches that provide better signal quality than other wet electrodes [96, 123, 194] • Quasi-dry electrode record signals similar to commercially available Ag/ AgCl electrodes [210] • An auricle electrode has been proposed to increase the signal-to-noise ratio [220] • An electrochemical transistor-based sensor can collect neural signals directly from the brain surface and has a better signal-to-noise ratio [27, 162] • Carbon nanotubes reduce the electrode impedance and enhance the signal quality [61, 159] • With advances in nanotechnology, nanowire field-effect transistors have the potential for neurosensory modalities for intracellular recordings [170, 187, 318] • Calcium imaging-based sensors [98, 111] • Multifunctional soft implants and the multilevel two-photon microscope have been proposed to capture the multilayered neural structures [92, 122, 168] • An ultrasonic-based wireless system has been suggested that enables the recording of EMG and EEG on an excellent scale [268]
Gaming, Robotics, and Virtual Reality	• Future computers will be expected to have emotional and perceptual abilities to make decisions and support people [238] • Computers can identify and interpret potentially underlying affective states using physiological and behavioral attributes [332] • BCI is a future tool for studying affective states and extending its applications to psychology [15, 18] • Various players can participate in a game that requires shared decision-making and linking brain functions to another stimulus during a virtual reality environment [242, 297] • Two brain signals can better judge a challenge because of the inter-individual variations in human perception and abilities [267] • The EEG-based BCI can control a wheelchair, was recently demonstrated [76, 284] • Using Virtual reality technologies, BCI offers immersive experiences with several potential uses, including art, music, and neurofeedback [241] • VR is a better neurofeedback choice for BCI than the PC screen [151, 189, 275, 298] • BCI can be used with AR to remotely control a robot, providing advanced assistive technology for people with mobility impairments [20] • Brain-to-brain interface (BBI) experiments have recently been investigated [110, 148, 228, 235] • BCI can also control humanoid robots in mines and space without gravity [204, 281] • The integration of VR and BCI into one platform is used for motor rehabilitation [287] • Brain teleoperation control of a nonholonomic mobile robot using quadrupole potential function [289, 323]

and its treatment. Open hand, palmar grip, and other hand variations were examined, and the study shows that the various signals originate from the central motor area. This innovation is helpful for patients and aged persons having paraplegia. Ahn et al. [5] proposed a wearable stress management device; heart rate variations [HRV] and electroencephalogram [EEG] is used to measure stress in daily life. One step ahead, Goodday et al. [109] suggested understanding the stress and predicting its importance using a digital platform. The authors also discussed the growth and availability of various digital platforms that require appropriate devices and mobile phone applications. In the future, researchers can examine the affordable and readily available techniques that are helpful to society. Waelde et al. [300] explain how chronic pain in children is affected by multiple mindfulness meditation sessions. Gupta et al. [118] investigated how the short-term musical stimulus affects the cognitive abilities of the human brain. The study shows how Indian classical music changes EEG performances and functional activity and may be adopted for stress release in the future. The authors also developed a model that explained how music improves cognitive abilities and brain performance.

With the help of EEG signals, human facial expressions can easily be related to our psychological states. Numerous approaches are available for feature extraction and classification, such as Fourier transformation, wavelet transformation, power spectral density (PSD), and common spatial patterns. To be able to deal better with the enormous size of two-dimensional EEG data, various algorithmic programs for machine learning are also available, such as Multi-Layer Perceptron (MLP), K-Nearest Neighbour (KNN), Support Vector Machine (SVM), FUZZY Logic, Adaptive Neuro-Fuzzy Interface System (ANFIS). Convolutional Neural Network (CNN) is one of the most important deep learning methods because of its advanced feature extraction capability. Zeng et al. [325] suggested an improved framework called SincNet-R for emotional categorization and identification from the EEG signal. Xu et al. [314] also proposed a multilayer CNN for categorizing EEG waveforms. Environmental parameters such as temperature, humidity, and air pressure can influence people's cognitive abilities. Zhu et al. [335] suggested a test-based cognitive study that demonstrated the variations of EEG signals during the experimental activity for different physical parameters. Svetlov et al. [280] demonstrated the effects of Muse EEG tape-based neurofeedback devices on mindfulness-based relaxation activities. Zabielska et al. [324] examined the sensorimotor rhythm desynchronization during motor imagery tasks. The authors also explained how the power in alpha and beta bands has decreased with the difficulty of both actual and unreal movements. Rahimi et al. [245] investigated the various states of consciousness and attention. The authors explained the significant differences between different states of consciousness and awareness. Rodriguez et al. [258] examined the cross-frequency relationship for different mental states (rest, meditation, and arithmetic). The experiment was performed on 43 experienced meditators using a 19-channel EEG data acquisition system. The findings illustrated that the alpha-theta cross-frequency relationship occurred maximally during the arithmetic condition and minimally during the state of mental void (meditation). Gao et al. [103] investigated the effects of the binaural beats on neural oscillations and cognitive functions.

Sleep quality is one of the essential vital parameters for a person's health. Poor sleep disrupts our day-to-day tasks and causes insomnia. Ko et al. [167] proposed an aromatherapy-based study that shows the increment in delta waves and a decrement in alpha waves during aromatherapy. The experiment was conducted on nine healthy and young participants with no sleep problems. Kim et al. [164] proposed a new EEG-based method for performance evaluation. Thirty-six subjects were tested as either excellent or bad performers. The study results suggested that the microstate reflected cognitive task performance.

Vecsei et al. [294] experimented with the effect of radiofrequency exposure on EEG- based cognitive tasks. Test performance was checked before and after the recording. The results indicated a noticeable decrease in EEG-alpha performance during the radiofrequency exposure. Kalantari et al. [153] compared physiological parameters during a cognitive test in virtual and real environments. Head acceleration and galvanic skin response (GRS) variations are lower in the case of a virtual environment. Former et al. [99] predicted human behavior and performance for the rewards. The study showed that the participants put more cognitive effort when receiving prizes. Reiser et al. [251] recorded mobile EEG during cognitive and motor tasks. The authors performed a cognitive task in real-world situations and observed a relationship between workload and performance. Borghini et al. [41] proposed a study that was carried out on 37 professional air traffic controllers, and the results showed that the specific brain features could be characterized and differentiated accordingly. Jia et al. [146] experimented with different ways of thinking, such as the generation of an idea, evolution of an idea, and controlled creative thinking. The EEG microstate-based methodology was used to analyze the EEG data. The authors found that the alpha performance decreased significantly in the three conditions of the experiment. The results also showed that the idea of evolution requires less concentration than the other two conditions. Widge et al. [308] proposed deep brain stimulation (DBS) -based method for treating major depressive disorder (MDD) and obsessive–compulsive disorder (OCD). Cognitive control is impaired in both MDD and OCD conditions, and DBS improves the subjects' efficacy in a cognitive task.

P3 is an essential event-related potential adopted to identify cognitive activity and utilized in clinical diagnosis. Li et al. [176] found a linkage between P3 and resting-state brain activity. In addition, the long-range interactions between the frontal and occipital brain regions were functionally relevant to P3 parameters. Apicella et al. [17] proposed a method for EEG-based distraction detection during a motor rehabilitation task. The experiment was carried out on 17 healthy volunteers. Various feature extraction techniques such as time domain, frequency domain, and multiple classifiers were used in this study. A k-nearest neighbor classifier achieved an accuracy of 92.8%. Guyon et al. proposed [119] a method to identify the variability between the different vital parameters during stress. The authors used a muse band-based rapid relaxation device to identify how stress changes critical body parameters. Arsalan et al. [21] proposed a study that classified exposure during public speaking. Forty participants were involved in this study. Their physical parameters such as galvanic resistance of the skin, blood volume flow, EEG, and heart rate were determined before and after the public speaking test. Romero et al. [260] proposed a low-cost EEG-based BCI for lower-limb motor recovery in post-stroke patients. The test was performed on eight health and two post-stroke patients. Results showed that the post-stroke patients attained 41.67% and 91.67% accuracy during the task. Park et al. [230] experimented with some tasks (active, passive, and motor imagery) during spinal and grasping movements and found that the patterns differ for two different movements. Wei et al. [306] proposed a method of hierarchical clustering to find the inter-and intra-subjective variability in the EEG dataset. The data were collected in a driving task and validated the feasibility of the EEG-based models for fatigue detection. The results were helpful for plug-and-play drowsiness detection. Alkeide et al. [10] proposed an event-driven BCI method for the Peabody-Image Vocabulary Test (PPVT-IV). The authors applied this approach to subjects with normal development and cerebral disorders. The results suggested that people could benefit from this BCI-assisted approach.

Rezazadeh et al. [253] proposed a hybrid multi-class fNIRS-EEG-BCI model for imaginary speech. Eleven subjects performed different tasks repeatedly. The authors attained an average classification accuracy of 70.45%, considerably more than previous results. The results indicated that a hybrid EEG and fNIRS-based model increased the classification accuracy of BCIs for imagined speech. Corsi et al. [70] proposed a fusion method that combines attributes of simultaneously recorded electroencephalographic (EEG) and magnetoencephalographic (MEG) signals to enhance the performances of motor imagery-based brain-computer interfaces (BCI). Fifteen subjects found a considerable enhancement in the classification accuracy compared to the standard single-modality methods. Islam et al. [140] proposed a deep machine learning approach to detect emotions. Firstly the EEG data was converted into images and then given to the CNN to recognize the emotions. It is a unique and recent approach that may be helpful for future BCI users. Table 8 shows some recent proposed works in the field of BCI.

5 BCI Challenges

Over the past decade, plenty of work has been done in the field of BCI. The appearance of non-invasive BCI devices based on an EEG signal expanded the great possibilities for future technologies. Still, there are various challenges. We know that invasive type electrodes can be installed accurately and require a specialist to reduce the error rate. The brain is a complex structure, so the brain signal contains nonlinearity and noise. As a result of this non-linear behavior of brain signals, various non-linear methods are also used with available linear ones. Researchers and developers are working to resolve this nonlinearity problem. A non-stationary signal is challenging to capture compared to a stationary one because the signal constantly changes during recording. Noise, fatigue, concentration, movement artifacts, and blinking of the eyes are significant factors that cause a non-stationary signal. The placement of electrodes in the scalp is also a factor. If the electrode placement is incorrect, it also causes a transient and noisy signal [181]. Some ambient noise and electromagnetic effects due to power line interferences are also considered as artifacts [59]. Different BCI devices have been developed depending on the applications. The issue with such devices is that they are developed globally, and the standardization of all devices is very difficult. BCI research groups have followed some common standards worldwide, such as data acquisition and EEG electrode placement. Aside from such developments, there is still a lack of standardization in BCI communities worldwide. One of the main issues with the recorded EEG signal is its high dimensionality. The main reason for this high dimensionality is recording the data from multiple channels. Various feature extraction techniques have been developed to reduce the dimensions, i.e., time domain, frequency domain, and combined time–frequency domain.

Various signal processing techniques have been developed to extract features from the acquired signals. Hybrid BCIs using more than one signal, i.e., SSVEP/ERP and SSVEP/MI, offer more robust and accurate functions [236]. Today researchers are trying to explore the new EEG paradigms. The information transfer rate (ITR) is another crucial issue as we have a limited number of bits available per second. We can get a quick response and save time with high ITR BCIs [321]. The target identification accuracy and the target identification time are the factors that affect the ITR. If we shorten the target recognition time and increase the recognition accuracy, the ITR can also be improved. If we want to adopt something new, our brain needs training. Training the user is a significant challenge in BCI. It's a time-consuming process. The applicants must understand how they are compatible with the system and control it with a response signal [135]. The user must be trained to

Table 8 Proposed works on EEG-based BCI

S.No	Reference	Method(s) used	Application	Remarks
1	Lim et al. [179]	Absolute power analysis	Healthcare	Differentiates two different states of the human mind, i.e., concentration and immersion
2	Nguyen et al. [216]	Oxy-hemoglobin concentration and alpha and beta band power analysis	Safety	Drowsiness detection while driving the car
3	Gao et al. [104]	Spatial–temporal convolutional-based neural network	Safety	Fatigue detection while driving the car
4	Chikara et al. [58]	Neural activity classification	Safety	Neurological operations of successful stopping and failed stopping trials in the reaction of the right hand and the inhibition
5	Catrambone et al. [49]	EEG spectral and frequency analysis	Gesture Prediction	An EEG-based classification method to predict mechanically transient, non-transitive, and device-arbitrated movements of the upper limb
6	Qu et al. [243]	Power spectral density analysis	Healthcare	Device-arbitrated movements of the upper limb
7	Baik et al. [28]	HRV and EEG alpha relationship	Clinical physiology	How Heart rate variability (HRV) affects the association between frontal and partial inequality and depression
8	Ofner et al. [222]	Time zone and frequency zone analysis	Healthcare	Examined arm and hand variations in patients with paraplegia
9	Fan et al. [88]	Spectral graph theory features	Healthcare	Different synchronization patterns of the epileptic human mind
10	Ahn et al. [5]	EEG and ECG measurements	Healthcare	Wearable stress management device: Heart rate variations and electroencephalogram are used to measure stress
11	Goodday et al. [109]	EEG, HRV,body temperature,BP measurement	Healthcare	Stress and its consequences
12	Waelde et al. [300]	Graph theory	Healthcare	How the chronic pain in children is affected by multiple mindfulness meditation sessions
13	Gupta et al. [118]	Band power features, ICA	Healthcare	How the short-term the musical stimulus affects the cognitive abilities of the human brain

Table 8 (continued)

S.No	Reference	Method(s) used	Application	Remarks
14	Zeng et al. [325]	Neural network	Emotion classification	An improved framework for emotional categorization and identification
15	Xu et al. [314]	Neural network	Motor imagery	A multilayer CNN for categorizing EEG waveforms
16	Zhu et al. [335]	Time zone as well as frequency zone analysis	Healthcare	A test-based cognitive study that demonstrated the variations of EEG signal during the experimental activity
17	Svetlov et al. [280]	Time zone analysis	Healthcare	The effects of Muse EEG tape-based neurofeedback devices on mindfulness-based relaxation activities
18	Zabielska et al. [324]	Time zone as well as frequency zone analysis	Motor imagery	The sensorimotor rhythm desynchronization during the execution of motor imagery tasks of variable
19	Rahimi et al. [245]	Time zone and frequency zone analysis	Healthcare	The various states of consciousness and attention
20	Rodriguez et al. [258]	Alpha and theta cross-frequency analysis	Meditation	The cross-frequency relationship for different mental states
21	Gao et al. [258]	Frequency domain analysis	Healthcare	The effects of two frequencies of the binaural beats on the neural oscillations and cognitive functions
22	Ko et al. [167]	STFT,PSD,T-test	Healthcare	An aromatherapy-based study
23	Kim et al. [164]	Frequency domain analysis, KNN, SVM, Microstate based comparisons	Mental task performance	A new EEG-based method for performance evaluation based on microstate features
24	Vecsei et al. [294]	Frequency domain analysis, ANOVA, t-test	Cognitive performance	The effect of radiofrequency exposure on EEG- based cognitive tasks
25	Kalantari et al. [153]	Frequency domain analysis, ANOVA	Cognitive performance	Compared physiological parameters during a cognitive test in virtual and real environments
26	Fromar et al. [99]	Event-related potentials	Human behavior	Predicts the human behavior and performance for the rewards

Table 8 (continued)

S.No	Reference	Method(s) used	Application	Remarks
27	Reiser et al. [251]	Event-related potentials, ANOVA	Cognitive and motor functioning	Perform a cognitive task in real-world situations and observe an increase in workload and a decrease in performance with the increasing complexity of movement
28	Borghini et al. [41]	Frequency domain, ANOVA	Behavior assessment	How the neurophysiological signals study human behavior
29	Jia et al. [146]	Task-related power comparison, ANOVA	Creative experiment	An experiment in different ways of thinking such as generation of an idea, evolution of the idea, and controlled creative thinking
30	Widge et al. [308]	Time and frequency domain analysis, T-test	Healthcare	Deep brain stimulation (DBS) -based method for treating major depressive disorder (MDD) and obsessive–compulsive disorder (OCD)
31	Li et al. [176]	Time and frequency domain analysis, ANOVA	Cognitive study	Found a linkage between P3 and resting-state brain activity
32	Apicella et al. [17]	Time and frequency domain analysis	Motor rehabilitation	Different classification approaches on EEG dataset
33	Guyon et al.[119]	EEG frequency domain analysis, ANOVA	Healthcare	A method to identify the variability between the different vital parameters during stress
34	Arsalan et al.[21]	Time and frequency domain analysis, T-test	Healthcare	Classified exposure during public speaking: dependency on physiological parameters
35	Romera et al.[260]	Riemannian geometry, Time–frequency analysis	Lower limb rehabilitation	A low-cost EEG-based BCI for lower-limb motor recovery for the post-stroke patients
36	Park et al. [230]	Topographical analysis,BOX plot,P300,LDA	Spinal Cord injury rehabilitation	We experimented with some motor tasks with spinal and grasping movements
37	Wei et al. [306]	PCA,LDA,SVM	Drowsiness detection	A method of hierarchical clustering to find the inter- and intra-subjective variability in the EEG dataset
38	Alcaide et al. [10]	LDA,p300	Cognitive assessment	An event-driven potentially BCI method for the Peabody- Image Vocabulary Test
39	Rezazadeh et al. [253]	WT,LDA	Robotic control	A hybrid multi-class fNIRS-EEG-BCI model for imaginary language

Table 8 (continued)

S.No	Reference	Method(s) used	Application	Remarks
40	Corsi et al. [70]	LDA	Motor rehabilitation	A fusion method that combines attributes of simultaneously recorded EEG and MEG signals to enhance classification performances in MI-based BCI
41	Islam et al. [140]	Deep learning-based models	Emotion recognition	A deep learning approach for emotion recognition

incorporate and respond after the feedback signal. The training sets can be small or large, depending on the system's usability.

The design of BCIs for everyday use is also important instead of laboratory-based BCIs. Today, very few easy-to-use and plug-and-play BCIs are available [7, 157]. For the real-life applications of BCI, the costs must be minimized. Inexpensive hardware and software development is also an issue [208]. Ethical clearance and security are also associated with the advancement of a BCI [120]. However, some institutes and research organizations have an ethics committee to resolve such issues. Security is also an issue with the BCI systems [67]. The user's private information needs to be protected. Table 9 included some important articles on BCI challenges.

6 Discussion

The authors discussed the paper's findings from the application and challenges perspective.

6.1 Based on the applications

The closed-loop BCI having neurofeedback assistance helps the persons involved in self-regulation and can control specific brain rhythms such as alpha waves to control their brain activities [26]. Findings also revealed that BCI neurofeedback-based training induced the plasticity of the brain and helped to repair and control the output of the nervous system [108, 256]. Plasticity induced by training aids therapy-based motor rehabilitation [225, 282]. BCI training re-excited the relevant neural substrate to re-establish lost control for neuroprosthetics and hence improve human functioning skills [80, 81]. There are two approaches to constructing a rehabilitative BCI. In the first approach, the injured part can be attached with a neural prosthesis, and in the second, we must re-stimulate the damaged synaptic networks [226, 248, 303, 307]. Differentiating a task-generated and resting activity is crucial for regulating the stimulation modality in rehabilitative BCI. The extent of neuroplasticity depends on person-to-person individual training sessions [38, 173]. External magnetic or electric field stimulus also affects the brain during rehabilitation. The brain's white matter induced neuroplasticity when the motor imagery stimulus was applied to the stroke patients. Different rehabilitative approaches, neuroplasticity-based treatments, and training-induced techniques are the future of BCI. Brain stroke [79, 95, 107, 149], spinal cord injuries [132, 160, 223, 288], cerebral palsy [57, 137, 239], amyotrophic lateral sclerosis [270], etc., can be treated more effectively in future using BCI. We have found that BCI provides an extended degree of freedom for physically disabled users [102, 182]

The sensor design also depends on the SNR, resolution, ergonomics, low cost, etc. Electrochemical transistor-based electrodes have a better signal quality and wireless communication with faster data transfer. Neurosensory can be built in various ways, including electrical, optical, chemical, and biological [112, 165]. Both dry and wet sensors have their own set of restrictions and advantages. Dry EEG electrodes are more convenient, although they have a poorer signal-to-noise ratio than wet electrodes [96, 194]. The wet electrodes have conductive gel and require proper skin preparation to reduce skin–electrode impedance, which might be inconvenient for users [123]. Further research suggests that dry electrodes with wireless devices could provide similar signal quality to wet electrodes. A quasi-dry electrode has been developed with the benefits of both dry and wet electrodes and is also compatible with Ag/ AgCl electrodes [210]. A stretchable connector-based auricle

Table 9 BCI Challenges

Challenges	Summary
Neurological	• Motivation enhances the human brain's cognitive abilities, increasing BCI performance [31] • Physiological factors such as attention, memory load, fatigue, and cognitive processes also depend on brain dynamics [73, 156] • Resting-state physiological parameters are also involved in BCI performance, i.e., resting-state heart rate variability, respiration rate, ECG, etc. [71, 158] • A well-organized BCI system has to be unaffected by physiological disturbances to impair the BCI system's stability [105] • A person's current brain dynamics depend on several parameters, i.e., lifestyle, age, memory usage, empathy, gender, etc. [154] • Physiological features in the frequency domain, i.e., spectral entropy and power density, etc., extracted from the quiescent state, can correlate with BCI performance [286] • Case-eccentric neurophysiologic methods provide more insights into the subject and enhance BCI performances [246] • A case-eccentric BCI design that considers typical brain function shows better rehabilitative services. An individualized BCI has been proposed to rehabilitate neurological disease [252] • Neurophysiology trials-based machine learning methodology has been incorporated to reduce BCI illiteracy [33]
Technological	• External stimuli like ERPs and SSVEPs are aim-specific [199, 211] • These methods offer the highest ITR; limitations of these techniques include visual fatigue from focusing on a display for an extended period [56] • Minimally invasive stent-electrode for neural activity recording [227] • MI is not suitable for controlling video games and virtual things due to the slow action control [174] • Hybrid BCIs, i.e., SSVEP/ERP and SSVEP/MI, seem to offer more robust features, but the performance is still unsatisfactory [68, 91, 152, 319] • Various neuroimaging techniques have been used to explore cortical activities, but they fail in cost-effectiveness, efficiency, portability or ease of maintenance, etc.[205, 214] • Activities dependent on blood oxygen level are typically recorded with fMRI, which is impossible with EEG-based BCIs [190, 322] • The functions that estimate the prototype parameters should be selected based on the classifier type for optimal performance when developing the BCI [32, 305] • MI-based BCI is used to map task-related brain signals explicitly [197] • Both invasive and non-invasive signal recordings have demonstrated the long-term application of BCI systems [48]
Socioeconomic	• Because of communication issues, it is complicated to find ethical approval from patients [144] • Awareness of ethical guidelines and the safety of the BCI user is essential [42, 136, 200] • BCIs can affect the nature of the subject, i.e., emotions, personality, memories, etc. [150] • The variations in human cognition are possible and challenging to predict whether the cognitive changes are reversible or not [213] • Cryptographic protocols are an integral part of BCI to protect a user's privacy by hiding sensitive information [64, 279] • A common platform for BCI research and an extensive list of international guidelines are necessary for sustained progress in BCI [45, 77, 125] • For further knowledge development in neurosciences, health security, and ethical guidance, the European Union has initiated the BCI projects with its partner schools [12, 72] • Maintenance of the implanted electrodes is mandatory to avoid neurological side effects, bleeding, and infections [75] • An expanded look at the fundamental BCI aspect will ascertain the basic BCI structure, efficacy, and future BCI applications [113]

electrode has been developed to boost portability and is helpful for long-term recordings [220]. The transistor-based approach amplified the collected signals, resulting in a substantially superior SNR than traditional ECoG [162]. Carbon coating can decrease electrode resistance to improve signal quality [61, 159]. Thanks to exceptional progress in nanotechnology, the nanowire FET and P–N junction-based devices can sense and record deep brain activities [170, 187, 318]. Gaining neural impulses directly from the brain surface is possible by a new organic electrochemical transistor-based sensor [27]. Nowadays, the electrodes are developed with less invasiveness. The electrodes can be inserted in arteries/veins within the brain architecture utilizing computer-guided catheter angiography. The risk of craniotomy will be significantly reduced because of this technology. Calcium imaging and improved microscopes with chronically implanted lenses are two imaging approaches that could be used to investigate cell signaling [98, 111]. A new wireless-based ultrasonic device allows EEG and EMG recordings on the mm scale [268].

Future computers may be expected to have emotional and perceptual capacities such as making judgments [238]. Based on physiological and behavioral characteristics, computers may be able to discern and interpret underlying affective states [332]. BCI has the potential to be used to examine affective states, broadening its psychological applications [15, 18]. Affective state, video games, and virtual environments are some of the latest BCI trends [242, 297]. Some other researchers also demonstrated how the different players could collaboratively participate in a video game that requires a cooperative decision [267]. BCI offers more immersive experiences in arts, music, and neurofeedback using virtual reality techniques [241]. VR-BCI can help with neuroeconomics by measuring cognitive workload and motor rehabilitation [287]. BCI-based wheelchair and mobile robot control have demonstrated their importance in the robotic industry [76, 284]. In various studies, immersive VR is a better neurofeedback option than a computer screen [151, 189, 275, 298]. Brain to Brain interface (BBI) is another perspective of the BCI developments [110, 148, 228]. Two human brains are involved in the BBI interfacing. The transmitter's cognitive objectives have been decoded and converted into commands/instructions to the receiver's brain in the BBI interfacing [235]. Astronauts' usefulness, efficiency, and safety could benefit from a BCI-driven system. This technology can also be used to control humanoid robots in hazardous environments, such as sending a robot into a coal mine or space to perform a potentially dangerous task for humans [204, 281]. BCI can be used in space to track astronauts' working capacity and control an exoskeleton. Working becomes dull and uncomfortable when gravity is absent. The BCI application evolution is shown in Fig. 8.

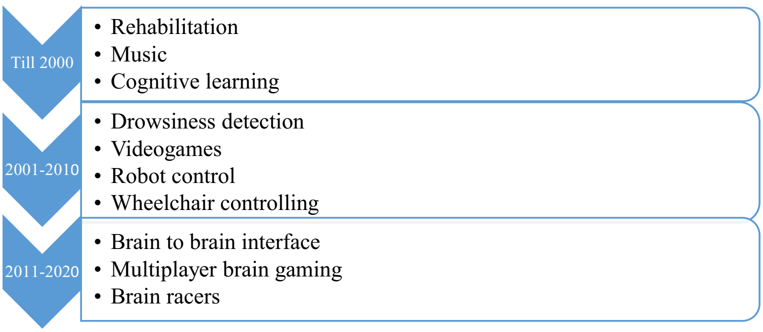

Fig. 8 BCI application evolution

6.2 Based on the challenges

BCI performance can be affected by motivation and encouragement [31]. Various physiological factors such as attention, memory, load, fatigue, age, gender, lifestyle, and places influence a person's brain dynamics [73, 154, 156]. A sensitive or emotional subject will have different performance or brain waves than a passionate subject during the same task. Robustness is also a requirement for an efficient BCI system. An ideal BCI system must be robust to a subject's physiological or essential characteristics [105]. Head anatomy should also be considered a factor for the BCI performance. Physiological predictors such as spectral entropy and power spectral densities can be compared to discover some insights [286]. Case-specific investigations are also trending nowadays for the rehabilitation of stroke survivors [246]. An individual-designed BCI is helpful for rehabilitative interventions [252]. BCI literacy is another issue faced by BCI researchers. During any task, 15 to 30% of the people cannot produce enough robust EEG signals that may be useful for a BCI system. Some researchers proposed methods to reduce BCI illiteracy, and some techniques have been proposed based on the adaptive machine learning approaches [33]. Event-related potentials, steady-state visual evoked potentials, auditory evoked potentials, steady-state somatosensory evoked potentials, and motor imagery are all proposed to detect some brain activities. Still, most of them are application-specific and cannot use for every application. ERP and SSVERP are target specific and need a correct vision of the subject [199, 211]. These techniques cannot be used for a visually impaired person. In such cases, an auditory evoked potential can be used. While the ITR is maximum in SSVEP, visual fatigue is the problem with this method because the subjects have to be continuously focused on the computer screen [56]. To overcome this, some researchers proposed MI-based BCI. But the MI-based BCI is slow and thus not used for video games and virtual reality environments [174]. Thus a hybrid BCI is the option to overcome these issues, e.g., SSVEP/ERP and SSVEP/MI offer more robust features [68, 152, 319]. There are four essential criteria to design an ideal BCI modality: low cost, transportable, low maintenance, and nonsurgical. We have several techniques to acquire the signal efficiently, but none of the single modalities is always preferred [205, 214]. Both invasive and noninvasive methods have their advantages and drawbacks. For example, EEG provides poor spectral resolutions but more acceptable temporal resolutions. Some activities that depend on blood oxygen can be captured by fMRI [190, 322]. Integrating EEG with fMRI is a better option in various applications.

Regardless of scientific breakthroughs in the field of BCI, some other important factors such as privacy protection, data confidentiality, safety, ethics, and socioeconomic issues must be considered while using BCI. Due to communication difficulties and a lack of alternatives, it is difficult for a BCI researcher to obtain ethical consent or permission from a BCI-wearing patient [144]. Various invasive techniques have physiological and neurological side effects. Nowadays, bleeding and infection cases are very few, but they may occur. That's why it is necessary to maintain such electrodes very well [42]. Due to the direct interfacing with the brain, BCI devices can affect the user's behavior, nature, emotion, memory, personality, and thinking [150]. That's why the guidelines are essential for advanced neuroimaging techniques. Changing a person's cognitive capabilities creates a difficult ethical challenge because it's unclear whether the cognitive alterations are reversible and effective [213]. BCI provides an extended degree of freedom, but these risk factors can reduce the benefits of this technology. It is vital to pass legislation that allows the legal use of BCI while also protecting the privacy and confidentiality of stored data. A combination of machine learning and signal processing techniques has been shown in recent research to play a crucial role in translating any signal from the brain to the computer. To keep in mind such important aspects of BCI, the European Union has initiated BCI projects with its partner schools. Table 10 illustrates various BCI issues and recommendations.

7 Conclusions and Future Scope

BCI has undergone explosive growth over the last 20–30 years resulting in the advancements, innovations, and improvements of non-invasive BCI. Because of its direct communication with the brain, BCI is one of the fascinating areas of research. This review provides information about the origin of BCI technology, its growth and applications, the hardware and software used, and its suitability. BCI's recent advancements and challenges discussed in this review can assist future BCI developments. The market shares of the BCI companies increased from 2014 to 2020, which is also a positive sign for BCI developers. Wearable, affordable, less invasive sensor design and brain-to-brain information transfer are some trending topics for the BCI community. For the better future of BCI, the researchers and developers have to:

- Focus on BCI investigations based on physiological, neurological, and technological factors.
- Focus on the commercialization of BCIs, case-specific investigations, and hybrid BCIs.
- Focus on the ethical and safety issues for the BCI users.
- Focus on designing affordable, non-invasive, portable, and easy-to-maintain data acquisition devices.

Table 10 Various BCI issues and recommendations

S.No	Issues/Challenges	Recommendations
1	Study/Experimental design	To understand how the BCI depends on physiological factors and how these factors affect BCI performance
2	Robustness	The BCI system must be stable during regular use and robust with respect to abnormalities
3	Cost-effective	Most of the BCIs available are too costly for a typical user. The prices should be affordable for all kinds of users
4	Hardware developments	Development of less invasive neuro sensors with considerable SNR, high resolution, increased accuracy, ergonomic design, portability, fast information transfer rate, etc
5	Lab-based BCI technology	Most of the BCI experiments have been conducted in the lab instead of in the real outdoor environment. The acquired EEG signal is surely different in the outside environment due to different stimulations like sound, movements, smell, etc
6	Commercialization of EEG-based BCI technology	Pay more attention to the wireless BCI: which can easily be operated over long distances and benefit people in remote areas
7	Hybrid BCIs	The researchers have to pay more attention to hybrid BCI. Different deep learning models and hybrid combinations can make the BCI system more accurate, robust, and intelligent
8	Ethical issues	Pay attention to ethical issues. Raise public awareness through BCI to obtain ethical approvals for R&D in BCI
9	Case-specific investigations	Pay attention to case-specific investigations for the rehabilitation of stroke survivors

Acknowledgements The authors are truly thankful to all the faculty members and research scholars of the Dept. of Electrical and Instrumentation Engineering, SLIET, for their support and encouragement.

Author's contributions Hitesh Yadav: Conceptualization, Methodology, Literature search, Writing. Surita Maini: Supervision, Review, and Editing.

Data availability Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

Declarations

Competing interests 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.

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