Brain Computer Interfaces: The Future of Communication Between the Brain and the External World

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Abstract

This paper provides a comprehensive review of the current state of research on Brain Computer Interfaces (BCIs) and their potential applications. The objective of this study was to gather information from various sources, including journal articles, conference papers, and books, to analyze the advancements and limitations of BCIs. A systematic literature review was conducted using databases such as PubMed, IEEE Xplore, and Google Scholar, with specific keywords related to BCIs and their applications. The selected studies were thoroughly analyzed to identify common themes, methodologies, and key findings. The main contributions of this review include an overview of different types of BCIs, their applications in fields such as medicine, entertainment, and education, and the challenges and limitations faced by BCI technology. The findings highlight the potential of BCIs in restoring motor function, improving the quality of life for individuals with various conditions, and enhancing human-technology interaction. Furthermore, the review identifies future research directions, including signal processing improvements, exploring hybrid and multimodal approaches, conducting long-term real-world studies, addressing ethical considerations, and prioritizing user-centred design. This comprehensive analysis of existing literature provides valuable insights for researchers and practitioners in the field of BCIs and sets the stage for future advancements in this rapidly evolving domain.

Keywords: *Brain Computer Interfaces (BCIs), electroencephalography (EEG), classification, feature extraction, signal acquisition.*

1. Introduction

Brain Computer Interfaces (BCIs) represent a new and exciting technology that allows for direct communication between the brain and an external device or system [1]. The potential applications of BCIs are vast and varied, spanning across many areas of life, from medicine to entertainment [2,3]. In this review research paper, we will provide an overview of the current state of BCI research, including the various types of BCIs, their applications, and their limitations. Additionally, we will discuss potential future directions for BCI research, highlighting areas for further study and development. BCIs hold great promise for revolutionizing many aspects of human life. In medicine, for example, BCIs have already been used to restore lost motor function to paralyzed patients [4-6]. By detecting and interpreting the electrical signals generated by the brain, BCIs can enable individuals with paralysis to control robotic limbs or other external devices with their thoughts [7,8]. BCIs also hold potential for improving the lives of individuals with a range of other conditions, including neurological disorders, hearing and visual impairments, and chronic pain [9-11]. Beyond medicine, BCIs have the potential to enhance the way we

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interact with technology and the world around us. In entertainment, for instance, BCIs can be used to create immersive experiences that respond to the user's thoughts and emotions. They can also be used to create new forms of interactive media that allow users to control games, movies, and other content using their thoughts. In education, BCIs can be used to provide personalized learning experiences that adapt to each individual student's needs and preferences [12-15].

Despite their potential, however, BCIs face a number of challenges and limitations. One of the biggest challenges is the development of reliable and accurate methods for detecting and interpreting brain signals. Current BCI technology is often limited by the signal-to-noise ratio of the brain signals, which can be affected by a range of factors, such as movement, fatigue, and distractions. Additionally, there are concerns around the privacy and security of the data collected by BCIs, as well as the potential for misuse of this technology [16-19].

Despite these challenges, researchers and developers are actively working to improve BCI technology and expand its applications. There are a range of different types of BCIs currently being developed, including invasive, partially invasive, and non-invasive BCIs. Invasive BCIs involve implanting electrodes directly into the brain tissue, while partially invasive BCIs use electrodes that are placed on or beneath the skull but not directly in the brain tissue. Non-invasive BCIs, on the other hand, use sensors placed on the scalp or other parts of the body to detect brain signals. Each type of BCI has its own advantages and limitations, and researchers are exploring ways to improve their effectiveness and reliability [20].

Looking to the future, there are many exciting developments on the horizon for BCI research. One area of focus is the development of hybrid BCIs, which combine different types of BCI technology to create more effective and versatile systems [21,22]. Another area of focus is the development of closed-loop BCIs, which use real-time feedback to adjust the stimulation or intervention being delivered by the BCI [23,24]. This could have implications for the treatment of conditions such as epilepsy, where timely intervention can prevent seizures. Additionally, researchers are exploring the potential for BCIs to enhance cognitive and emotional states, such as improving attention or reducing anxiety [25-27].

The objectives of this paper are to provide an overview of the current state of BCIs research, discuss the various types of BCIs and their applications, highlight the challenges and limitations faced by BCIs, and present potential future directions for BCI research. The paper aims to contribute to the existing knowledge by providing insights into the advancements, opportunities, and areas for further exploration in the field of BCIs.

In this paper, a comprehensive review of the literature on BCIs were presented. The paper begins with an introduction to BCIs, their potential applications, and the challenges they face. This is followed by a detailed methodology section that explains the process of literature review and data collection. The results section provides a summary of key studies in the field, focusing on the use of BCIs for controlling robots. The discussion section analyzes the findings, highlights the contributions of the reviewed studies, and identifies their limitations. Finally, the conclusion section summarizes the main insights gained from the literature review and outlines future research directions.

2. Main Components of A BCI System

Brain-Computer Interface (BCI) is a system that allows direct communication between the human brain and an external device, such as a computer. The BCI system works by detecting, processing, and interpreting brain signals in real-time, enabling users to control external devices using their thoughts, the main component of the system is described in Figure 1.

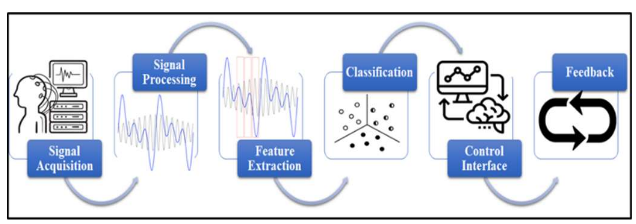


Figure 1. The main components of a BCI system.

- *Signal Acquisition*

Signal acquisition is the process of recording the electrical signals generated by the brain using various methods such as electroencephalography (EEG) magnetoencephalography (MEG), or functional magnetic resonance imaging (fMRI) as showing in Figure 2. In a BCI system, EEG is the most commonly used method for signal acquisition. EEG electrodes are placed on the scalp to record the electrical activity of the brain. These signals are then amplified, filtered, and digitized for further processing [28].

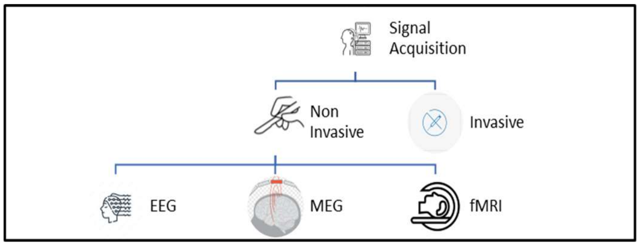


Figure 2. Signal acquisition.

- *Signal Processing*

Signal processing is the next step in BCI applications and involves several steps, including pre-processing, filtering, and data normalization. Pre-processing includes artefact removal, noise reduction, and signal denoising to ensure that the acquired signals are reliable and accurate. Filtering is used to remove unwanted noise from the signal and improve its quality. Data normalization is used to scale the features to the same range, which is essential for accurate classification [29,30].

- *Feature Extraction*

Feature extraction is a process that aims to identify and extract relevant features from the signal that can be used for further processing and classification. The extracted features are usually based on frequency, time, or space domain analysis, and they are used to identify patterns in the data that are relevant to the task at hand. For example, in a motor imagery BCI task, the features extracted may include the power spectral density in the alpha or beta frequency bands, which are known to be associated with motor activity [30,31].

- *Classification:*

The classification component is responsible for categorizing the brain patterns extracted by the feature extractor. It transforms the independent variable into the dependent variable by using various classification algorithms, which can either be linear, such as Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM), or non-linear, such as neural networks [30].

- *Control Interface*

The control interface is the component of the BCI system that translates the user's intention into a control signal that can be used to operate an external device. This interface can be a computer screen, a robotic arm, or any other device that can be controlled by a computer. The interface is designed to be intuitive and easy to use, allowing the user to control the device with their thoughts in real-time [30].

- *Feedback*

Feedback is a critical component of a BCI system as it provides the user with information about the system's performance and their own brain activity. Feedback can be visual, auditory, or tactile, and it is used to inform the user whether their intended action has been correctly identified and executed. Feedback is essential for BCI training and can help users learn to control their brain signals more effectively over time [32-34].

3. Electroencephalography (EEG)

EEG is a non-invasive technique used to measure the electrical activity of the brain. It involves placing electrodes on the scalp to record the electrical signals produced by the neurons in the brain. The 10-20 system is a widely accepted technique for defining and utilizing the placement of scalp electrodes during an EEG assessment as presented in Figure 3.

EEG signals are typically used in BCI applications to detect changes in brain activity and translate them into commands that can be used to control devices or communicate with the environment. EEG is a commonly used technique in neuroscience research and clinical applications, as it provides insights into the brain's functional and pathological states [35-36]. The classification of EEG signals is based on their frequency, ranging from 0 to 100 Hz. EEG signals can also be categorized based on their amplitude, and be recognized based on their shape as illustrated in Table 1 [37-38].

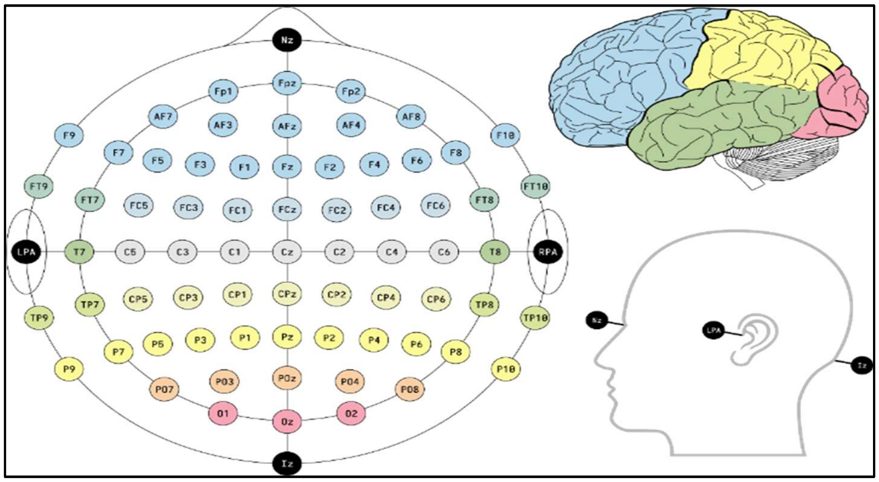


Figure 3. EEG 10-20 System.

Table 1. The classification of EEG signals.

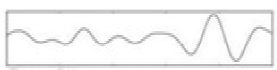
Frequency	*Characteristic*	*Image*
Delta (0.1-4) Hz	Deepest level of relaxation deep sleep	
Theta (4-8) Hz	Rapid eye movement sleep deep and raw emotions cognitive processing	
Alpha (8-13) Hz	Relaxation drowsy state	
Beta (13-30) Hz	Conscious state	
Gamma (30-100) Hz	Two different senses at the same time	

Table 2 presents a summary of recent EEG devices commonly used in BCI applications. These devices vary in terms of the number of channels, electrode types, sampling rates, and connectivity options. The devices listed include both research-grade and consumer-grade EEG systems. Research-grade systems, such as those manufactured by Brain Products, g.tec, and BioSemi, offer higher channel counts and sampling rates, as well as advanced signal processing and analysis tools. Consumer-grade systems, such as those offered by Emotiv and NeuroSky, are designed for personal use and offer lower channel counts and sampling rates. The choice of EEG device depends on the specific BCI application, the user's requirements, and the available budget [39-43].

3.1 Event-Related Potentials

Event-Related Potentials (ERPs) are changes in the brain's electrical activity that are time-locked to specific events or stimuli. ERPs are a type of EEG measurement that is widely used in neuroscience research and clinical settings to study cognitive processes such as attention, perception, memory, and decision-making. One promising application of ERPs is in BCIs, which are systems that allow individuals to communicate or control external devices using their brain signals. EEG-based BCIs have become increasingly popular due to their non-invasive nature and high temporal resolution. ERP components have been used as control signals in EEG-based BCIs, as they can be reliably elicited by specific events or stimuli, and are easy to interpret. By using ERP-based control signals, BCIs can provide more natural and intuitive control for individuals with motor disabilities, allowing them to communicate and interact with their environment in ways that were previously impossible. ERP graph is a graphical representation of the brain's electrical activity in response to a specific stimulus or event as demonstrated in Figure 4.

It is usually plotted as voltage (y-axis) over time (x-axis). The graph shows a series of peaks and troughs in voltage, known as components, that occur at specific time points after the onset of the stimulus. The ERP waveform typically consists of several components that reflect different cognitive processes, such as perception, attention, and memory. Each component has a specific latency (the time between the stimulus and the peak of the component) and amplitude (the height of the peak).

Table 1. Summary of recent EEG devices commonly used in BCI applications

EEG Manufacturer	Model	Sensor	Channel	Sampling Rate	Communication
Emotiv	INSIGHT 2.0	Dry	5	128 [Hz]	Wireless
	EPOC+	Wet	14	-	Wireless
	EPOC FLEX	Wet	32	-	Wireless
	MN8	Dry	2	-	Wireless
Interaxon	Muse 2	Dry	4	256 [Hz]	Wireless
	Muse S (Gen 2)	Dry	4	256 [Hz]	Wireless
NeuroSky	MindWave Mobile 2	Dry	1	512 [Hz]	Wireless
Open BCI	ULTRACORTEX MARK IV	Dry	8, 16	250, 125 [Hz]	Wireless
	EEG Electrode Cap Kit	Wet	21	-	Wireless
Advanced Brain Monitoring	B-Alert X10	Wet	9	256 [Hz]	Wireless
	B-Alert X24	Wet	20	256 [Hz]	Wireless
Neuroelectrics	Enobio 20	Wet	20	500 [Hz]	Wireless
Brain Products	LiveAmp	Wet	8, 16, 32, 64	250, 500, 1.000 [Hz]	Wireless
G.Tec	g.Nautilus	Dry / Wet	8, 16,32, 64	250 / 500 [Hz]	Wireless
BioSemi	ActiveTwo AD-box	-	16, 32, 64	2, 4, 8, 16 [kHz]	Wired
Neurosity	Crown	Dry	8	256 [Hz]	Wireless

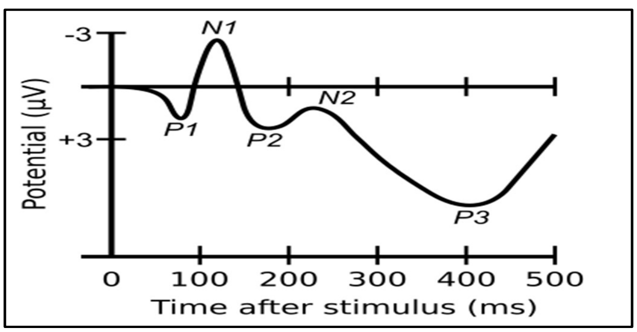


Figure 4. ERP graph.

The earliest component of the ERP is the P1, which reflects early sensory processing. This is followed by the N1, which reflects attention allocation and perceptual processing. Later components such as the P300 or N400 may reflect cognitive processes such as decision-making, memory, or semantic processing. The ERP graph is typically analyzed by comparing the waveform of different conditions or groups to determine if there are differences in the timing or amplitude of specific components. These differences can provide insights into the underlying cognitive processes and neural mechanisms involved in the processing of the stimulus or event [20].

4. Types of BCIs

There are different types of BCIs that vary in their invasiveness, from fully invasive to non-invasive as shown in Figure 5. Each type of BCI has its own advantages and limitations, making them suitable for different applications. Invasive BCIs are implanted directly into the brain tissue, allowing for the highest level of signal resolution and accuracy. These BCIs involve electrodes that are implanted in the cortex of the brain and are used to record neural activity. Invasive BCIs are primarily used in research and medical settings to help individuals with paralysis or neurological disorders to control prosthetic devices or to restore lost function. The main advantage of invasive BCIs is their high level of accuracy in signal detection, which allows for precise control of devices or systems [3,20,44].

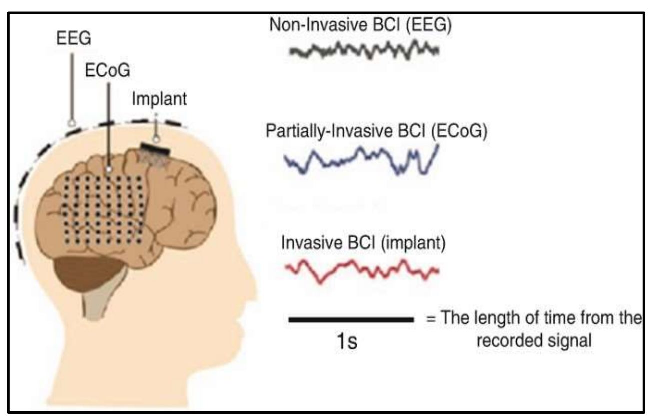


Figure 5. Types of BCIs [45].

Partially invasive BCIs are those that are implanted under the scalp or on the surface of the brain. These BCIs involve electrodes that are placed either directly on the surface of the brain or beneath the skull, but not implanted into the brain tissue. Partially invasive BCIs are less invasive than fully invasive BCIs, but they still provide a high level of signal resolution. Partially invasive BCIs are used in research and medical settings to help individuals with neurological disorders or paralysis to control prosthetic devices or to restore lost function. The main advantage of partially invasive BCIs is their ability to provide a high level of signal detection accuracy while being less invasive than fully invasive BCIs [3,20,44].

Non-invasive BCIs are those that do not require any surgical intervention and are applied to the scalp or the surface of the head. These BCIs involve the use of sensors, such as EEG or MEG, to record neural activity. Non-invasive BCIs are the least invasive type of BCI and are commonly used in research and medical settings to help individuals with neurological disorders to control prosthetic devices or to restore lost function. The main advantage of non-invasive BCIs is their ease of use and non-invasiveness, which makes them suitable for a wide range of applications [3,20,44].

5. Applications of BCIs

Brain Computer Interfaces (BCIs) have a wide range of applications, from communication to entertainment, and from medicine to robotics. In this article, we will discuss the various applications of BCIs and provide examples of how they are being used in different areas.

- Communication: BCIs can be used to assist individuals with disabilities to communicate, such as those with locked-in syndrome, cerebral palsy, or amyotrophic lateral sclerosis (ALS) [45-47]. By interpreting the user's brain signals, BCIs can help individuals with limited or no physical movement to communicate through a computer or other devices. One example is the Brain Gate system, which has been used to allow people with paralysis to type on a computer, send emails, and even control a robotic arm [48].
- Assistive technology: BCIs can be used to control prosthetic limbs, allowing individuals with amputations or spinal cord injuries to regain some of their lost mobility [49]. The user's brain signals are translated into movements of the prosthetic, allowing them to perform daily activities such as grasping objects or walking [50].
- Gaming: BCIs can also be used for gaming purposes. One example is the Mindflex game, which uses EEG technology to detect the user's brain signals and move a ball through an obstacle course [51]. Another example is the Puzzlebox Orbit, a BCI-controlled helicopter that users can fly using their brain signals [52].
- Medical applications: BCIs have significant potential for medical applications, such as diagnosis, treatment, and rehabilitation. For example, BCIs can be used to monitor brain activity during surgeries, diagnose neurological disorders, or treat conditions such as chronic pain or epilepsy [9-11, 25-27].
- Robotics: BCI can be used to control robotic prosthetic limbs or exoskeletons, allowing individuals with disabilities to regain mobility and independence. Robotics can also be used to assist in the training and rehabilitation of individuals providing a more interactive and engaging experience, BCIs can also be used to control humanoid robots, which can assist in caregiving or other tasks [7-11,30].
- Entertainment: BCIs can also be used for entertainment purposes, such as virtual reality or immersive experiences. For example, a BCI-controlled video game can provide a more immersive and interactive experience for players [53,54].

6. Methodology

For this research, a comprehensive literature review was conducted to gather information on the current state of the field of BCIs and their potential as a means of communication between the brain and the external world. The literature review identified several key challenges in the field of BCIs. The parameters for comparisons were selected based on their relevance to the research objective and study focus, ensuring meaningful insights and comprehensive evaluation. These challenges include the need for improved signal detection and interpretation methods, addressing the signal-to-noise ratio, and enhancing privacy and security of collected data. These areas represent important avenues for future research in the field of BCIs. The review methodology involved a systematic sampling strategy to select relevant studies and sources from prominent databases such as PubMed, IEEE Xplore, and Google Scholar. Specific keywords, including "brain computer interfaces," "brain machine interfaces," "EEG controlling robots," "EEG controlling machine," "EEG BCI," and "BCI algorithms," were used to identify studies published between 2010 and 2022 that focused on the application of classification algorithms in controlling robots through BCIs. The literature review included both primary studies and secondary sources, including studies that were cited by or cited the identified studies, to ensure a comprehensive coverage of the topic. Data collection involved reading and thorough analysis of the selected studies and sources. Detailed notes were taken on the research questions, methods, findings, and conclusions of each study, allowing for a comprehensive understanding of the research landscape in this area. Common themes and patterns in the literature were identified, and any gaps or inconsistencies were carefully noted.

The review encompassed a total of 70 studies that met the inclusion criteria, which consisted of studies published within the specified timeframe, written in the English language, and focused on BCIs. Studies that were published before 2010 or after 2022, as well as those that were deemed irrelevant or non-BCI related, were excluded from the review. The search strategy and study selection process ensured a rigorous and systematic approach to capturing the most relevant and up-to-date information on the topic. By employing this robust methodology, the review provides a comprehensive overview of the current state of the field, with a specific focus on the application of classification algorithms in BCI-based control of robots. The findings of this review contribute to the existing body of knowledge and offer valuable insights for researchers and practitioners in the field of BCIs.

7. Results

Table 3 provides a summary of studies exploring the use of BCIs for controlling robots through motor imagery or hybrid BCI approaches. The studies utilized various classifier algorithms, such as SVM, LDA, and artificial neural networks (ANN), to control different types of robots, including robotic arms, mobile robots, quadcopters, and exoskeletons. The output commands varied depending on the control object and included movements such as turning left and right, going forward and backward, lifting and dropping, and flexion and extension of the hand fingers. These studies demonstrate the potential of BCIs in enabling individuals with motor impairments to control robots and devices through their thoughts, opening up possibilities for assistive technology and neurorehabilitation [55-68].

Specifically, one study [55] utilized an interval type-2 fuzzy logic based multiclass ANFIS algorithm to control a robotic manipulator with a 3-fingered hand, with output commands including relaxation, left and right movement, and forward and backward movement. Another study [56] utilized an SVM algorithm to control a mobile robot, with output commands including turning left and right, and going forward and backward. A study [57] constructed neural nets in a BCI for robot arm steering, with output commands including left and right movement, and start and stop. Another study by [58] used an artificial neural network to control a quadcopter, with output commands including left and right movement. In a study [59], a motor imagery-based BCI coupled to a robotic hand orthosis was used for neurorehabilitation of stroke patients, with output commands including flexion and extension of the hand fingers. Another study [60] utilized an RBF-SVM algorithm to control a robotic arm, with output commands including right and left movement of the base and upward movement of the elbow. A study [61] used an LDA algorithm to control a mobile robot, with output commands including turning left and right, and going forward and stopping.

A study [62] used an SVM algorithm to control a dual-arm robot, with output commands including lifting and dropping. Another study [63] utilized an LDA algorithm to control a robotic arm, with output commands including left and right movement. In a [64] study an SVM algorithm was used to control a robotic arm, with output commands including turning the link clockwise or counterclockwise and moving the link forward.

In a study [65], an LDA algorithm was used to control a quadcopter, with output commands including left and right movement, and forward and backward movement. Another study [66] utilized LDA and SVM algorithms to control an exoskeleton robot, with output commands including moving left and right. A study by [67] used an SVM algorithm to control a quadcopter, with output commands including activating, turning left and right.

Table 3. A summary of different studies that have explored the use of BCIs for controlling robots.

Paper Title	Year of Publication	Classifier Algorithm	Control Objects	Output Commands	Reference
Interval type-2 fuzzy logic based multiclass ANFIS algorithm for real-time EEG based movement control of a robot arm	2015	OVO-IT2FLF-ANFIS	axis robotic manipulator with a3 fingers hand	Relax, left and right, forward and backward	[55]
Autonomuos robot control based on EEG and cross-correlation	2016	SVM	Mobile robot	Turning left and right, going forward and backward	[56]
Construction of neural nets in brain-computer interface for robot arm steering	2016	Artificial neural networks	Robotic arm	Left and right, start and stop	[57]
A performance study of 14-channel and 5-channel EEG systems for real-time control of unmanned aerial vehicles (UAVs)	2018	Artificial neural networks	Quadcopter	Left and right	[58]
Motor imagery-based brain-computer interface coupled to a robotic hand orthosis aimed for neurorehabilitation of stroke patients	2018	LDA	Robotic hand orthosis	Flexion and extension of the hand fingers	[59]
EEG based brain computer interface for controlling a robot arm movement through thought	2018	RBF-SVM	Robotic arm	The base moves right and left, the elbow points up	[60]
Robot navigation using a brain computer interface based on motor imagery	2019	LDA	Mobile robot	Turning left and right, going forward and stopping	[61]
Motor-imagery-based teleoperation of a dual-arm robot performing manipulation tasks	2019	SVM	Dual-arm robot	Lift and drop	[62]
Shared control of a robotic arm using non-invasive brain–computer interface and computer vision guidance	2019	LDA	Robotic arm	Left fornt and right front movement	[63]
Motor imagery and error related potential induced position control of a robotic arm	2017	SVM	Robotic arm	Turn the link clockwise or counterclockwise, move the link forward	[64]
Quadcopter control system using a hybrid BCI based on off-line optimization and enhanced human-machine interaction	2019	LDA	Quadcopter	Left and right, forward and backward	[65]
Hybrid MI-SSSEP Paradigm for classifying left and right movement toward BCI for exoskeleton control	2019	LDA and SVM	Exoskeleton robot	Moving left and right	[66]
Application of hybrid brain-computer interface with augmented reality on quadcopter control	2020	SVM	Quadcopter	Activating, turning left and right	[67]
A hybrid brain-computer interface for closed-loop position control of a robot arm	2020	LSVM, RBF-SVM	Robot arm	Link selection, motion initiation, automatic reversal, oscillation continues, object position	[68]

Finally, a study [68] utilized LSVM and RBF-SVM algorithms to control a robot arm, with output commands including link selection, motion initiation, automatic reversal, oscillation continues, and object position. Overall, these studies demonstrate the potential of BCIs in enabling individuals with motor impairments to control robots and devices through their thoughts, providing new avenues for assistive technology and neurorehabilitation.

8. Discussion

The results of this literature review demonstrate the potential of BCIs in enabling individuals with motor impairments to control robots and devices through their thoughts. The findings suggest that the use of BCIs in controlling robots can improve the quality of life of individuals with motor impairments and provide new possibilities for assistive technology and neurorehabilitation. BCI have the potential to revolutionize the way we interact with the world around us, but there are several challenges and limitations that need to be addressed in order to fully realize their potential. In this regard, this section will discuss some of the major challenges and limitations associated with the use of BCIs. One of the biggest challenges associated with BCIs is the need for highly skilled professionals to operate them. The technical complexity of BCIs requires trained professionals with a deep understanding of neuroscience and computer engineering. Furthermore, BCI technology is constantly evolving, which means that professionals working with BCIs must stay up-to-date with the latest developments in the field [69].

Another challenge associated with BCIs is the limited availability of devices. Currently, the cost of BCI devices is relatively high, and they are not widely available to the general public. This limits the accessibility of BCIs to those who could potentially benefit from them, such as individuals with disabilities or neurological conditions. In addition, achieving accurate and reliable signal detection is a major challenge in BCI research. The signals that are measured by BCIs are very small and can be easily disrupted by other electrical activity in the brain or by external factors such as movement or environmental noise. This can lead to inaccuracies in the data collected by BCIs, which can impact the effectiveness of the technology [70].

Moreover, there are also challenges associated with the physical design and comfort of BCIs. Some BCIs are invasive, requiring surgery to implant electrodes directly into the brain, which can carry risks and complications. Partially invasive BCIs involve implanting electrodes on the surface of the brain, while non-invasive BCIs rely on external sensors to detect brain activity. However, non-invasive BCIs can be uncomfortable to wear for extended periods of time and can be affected by the user's hair, skin, and other physical characteristics [71, 72].

9. Future Directions

The field of BCI is rapidly evolving, with new developments and advancements being made on a regular basis. BCI hold tremendous promise in revolutionizing how humans interact with technology. In the future, research in BCIs should focus on a number of key areas. One important area is improving signal detection and interpretation. This involves developing more reliable and accurate methods for detecting and interpreting brain signals, improving the signal-to-noise ratio, addressing movement and distractions, and increasing privacy and security of collected data.

Another important area of focus for future research in BCIs is advancing the technology itself. This includes exploring and developing different types of BCIs, such as invasive, partially invasive, and non-invasive BCIs, improving their effectiveness and reliability, and exploring ways to combine different types of BCI technology to create more effective and versatile systems.

Enhancing cognitive and emotional states through BCIs is another area of potential research. BCIs could be used to improve attention or reduce anxiety, for example, by using real-time feedback to adjust stimulation or intervention being delivered by the BCI. Closed-loop BCIs, which use real-time feedback to adjust the stimulation or intervention being delivered by the BCI, could have implications for the treatment of conditions such as epilepsy, where timely intervention can prevent seizures.

Another important area of focus for future research in BCIs is exploring new and innovative applications in various fields, such as education, entertainment, and sports. For example, personalized learning experiences that adapt to each individual student's needs and preferences could be developed, and immersive experiences that respond to the user's thoughts and emotions could be created.

Finally, researchers must address ethical concerns related to the use of BCIs, including issues around privacy and security, as well as the potential for misuse of this technology. Overall, future research in BCIs has the potential to bring significant advancements to the field and improve the quality of human life. By improving the accuracy and reliability of BCIs, enhancing cognitive and emotional states, developing new applications, and addressing ethical concerns, researchers can make great strides in this exciting and rapidly developing field

10. Conclusion

In conclusion, BCIs represent a revolutionary technology that holds great promise for transforming various aspects of human life, from medicine to entertainment, education, and industry. BCIs have the potential to restore lost motor function to paralyzed patients, improve the lives of individuals with a range of neurological disorders, and create immersive experiences that respond to the user's thoughts and emotions. However, BCIs face several challenges, such as developing reliable and accurate methods for detecting and interpreting brain signals, privacy and security concerns, and potential misuse of the technology. To overcome these challenges, researchers and developers are actively working to improve BCI technology and expand its applications. The future of BCI research looks promising, with hybrid BCIs, closed-loop BCIs, and BCIs that enhance cognitive and emotional states being developed. While there is still much to be explored and developed, the potential impact of BCIs on human life is significant, and we can expect to see more advancements and applications of this technology in the future.

Nomenclature

BCIs	Brain Computer Interfaces
EEG	electroencephalography
MEG	magnetoencephalography
fMRI	functional magnetic resonance imaging
LDA	Linear Discriminant Analysis
SVM	Support Vector Machine
ANN	Artificial neural networks

Competing Interests

All authors have no conflict of interest to report.

Data and Materials Availability Declaration

The data and materials used in this study are available upon request.

Authors' Contributions

Mohamed Alseddiqi and *Anwar AL-Mofleh*: provided the conception and design of the study, acquisition of data, analysis and interpretation of data, drafting the article, revised it critically for important intellectual content, and final approval of the version to be submitted; *Osama Najam*: supplied the acquisition of data, drafting of paper; *Leena Albalooshi*: supplied the design of study, analysis and interpretation; supplied the acquisition of data; *Abdulla Alheddi:* was responsible for the article critically for important intellectual content; and *Ahmed Alshaimi*: provided the revised the article critically for important intellectual content and gave final approval of the version to be submitted.

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