A Comprehensive Review on Brain Computer Interface

Arun Kumar S[1], L Anand[2], Anil Kannur[3]

Abstract

Brain-computer interface (BCI) technologies allow direct connection between the activity of the brain and the activity of an external device. Communication is established as a result of neural responses that occur within the brain. Muscular and non-muscular acts are included in the definition of means of communication in this context. These signals from the brain are applied to a physical device to fulfill a certain job. They are extremely valuable and have the potential to enhance or completely replace human peripheral working capabilities, with applications in various fields. Nonetheless, despite the effectiveness of BCIs, their uptake has been minimal. Recently, there is a significant increase in research on BCI. This review paper examines past and present research investigations on BCI as well as the implications of these findings. The BCI research work begins with the acquisition of brain signals and proceeds through a pipeline that includes pre-processing, extracting important features from processed signals, classification of signals using emerging technologies such as machine learning and deep learning, evaluation of the designed model, and finally interface with devices in the real world. This review, first, examines the different signal acquisition methods, each monitor's different functional brain activity, including electrical and magnetic to identify brain activity, and shows the various types of signal acquisition methods. Second, it includes the procedures that can be applied to raw signals to pre-process them. Third, it describes the feature extraction algorithm that was used to extract information from the BCI signal. Next, the classification method and evaluation techniques are discussed in detail. Finally, explain how BCI can be applied in several real-world situations. This review will provide a better understanding to the researchers who are willing to start the work on BCI.

Key Words: Brain, Signal, Transform, Accuracy, Features, Pre-processing.

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Introduction

To facilitate nonverbal communication between humans and machines, BCI makes use of the observed brain signals for communication. ' Data about users' brain activity is collected by BCI, which communicate it to computers through sensors. A user's brain input can be used to operate computer programs through the use of EEG [1]. Despite this, the EEG is particularly sensitive to other bio-signals, such as heart rate and eye movement, and can detect these signals. The constraints of employing BCI with only EEG have resulted in the inclusion of alternative bio-signal detection modalities, such as an electrocardiogram (ECG) [2], photoplethysmography (PPG) [3], electromyogram (EMG) [4], electrooculogram (EOG) [5], and Galvanic Skin Reflex (GSR) [6] as supplements to EEG in BCI. When employing BCI technologies, our brains do not connect with our bodies through our peripheral nerves. An approach is to employ BCI devices to directly capture and decode commands, rather than using a third-party system. These signals make it feasible to control external devices as well as computer applications.

Corresponding author: Arun Kumar S
Address: [1]Research Scholar, School of Computing, SRM Institute of Science and Technology, Potheri, SRM Nagar, Kattankulathur, Tamil Nadu 603203,[2]School of Computing, SRM Institute of Science and Technology, Potheri, SRM Nagar, Kattankulathur, Tamil Nadu 603203,[3]Nagarjuna College of Engineering and Technology, Information Science & Engineering, Mudugurki, VenkatagiriKote Post, Devanhalli, Bangalore- 562 164
E-mail: aarunkumar889@gmail.com[1], anandl@srmist.edu.in[2], anilkannur1978@gmail.com[3]

To move a cursor around the screen, pointer control, for example, relies on signals transmitted directly from the brain rather than the "route" taken by a mouse through peripheral nerves. Because of this technology, communicating with computers and other external equipment, such as prosthetic devices, is made easy. The aeromedical field, the educational and entertainment industries, as well as marketing and advertising [7], have all embraced BCI technology, to name a few examples. The fact that BCI device and app designers aren't paying more attention to security and privacy considerations when developing their devices is a disappointment to me. Malicious third-party applications can gain access to personal information when utilizing these devices.

In the past, it has been difficult to do a relevant scientific study using brain-computer interface technologies. In the past, the notion that brain activity could be utilized to read someone's thoughts or intentions was dismissed as unrealistic. However, recent research suggests that this is not the case. As a result, research into brain activity has been restricted in scope to either the diagnosis of neurological disorders or the investigation of brain activities. Because there was a scarcity of information that could be gathered from a person's brain, it was considered that designing a BCI would be prohibitively difficult. Moreover, real-time signal processing is required by BCI devices, which has previously been either unavailable or excessively expensive [8]. When it comes to BCI research, researchers from several fields, including neuroscience, physiology, psychology, and engineering, collaborate with colleagues from computer science and rehabilitation to advance the field. As a result, a common language has not yet been established, and existing BCI systems range substantially from one another, making comparison difficult and research progress slow. A comprehensive approach to BCI design has therefore been advocated by BCI researchers [9] as a result of this.

A. History

Since the eighteenth century, humans have been able to communicate with their bodies and brains through the use of electrical signals [10]. While conducting research together (1737–1798), Luigi et al(1743–1788) discovered that an electrical spark given to a nerve may cause a muscle to contract that had been otherwise paralyzed by the shock. EEG was invented by Hans Berger, who made finding of electrical activity in the human brain in 1895, and it was the first step in the development of BCI. Berger was the first person to utilize EEG to record brain activity, back in 1924 [11]. In his EEG recordings, Berger was able to identify oscillatory brain activity, which he later confirmed. The alpha wave, often known as Berger's wave, was one of the waves that he discovered and named after himself. For the first few months, Berger recorded his thoughts and sensations with a rudimentary device. He was the one who implanted silver wires into the scalps of his patients. Later, silver foils secured to the patients' heads with rubber bandages were used in place of the previous ones. Berger attempted to link these sensors with the help of a Lippmann capillary electrometer. The employment of a Siemens double-coil recording galvanometer capable of recording electric voltages as low as one-tenth of a volt was important in achieving the necessary findings. Berger examined the alternations in his EEG wave diagrams throughout time to evaluate the association between his EEG wave diagrams and brain illnesses. The use of EEGs gives up a slew of new options for studying human brain activity. In the 1970s, a National Science Foundation grant and a Defense Advanced Research Projects Agency (DARPA) contract sparked the creation of BCIs. Following this discovery, the term "brain-computer interface" was used for the first time in scientific literature.

Materials And Methods

Computers are utilized to collect and analyze brain impulses, to translate them into commands that are then sent to an output device to perform the desired activity. The result is that the typical output channels of peripheral nerves and muscles are not used in BCI applications. The term "BCI" refers exclusively to systems that measure and make use of brain signals in this meaning (CNS). As a result, a BCI is distinct from other types of communication systems, such as voice- or muscle-activated systems [12]. Additionally, EEG equipment alone is not a BCI because it only receives brain signals and produces no output that alters the user's environment. The notion that BCI can read the thoughts of its users is erroneous. BCI does not, by any means, allow individuals to listen in on their thoughts, but they do give them the power to affect the physical environment by sending brain impulses rather than using their muscles to move. It takes a collaborative effort on the part of the user and the BCI. The user generates brain signals that contain goals, which are processed by a brain-computer interface after training, and commands are transferred to an external application that carries out the user's wishes. The complete workflow of the BCI system is shown in figure 1.

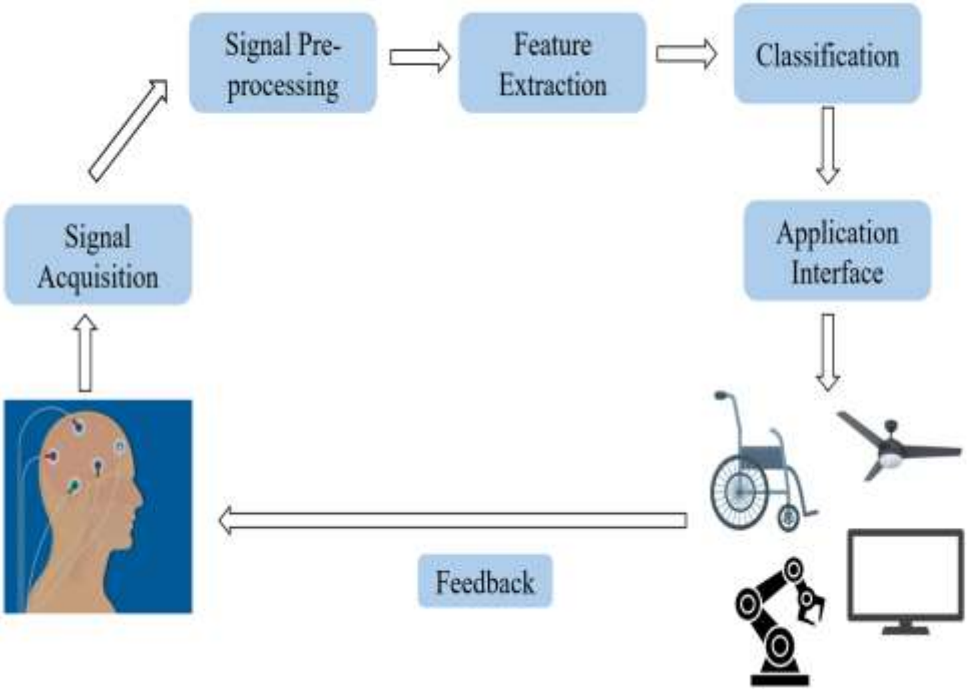

Fig. 1. The workflow of BCI controlled appliance

Signal Acquisition

Every BCI-based system relies on oscillations generated by the brain, and these oscillations are crucial components. It demonstrates how the user's current activity has an impact on the user's voluntary brain movements in the future. A large number of various signal acquisition techniques have been examined in depth. When it comes to BCI applications, the type of application and demographics of the people who will be using the application define which signal acquisition method and measurable phenomena are most appropriate. This is seen in figure 2, which distinguishes between invasive and non-invasive methods of treatment. It is possible to record brain activity using external sensors in non-invasive technologies rather than neurosurgically implanting electrodes within or on top of the brain by utilizing external sensors in non-invasive technologies [13]. There are different techniques available for acquiring the signal from the brain and all the techniques are compared in table 1.

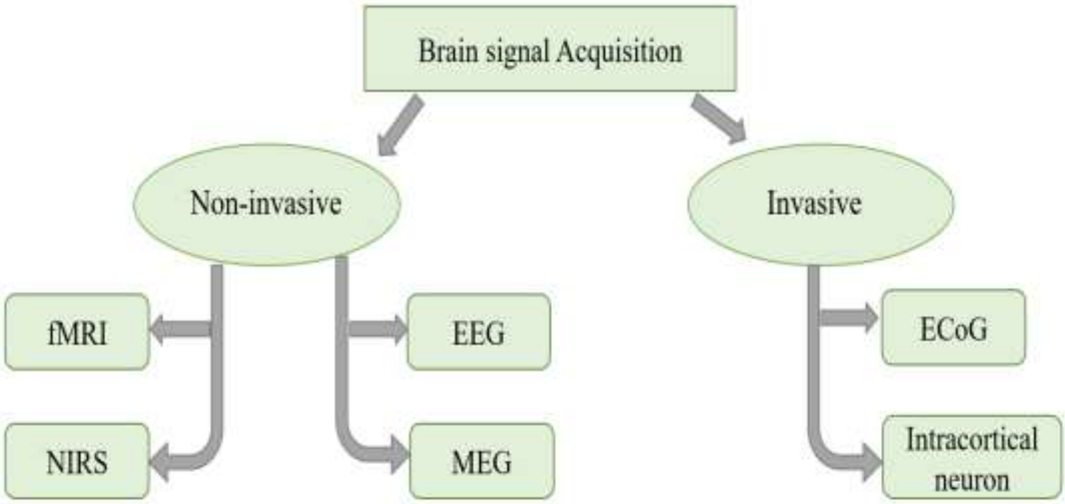

Fig. 2. BCI signal acquisition methods

Invasive

These recordings are made using non-invasive methods that do not require the implantation of external items into a subject's brain. This eliminates the need for intrusive acquisition methods and permanent device attachments, which would have otherwise been necessary. Methods for measuring and analyzing a wide range of signals, including fMRI, MEI, and EEG, are addressed in this chapter.

EEG: In part because of its sensitivity to secondary current effects, EEG has proven to be a very useful instrument for evaluating electrical brain activity. With the use of scalp electrodes, EEG signals may be recorded non-invasively, making this the most extensively utilized recording method today. However, because the signals must pass through the scalp, skull, and countless additional layers, the quality of the signals is extremely poor. The outcome is EEG signals that are weak, difficult to obtain, and of poor quality. Background noise, whether it is generated internally by the brain or externally by the scalp, has a substantial impact on the accuracy of this technique.

fMRI: The device, known as fMRI, may detect fluctuations in blood flow that are associated with brain activity [14]. As a result, it aids in the mapping of activity to the corresponding brain regions, which is known in the scientific community as the source localization problem. It is based on the truth that all brain activity requires an increase in blood flow, rather than asserting that all brain activity requires an increase in blood flow. It specifically employs the BOLD contrast technique, which is sensitive to variations in the quantity of oxygen in the blood flowing through the heart. The intensity of BOLD contrasts reflects changes in deoxyhemoglobin concentrations in the brain tissue under investigation. Despite its poor temporal resolution, fMRI can be utilized to obtain information from the deepest portions of the brain that electrical or magnetic techniques cannot reach.

Near-Infrared Spectroscopy (NIRS): It can detect changes in cerebral metabolism that occur as a result of neuronal activity using infrared light as an optical spectroscopic technique using infrared light. It is possible to detect variations in oxygen and deoxyhemoglobin concentrations at depths of around 1–3 cm below the surface of the skull due to the reduction in the intensity of the attenuated light. Because of the limited light penetration in the brain, this optical neuroimaging approach can only image the brain's outer cortical layer. A difficulty with NIRS, as well as with fMRI, is that the hemodynamic response occurs just a few seconds after the associated brain activity has occurred [15]. The spatial resolution of NIRS is approximately 1 cm, which is extremely inadequate. However, NIRS is less expensive, more portable, and has a temporal resolution of approximately 100 milliseconds.

Magnetoencephalography (MEG): Neuroimaging techniques such as MEG, capture the magnetic fields generated by electrical currents in the brain, which are then used to map the activity of the brain. For those looking for a reliable method of measuring the magnetic field created by brain currents, MEG is the most suitable choice [16]. Magnetic fields are less prone to damage than electricity, owing to the spatial blurring effect caused by the skull and intracerebral fluid in the brain. When it comes to MEG, tangential sources are the most sensitive, whereas radial sources are the least sensitive. When it comes to detecting high-frequency activity, the MEG is more accurate than the EEG in most cases " (e.g., above 60 Hz). Because magnetic fields flow through the skull and scalp while electrical fields are transmitted through tissues, the signal-to-noise ratio at high frequencies is lowered."

Noninvasive

During invasive recording methods, electrodes are placed beneath the skin of the scalp. A method known as electrocorticography (ECoG) can measure activity in the brain's motor cortex, either intracortical or on the cortex's surface. These devices are highly sought after due to their higher signal-to-noise ratio and great temporal and spatial resolution, among other characteristics. These methods, on the other hand, have several shortcomings. An additional set of challenges has emerged as a result of surgical procedures, including issues with the output of the system. These implants are considered to be one of them because the brain regions that they monitor are of relatively small size. Once implanted, they are unable to be relocated to another section of the brain to evaluate activity. Additionally, the body's attempt to adapt to a novel thing, which may fail, can result in medical complications. Implant stability and infection protection are two further issues that may arise. This has resulted in the use of real-world invasive recording being limited to the medical field for a small number of severely disabled persons [17]. According to [18], invasive systems have mostly been tested on monkeys in the context of BCI system research. Implanted electrodes have been used in a few tetraplegic individuals who have had their legs amputated. To learn more about these intrusive tactics the below sections help.

ECoG: Electrical activity in the cerebral cortex is calculated via ECoG, which involves putting electrodes on the brain's exposed surface. In the 1950s, the Montreal Neurological Institute became the first organization to make use of it. Even though the treatment is referred to as semi-invasive, the electrodes must be inserted through a craniotomy to be effective. Even when surgical intervention is essential for medical reasons, it is only used as a last resort (epilepsy for example). The electrodes can be inserted using epidural or subdural electrodes, depending on the situation (subdural). It is feasible to conduct a wide range of cognitive investigations utilizing the strip or grid electrodes (ranging from 4 to 256 electrodes) [19], which cover a large area of the brain and may be used to take more areas of cognitive examinations. The ECG has several advantageous qualities, including resolution and correctness, noise resistance, and low-risk complications.

Intracortical neuron: The intracortical acquisition technique [20] is the most invasive of the available procedures. It is located deep within the cortical layer of the brain. Individual neuronal activity impulses can be measured with a single electrode or an array of electrodes, depending on the application. Because the electrode tips are situated extremely close to the signal source, the arrays must stay stable for an extended period. Array stability is critical. Because of its high spatial resolution, it is highly recommended for usage in source localization applications. Long-term intracortical acquisition, on the other hand, may result in signal volatility due to the nature of the acquisition method being used. Cell death in neurons or an increase in tissue resistance may be responsible for this. If the device contains a stimulation component to stimulate the crippled limb, this additional input may have a significant impact on the overall noise level.

Table 1: Comparison of signal acquisition methods [21]

Acquisition Method	Method	Potability	Measurement type	Resolution	
				Temporal (s)	Spatial (mm)
EEG	Non-invasive	Yes	Direct	0.05	10
MEG	Non-invasive	No	Direct	0.05	5
fMRI	Non-invasive	No	Indirect	1	1
NIRS	Non-invasive	Yes	Indirect	1	5
ECoG	Invasive	Yes	Direct	0.003	1
Intracortical neuron	Invasive	Yes	Direct	0.003	1

Signal Pre-processing

It is necessary to collect information from brain signals to ensure that critical information is not lost, as well as clean and remove noise from signals to access the relevant information encoded in the signal. Pre-processing is the process of converting the raw signal into a useful form for the user's later analysis and interpretation, rather than the other way around. Pre-processing refers to the process of cleaning up data so that the original neural signals may be seen more clearly in the final product. For a variety of reasons, brain signal data must be pre-processed before use. It is possible that the signals picked up from the scalp do not accurately represent the brain impulses because spatial information is lost in the signals. A second issue is that the noise in brain signal data tends to obscure the weaker brain signals that are present. In some cases, movement artifacts, such as those induced by blinking or other muscular contractions, can cause the results to be distorted. Finally, to discriminate between the crucial neural signals and the random neural activity that occurs during the recording of brain data to make better decisions. There are many pre-processing steps required to make the BCI signal clean and the various techniques are illustrated in figure 3.

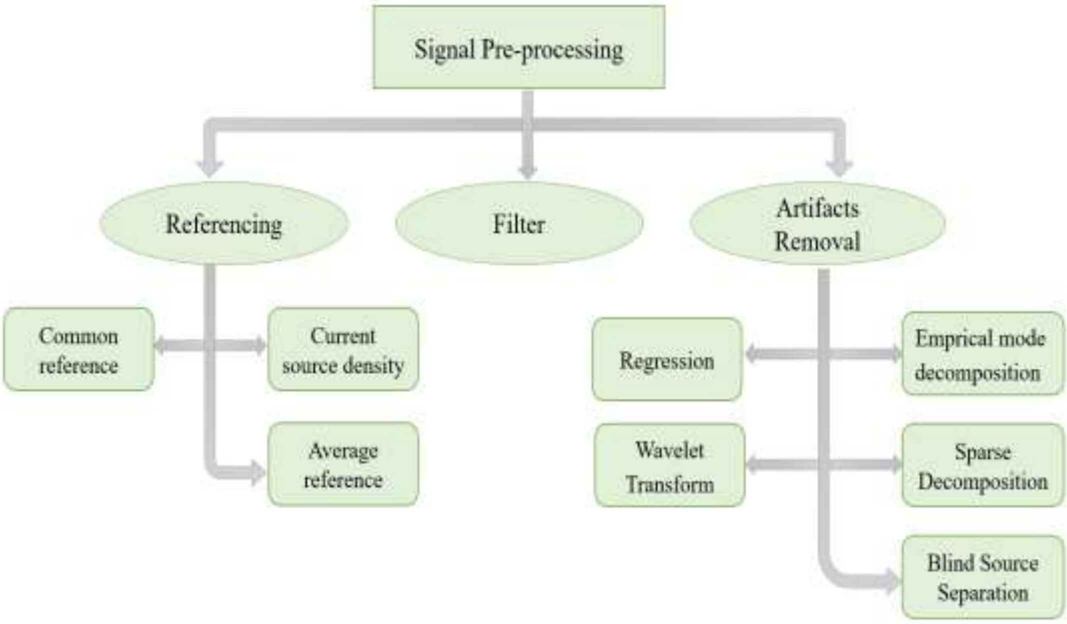

Fig. 3. BCI signal pre-processing methods

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Referencing

The voltage of each electrode is identified in proportion to the voltage of the other electrodes in the EEG data. An electrode or a collection of electrodes will be used as a reference to which the voltage will be measured with respect. In some cases, if brain activity at the reference electrode is also reflected in all of the other electrodes, signal may be tainted. Aside from that, choice of reference material could have a significant impact on outcomes. When choosing a reference electrode, it is important to consider how much of an impact it will have on signal placements. In practice, this means that either a single electrode or a mixture of numerous electrodes is used as a reference, depending on the situation. According to the journal [22], discrepancies in outcomes between research could be explained by changes in the study's frame of reference. In BCI recordings from both the cortex and the scalp, several electrodes are employed, and these electrodes are positioned in a range of different locations. The measurement of brain activity voltage made by one electrode can be compared to the measurement of a separate reference brain voltage made by another electrode using another reference brain voltage. Thus, the electrode signals, as well as reference site signals and background noise, are all captured on videotape. The reference point can be selected in a way that the amount of brain activity in that region is non-existent as a result.

Common reference: In BCIs, it is usual practice to employ a common reference technique as a starting point. In this technique, all electrodes are coupled to a single reference point, which is the center electrode. All of the electrodes are positioned at a significant distance from this reference location. As a result, there are no differences between electrode measurements since the activity at the reference site has the same effect on each measurement.

Average reference: The average reference is obtained by taking the readings and deducting the average activity across all electrodes from the total of the readings. A fundamental foundation of this technique is the notion that at any one time, there is no activity in the brain. An estimate of activity at the reference location can be produced as a result of averaging all of the data. In theory, by subtracting this average from the total, a dereferenced response can be achieved.

Current source density (CSD): Numerous BCIs make use of the CSD. The term "rate of change" refers to the pace at which current flows into and across the scalp [23]. For instance, it is feasible to determine the difference between an electrode's potential and a weighted average of the electrode's surroundings using EEG data. The CSD can be estimated using the laplacian. The laplacian can be used to calculate the disparities between electrodes by computing the sum of these differences. This judgment is valid when the electrodes are arranged in a two-dimensional plane and are spaced equally apart.

Filter

A variety of internal and external noises interfere with the brain's electrical impulses. Simple filters [24] can be used to remove them from system, and they are inexpensive. BCIs contain a great deal of relevant information that happens in the lower 30Hz frequency range. Because it has a set frequency, noise from the electrical network (e.g., 50Hz or 60Hz) may be reduced by employing a filter to reduce or eliminate it. Filters are available in several shapes and sizes, including:

Low-pass filter: It is feasible to keep low frequencies below a particular threshold, but high frequencies must be excluded from the calculation. This is referred to as a high-cut filter in some circles. It would be beneficial to have an audio version of this, which would remove all of the high notes from a sound.

High-pass filter: It is only the high frequencies that are retained, rather than all frequencies less than a specified threshold.

Band-pass filter: There are only those frequencies that fall between the higher and lower level that is kept intact. A band-cut filter, on the other hand, eliminates all frequencies that fall within a defined range of frequency values.

Notch filter: Band-cut filters are employed to remove a certain frequency range from a signal. Multiple notch filters can be used in conjunction to exclude a specific group of single frequencies, which is beneficial for a variety of applications such as electrical noise reduction.

IIR filter: It is a sort of digital filter designed to provide infinite impulse response in a dynamic system, and it is also known as the IIR filter. Because these filters include an internal feedback system, they can be utilized indefinitely without causing damage to the system. IIR filters are used by systems that provide infinite replies. LPFIR filters use fewer coefficients and memory than FIR filters to accomplish the same set of features, and so operate more quickly. Due to the minimal number of coefficients, this technique is well-suited for real-time control and high-speed radio frequency applications. Analog equivalent: similar to how digital filters are employed, s-z plane mapping operations can be used to imitate the properties of analog filters.

FIR Filter: Type of digital filter which reproduces the restricted impulse response of a dynamic system in a digital format. Alternatively, the filter's impulse response is limited in terms of temporal duration. Creating the linear phase of FIRs is a straightforward process. To prevent the relative harmonic relationships between the frequencies in the signal to be filtered from changing, it is required to modify all frequencies in time by the same amount. Filters with a non-linear phase characteristic, such as IIR filters, do not fall into this classification. In contrast to IIR filters, which rely on past output values to determine their current output values, FIR filters are fundamentally stable for all forms of input signals, regardless of the type of signal. With the help of the Parks-McClellan and ASN FilterScript functions, it is possible to construct an FIR with variable magnitude response. Consequently, when it comes to modification, an FIR offers greater flexibility than an IIR. The impact of quantization is less significant than the impact of an IIR.

Artifacts

It has been shown that artifacts in recording

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systems have a bigger impact on the data that they generate. The quality of the EEG data will likely be compromised as a result of these artifacts. It is essential to have a solid understanding of the many forms of artifacts or noise to successfully eliminate them. Artifacts are caused by a variety of factors, including environmental noise, experimental mistakes, and physiological anomalies. Those caused by the environment or an experiment error are separated from intrinsic artifacts, which are those caused by the body itself. Extrinsic artifacts include those caused by the environment or an experiment error (e.g., eye blinks, muscle contractions, heartbeats). It is possible to remove environmental artifacts with a simple filter since the frequency of such artifacts is inconsistent with the frequency of the signals that are desired. Process and preparation can help to lessen the likelihood of errors occurring. Because specific algorithms are required to eliminate the physiological artifacts, it is more difficult to remove them completely. Following that, we'll look at some of the most common EEG artifacts and how they affect the findings. The next section contains detailed advice on how to remove artifacts.

Regression: Regression analysis was used to identify samples that had artifacts and to further exclude those samples that did not belong to the system as part of the overall process [25]. Despite this, the reference channel continues to be a major stumbling hurdle for developers. Because of the non-stationary properties of BCI signals, linear regression is thus inapplicable to these applications as well. Processing a subset of artifactual inputs, rather than the entire breadth, is one of the additional capabilities.

Wavelet Transform (WT): A better time-frequency trade-off is obtained by employing WT rather than the Fourier transform, which is because of the superior customizable time-frequency trade-off and superiority of non-stationary signal analysis [26]. For example, wavelet theory-based techniques such as the discrete wavelet transform (DWT), the continuous wavelet transform (CWT), and the wavelet packet transform (WPT) are all based on wavelet theory (SWT). In general, DWT is the most often used technique in practice. DWT decomposition is followed by the removal of artifacts by applying the concept of thresholding to the coefficients that have been computed. After the new coefficients have been incorporated, the signal is reconstructed by adding them all together.

Blind Source Separation (BSS): Unsupervised learning is the foundation of BSS, which is widely regarded as one of the most effective ways of reducing artifacts. This technique is based on the concept of statistical independence, which implies that the signal sources are unrelated. This assumption is made if the number of observable channels is more than or equal to the total number of signal sources. Otherwise, it is not. The BSS algorithm implementations are included in the sections that follow.

Principal Component Analysis (PCA): Among the tools used in investigative data analysis and predictive model development, PCA is the most often used. In a static approach, observations of correlated variables are transformed into observations of linearly uncorrelated variables, which are known as principal components. Berg and Scherg [27] showed that ocular artifacts may be avoided. Using the EEG data, blinks and eye movements were removed to obtain the final product. As a result, it is possible to obtain an extremely accurate readout of the EEG signal. In cases where drifts and EEG potentials are equal, the PCA algorithm was unable to separate the subjects. As a result, in the future of research, more flexible approaches will be favored over rigid ones.

Independent Component Analysis (ICA): ICA, in its own right, is an essential component of BSS. As an illustration, the "cocktail party" task of listening to a single individual speak in a noisy environment is a fantastic application of this strategy to improve listening skills. Through the use of signal sources that are a direct mixture of the brain and others, it is feasible to break down EEG signals into their constituent independent components (IC). The IC is mined from raw signals using a technique known as independent component extraction. Artifact-containing integrated circuits are now rejected, and a new reconstructed integrated circuit is created in their place. It was shown that the improved version of ICA proposed by the researcher [28] was effective in minimizing artifacts.

Canonical Correlation Analysis (CCA): BSS approaches such as CCA are another type of method that is commonly used. Second-order statistics are employed in the CCA approach rather than higher-order statistics, which are used in the ICA approach and take more computation time. The conditions for separating components under CCA are likewise different from those under ICA. The ICA, in contrast to the CCA, distinguishes components derived from statistically independent sources [29]. CCA is a technique for determining the linear relationship between two multidimensional random variables by using pairwise correlations. A comparison of CCA and ICA reveals that CCA takes into account the autocorrelation of the source signal, whereas ICA only takes into account the statistical distribution of similar sample values. The CCA was first applied to the reduction of artifacts [30].

Morphological Component Analysis (MCA): It is possible to find a variety of various morphological qualities in the signal components that are decomposed from the original signal. Each of these components is just briefly explained in a lexicon that is far too vast in terms of coverage [31]. When using this strategy, the original artifact database must be easily accessible at all times for it to be effective.

Empirical mode decomposition (EMD): The EMD technique, which does not rely on the signal being stationary or linear, can be used to break down a time-domain signal into its AM and FM components. It is thus possible to produce a signal-dependent and adaptive decomposition based on the EMD. Using the EMD sifting process, it is possible to extract intrinsic mode functions (IMFs) from a signal, which is then represented as a superposition of the IMFs extracted. It is not possible to analyze brain signals using conventional methods such as Fourier and wavelet analysis. This is because the frequency of oscillations in biological systems such as the human brain's drift occurs in brain rhythms across various frequency bands. It has been discovered that the EMD approach outperforms STFT and wavelet methods for locating time-varying frequency components of mu and beta rhythms during MI in terms of locating time-varying frequency components. A finite number of IMFs can be considered band-limited and symmetric functions in the EMD approach [32], each of which has its own set of properties.

Sparse Decomposition Methods (SDM): An additional impact signal processing method is SDM, which deconstructs signals in an over-complete dictionary in an infrequently used manner [33]. Over-sampling can be used to create an over-complete lexicon from a complete dictionary by taking samples from the complete dictionary. Even though the basis in the dictionary is orthogonal, following oversampling, the orthogonality may be no longer valid. With several cycles of iteration, the SDM of the signal is built. Each subsequent iteration selects an optimal waveform based on the waveform that has the highest inner product between it and the residual signal.

Feature Extraction

BCI technology is capable of extracting useful information from EEG data that is quite complex. Brain signals obtained from subjects while they are engaged in a certain mental activity are utilized to identify important features from their brain signals. Features are provided to the classifier to train it, and they are then utilized to recognize patterns. Due to technical and biological factors namely subject attention, session variability, mental state, anatomical differences among individuals, the amplifier, and ambient noise, the signals become highly nonstationary and dynamic [34]. From the perspective of cognitive neuroscience, the oscillatory (frequency) characteristics are also distinct and non-stationary. This makes it difficult to accurately categorize BCI patterns as a result of these considerations. It is vital to choose the most appropriate feature extraction technique for BCI systems to increase their overall performance. The available various feature extraction techniques applied after pre-processing steps are shown in figure 4.

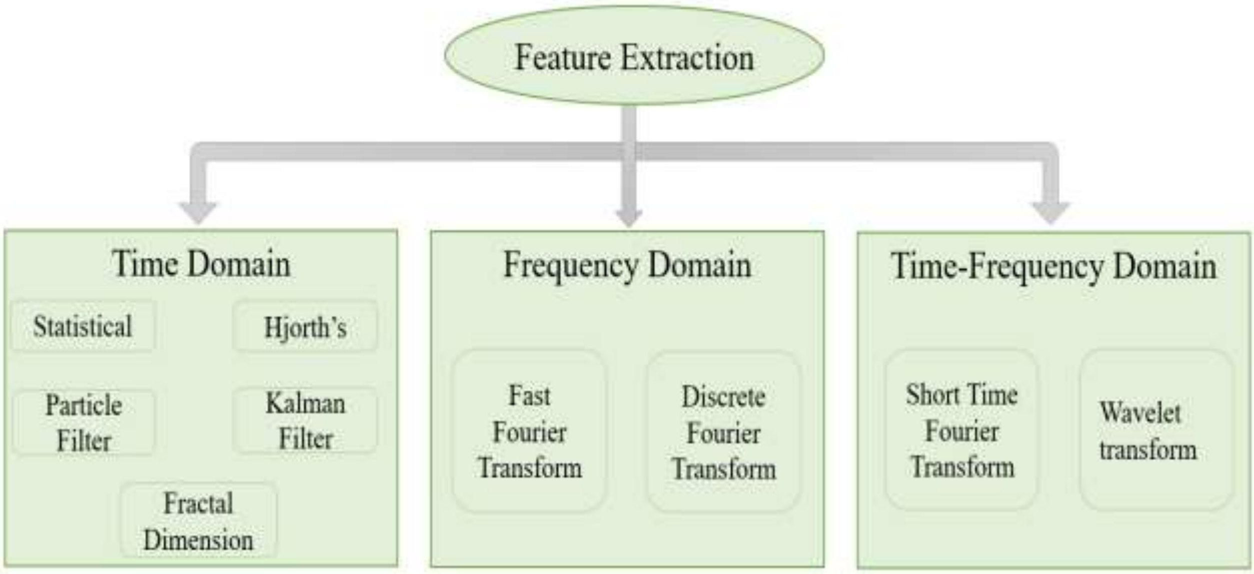

Fig. 4. Feature extraction techniques for BCI signal

Time-domain features

The time-domain technique is based on the characteristic statistical behavior of the waveform signal as it changes over time. These characteristics allow for the measurement of time-locked brain signal amplitudes.

Hjorth's parameters: In the field of signal processing, Hjorth's parameters were first presented by Bo Hjorth [35]. The three elements are as follows: complexity, activity, and mobility. The signal's variance and subsequent derivatives are linked to each other. In terms of the physical system they represent, these qualities have a significant significance, modeling the changes in amplitude and frequency that occur as well as the level of complexity that exists as compared to a simple sine wave. Because they can be computed at a lower cost than the frequency analysis approach, they can be employed in real-time and on platforms with restricted resources due to their low computational cost.

Statistical features: Signal characteristics are statistical metrics that are employed on the signal, including vibration signals, and are valuable in a wide range of applications. The presence of variations in these features can be used to detect alterations in the brain system. The brain signal can be distinguished by a variety of statistical metrics that are taken. When calculating the following features, which are often used in BCI research investigations, a vast number of data samples is taken into consideration: The standard deviation and mean are only a few of the statistics that are frequently employed. As a worsening fault signature intrudes on the regular signal, all of these variables are predicted to change. Higher-order statistics such as the kurtosis and skewness of the vibration signal are employed to get insight into the system's behavior.

All of these values are expected to alter as a deteriorating fault signature intrudes on the normal signal. The kurtosis and skewness of the vibration signal are two examples of higher-order statistics that can be used to get insight into the behavior of the system.

Fractal Dimension: Entropy and the quantity of information encoded in a signal have a direct relationship in signal processing (the measure of information density). The degree to which a signal meanders might be thought of as fractal dimension (or has roughness or irregularity). The Katz, Higuchi, and Peterson methods can all be used to calculate fractal dimension; however, the Katz method is strong [36] and hence was utilized in this study. In this stage, the Katz fractal dimension is calculated from the waveform.

Kalman filter: If the level of uncertainty associated with an estimate is taken into consideration before committing, it is possible to avoid making judgments based on faulty estimations. With the help of Bayesian filtering techniques, it is possible to estimate signal quality and their uncertainty with high statistical confidence and accuracy. The Kalman filter is one of the most well-known Bayesian filtering methods, and it is used in many applications. In some cases, such as when using

Kalman filtering, time-varying coefficients can be modified online using a recursive least squares optimization strategy. In subsequent processing, such as classification in a BCI, the coefficients can be used to represent changes in the signal's local statistical structure over time, which allows them to be used as features. Kalman filters are used to make assumptions about Gaussian dynamics and measurement process assumptions. In many real-world situations, however, this condensing theory may not be the dominant hypothesis.

Particle filter: BCI brain signals are acquired from the scalp of a human being using nonlinear BCI technology. Although the linear regression models used to analyze BCI contain a nonlinear component, this component cannot be captured by them. Alternatively, a nonlinear decoding model, such as a particle filter, might be used as a temporary workaround. It is possible to employ a particle filter to estimate a posterior distribution over the hidden state in the case of non-linear non-Gaussian processes. Based on recursive Bayesian filtering, Monte Carlo simulations are performed. Or, to put it another way, particle filtering is straightforward to implement and can scale to an alarmingly large number of simultaneous instance instances. Although a successful particle filter requires a large number of particles, particle filtering is expensive in computation because of the enormous particles required. If the distribution is unimodal, a Kalman filter should be employed to smooth it out. The fact that particle filters are non-deterministic makes forecasting and debugging their outputs challenging even though they are non-deterministic.

Frequency domain features

The limits of time-domain analysis can be alleviated by incorporating frequency-domain elements into the analysis process. The ability to analyze periodic waveform signals using frequency-domain methods is made feasible by the information included in the various frequency points and features that are formed during the generation of the signal.

Fast Fourier Transform (FFT): The FFT method digitally applies the DFT to the signal data to transform from time to frequency domain. Welch's technique, which provides Power Spectrum Density (PSD)in the frequency domain, can be used to identify filtered BCI signals in the frequency domain.

Discrete Fourier Transform (DFT): Simply described, Fourier analysis is the act of dividing a signal into the sum of sine and cosine waves of differing frequencies. The frequency content of a signal can be represented by the Fourier decomposition of its amplitudes. The IFT algorithm is used to restore the signal's original form. When employing a BCI, the brain impulses are often recorded over a consistent period. DFT is distinguished by the modification of the Fourier series and the application of this modification to discretely sampled signals. To acquire complex Fourier coefficients, the DFT transforms a time series sampled at locations t = 0, 1, ..., T into complex Fourier coefficients. Signal parameters such as amplitude and phase can be extracted from signals using these coefficients.

Time-frequency domain features

For these approaches to be effective, they require signals that are free of noise. As a result, just a minimal amount of preprocessing is required to ensure that all artifacts are removed from the image. When it comes to time-frequency techniques, windowing is critical in the preprocessing module since they deal with the stationary principle [37].

Short-Time Fourier Transform (STFT): Signals in the time-frequency domain are most typically investigated using spectrograms, which are a type of graph. This is performed by first applying STFT to a signal and then mapping it into the previously established two-dimensional frequency and time function [38]. To perform the STFT, divide the signal into many short-time signals by varying the time frame with considerable overlap [39]. A strategy known as hamming windowing is utilized to establish continuity between the starting and ending positions of the frames to prevent the spectrum from leaking. Finally, the local frequency spectrum of each segment is produced using the Discrete Fourier Transform (DFT).

Wavelet transform: Wavelets can be used for both feature extraction and denoising, and they are quite versatile. When a small x-axis shift is given to the mother wavelet, correlation coefficients can be determined for that wavelet. To repeat this technique, different scaling factors (also known as dilations) are added to the y-axis. Wavelet data analysis is separated into two sub-divisions namely Continuous Wavelet Transforms (CWT) and Discrete Wavelet Transforms (DWT). It is necessary to estimate the CWT coefficients for translation and dilation variables that change continuously throughout time (in microscopic increments). The input signals are handled by DWT through the use of finite impulse response filters.

The most typical application of CWT is the extraction of features from time-series data, which is described below. [40] To develop the CWT, he was inspired by the short-time Fourier transform (STFT), which involved extracting all frequencies within a specific time window defined by the user. The frequency-filter bank, which is used to eliminate unwanted frequencies and decompose the signal into a variety of levels via five layers of decomposition, each of which consists of the sample divided into two components, introduces redundancy in CWT. On the other hand, DWT makes use of the frequency filter bank, making it more efficient than CWT.

To provide the first phase of signal decomposition, the DWT technique separates a signal into approximation and detail coefficients. At each phase, the approximation and coefficients are divided into their respective portions [41]. The qualities of the time series can be demonstrated by extracting features from the detailed coefficients at various levels of detail or in other frequency bands, depending on the situation.

Classification Methods

When it comes to BCI systems, a variety of categorization algorithms are used [42,43]. Some of the most often used machine learning techniques are Naive Bayes (NB), Extra Tree (ET), Linear Discriminant Analysis (LDA), Logistic Regression (LR), Exploratory Discriminant Analysis (EDA), Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF). To perform pattern recognition and feature/representation inference, deep learning makes use of a hierarchical design with numerous layers of information processing to accomplish these tasks. A variety of BCI applications employ improved neural network techniques for categorization [44]. In neural networks, weights are tied to inputs, which are referred to as neurons. Weighted neurons are handled by processing units, which are divided into two categories. At the end of the day, these units combine to generate a summation section that is linked to the finished product. Several different types of neural networks (NN) exist, including Deep Neural Networks (DNN), Artificial Neural Networks (ANN), and Convolutional Neural Networks (CNN). The previous work on BCI is tabulated in table 2. Table 2 details the methods used in each stage to implement the work.

Table 2: Comparison of different BCI implementation techniques using evaluation metrics

Acquisition method	Pre-process	Feature Extraction	Classification	Evaluation	Application
EEG	Filter	FFT	Fuzzy Neural Networks (FNN) [45]	MAE-1.823, RMSE-0.257986	Wheel Chair
EEG	Band pass Filter	FFT	On-Line Sequential Extreme Learning Machine (OS-ELM) [46]	Ac-97.62%, Se-97.55%, Sp-99%	Wheel Chair
EEG	first order high-pass filter	Time Domain features	SVM [47]	Ac-77%, Kappa-0.6281, MAE-0.2736, RMSE-0.3542, RAE-66% and RRSE-	Robotic Arm

				77.8%	
fNIR	high-pass filter	-	DNN [48]	Ac- 66%.	Mobile Robot
EEG	Low pass, high pass and notch filter	-	CNN [49]	Ac-55.33% SD-3.615% K-0.173	Object movement
EEG	Artifact removal	RNN, CNN	XGBoost [50]	Ac- 95.53%	Typing
EEG	Band pass Filter	Not mentioned	linear discriminant analysis [51]	Ac-88.66%	Home Appliance
EEG	FIR bandpass filter	Frequency domain features	Batch Trained Classifier [52]	Ac-80%	Tetraplegic Patients
			Dynamic Trained Classifier [52]	Ac-82%	
MEG			Batch Trained Classifier	Ac-80%	
			Dynamic Trained Classifier [52]	Ac-85%	
MEG	band-pass Butterworth filter	Statistical Features and PSD	SVM [53]	Ac- 34%	wrist movements
MEG	low-pass, Butterworth filter, notch filter	Autoencoder	SVM [54]	Ac- 82.08%	Neural Speech Decoding
ECoG	Filter	Statistical and PCA	Long Short-Term Memory (LSTM) [55]	Ac- 82.4%	Hand gesture decoding
EOG and EEG	bandpass filter	Filter Bank Common Spatial Pattern (FBCSP)	SVM [56]	Ac- 87.31%	Vehicle Control
EEG	ICA	Power Spectrum Density Energy Diagram (PSDED)	DCNN [57]	Ac- 80%	Autism and Epilepsy classification
EEG	-	Variational Mode Decomposition (VMD)	SVM+ Predictor Importance Estimate (PIE) [58]	Ac- 98.08% Se- 100% Sp- 99.16% Pr-99.17% F- 99.58% GM- 99.57%	Diagnose ASD

Evaluation Metrics

Machine learning models are built on the assumption by receiving constructive feedback as they are being trained. While creating a model, gather feedback from metrics, make improvements, and repeat the process until achieving the desired degree of accuracy. The performance of a model can be explained by the metrics used to evaluate it. To effectively evaluate model outputs, evaluation measures must be able to distinguish between them. When analyzing machine learning models, it is critical to select the most appropriate metric available. For BCI systems to function well, it is required to use some evaluation criteria to determine their effectiveness. Accuracy or error rates are two of the most commonly utilized measures in the industry. Because of some severe conditions, accuracy is not always an acceptable criterion; as a result, a list of alternative evaluation criteria has been established in table 3.

Table 3: Evaluation metrics used on BCI research

Performance metric	Short Form	Equation
Accuracy	Ac	$\frac{TP+TN}{TP+TN+FP+FN} * 100$
Sensitivity	Se	$\frac{TP}{TP+FN} * 100$
Specificity	Sp	$\frac{TN}{TN+FP} * 100$
Precision	Pr	$\frac{TP}{TP+FP} * 100$
False Negative Rate	FNR	$\frac{FN}{TP+FN} * 100$
False Positive Rate	FPR	$\frac{FP}{FP+TN} * 100$
F1 Score	F1	$\frac{2TP}{2TP+FP+FN} * 100$
Area Under Curve	AUC	$\int_{-\infty}^{\infty} Se(t) * FPR(t) * dt$
Negative Predictive Value	NPV	$\frac{TN}{TN+FN} * 100$
Positive Predictive Value	PPV	$\frac{TP}{TP+FP} * 100$
Kappa Score	K	$\frac{Ac - Ac_{prob}}{1 - Ac_{prob}}$
Intersection over Union	IoU	$\frac{TP}{TP+FP+FN} * 100$
G-Mean	GM	$\sqrt{Se * Sp}$
Standard Deviation	SD	$\sqrt{\frac{\sum(x_i-\mu)^2}{N}}$
Mean Absolute Error	MAE	$\frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}\rvert$
Root Mean Square Error	RMSE	$\sqrt{\frac{\sum_{i=1}^{n}(y_i-\hat{y})^2}{n}}$
Relative Standard Error	RSE	$\frac{SDofmean}{Samplemean} * 100$

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Relative Absolute Error	RAE	$\frac{(\sum_{i=1}^{n}(y_i-\hat{y})^2)^{1/2}}{(\sum_{i=1}^{n}y^2)^{1/2}}$

Popular Bci Applications

BCI technology employs signals from the brain to control assistive technology. The usage of BCI has benefited in the completion of a large number of investigations. In medical settings, this term is frequently used. The range of applications has been widened to other fields. Researchers from all across the world are already looking into the possibility of a wide range of brain-computer interface applications. Control wheelchair, mental health monitoring, game, robot arm, virtual reality, and environmental management are just a few of the EEG-based BCI advancements that have been made. Figure 5 shows the BCI application in various fields.

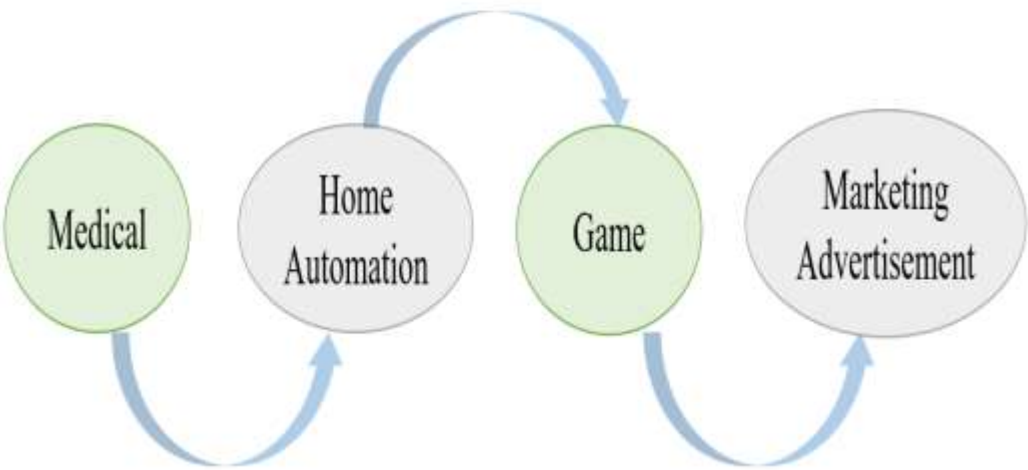

Fig. 5. BCI application in various field

Medical field

Previously unthinkable BCI systems are now being created by researchers all over the world, despite their origins in science fiction. Brain signals, recording equipment, and signal-processing algorithms are used in a range of signal-processing methodologies. Computer cursors, wheelchairs, and robotic arms are just a few of the instruments they can operate. A small number of people with severe disabilities already utilize BCIs for communication and control daily. If signal acquisition hardware can be improved, clinical validation can be established, workable dissemination models can be built, and, perhaps most crucially, dependability can be raised, BCIs could become a valuable communication and control tool for persons with and without disabilities [59].

BCI Home automation

An automated home automation system that is controlled by BCI can be used to activate a variety of household components, such as light fixtures, switches, and ceiling fans [60,61]. Audible orders from the user are the only means of controlling the devices. For the system to function, two smart home (voice-controlled) devices, a smart lamp, and a fan coupled to a smart socket were used in its implementation as smart home (voice-operated) devices. The testing consisted of three trials for each of the two application states, with a total of four test participants participating in the process. Took measurements to establish how quickly and accurately each activity was accomplished, as well as how well each task was completed. The smart plug could be programmed to perform many tasks, such as turning it on and off. It was necessary to accomplish several tasks including turning on, dimming, brightening, and shutting off the smart light bulb.

BCI Neuromarketing and advertisement

BCI researchers are also interested in the marketing industry, according to their findings. As a result of this work, scientists have explained the benefits of using EEG evaluation for commercial and political television advertising. A new study conducted by neuromarketing researchers investigated the impact of yet another cognitive function on the purchasing decision process. Their purpose was to determine how much people recall commercials from television, and as a result, they came up with this method of determining advertising efficacy [62, 63].

BCI game

Following the broad availability of consumer-grade EEG equipment, the first BCI-controlled games were developed. The games that have been developed may be labeled as competitive games in the entertainment business or medically serious games [64]. The vast majority of BCI games that can be considered serious games have been developed for usage with healthy persons in mind. Because BCI is meant to be replacing Human-Computer Interaction (HCI) in this process, BCI must be able to read and anticipate brain activity to translate it into meaningful commands that allow for seamless gameplay. To be clear, the delays in this cycle should be investigated, as should the treatments that have been identified and reported in the literature [65].

Conclusion

Individuals can control a computer just by thinking about it, thanks to the development of brain-computer interfaces. In the field of BCI, researchers are investigating a wide range of problems, including the acquisition and processing of brain signals, as well as the comprehension of these signals. The fields of physiology, technology, computers, and mathematics all play a role in brain-computer interface research. Because of its promise, BCI has received a great deal of interest. The field of BCI has seen considerable growth in recent years, both in terms of the technology available and the number of organizations working in the study and development of these systems. Some BCIs are now commercially available, having been developed as a result of laboratory trials. BCIs are no longer considered a sci-fi fantasy in the field of assistive technology, but rather a realistic prospect. This journal has gone over every stage of the BCI in great detail. Brain signals are collected and analyzed in the initial stage of the BCI process. There are both invasive and non-invasive methods of data collection accessible for use. Non-invasive procedures are chosen by scientists over intrusive approaches because they are less likely to cause harm than intrusive techniques. The second phase of BCI is concerned with the analysis and cleaning of brain signals. This review has discussed several feature extraction and classification techniques. Many different applications of BCI can be found, and this journal provides a quick review of some of the most current examples. The tactics employed to control hardware devices using BCI can differ from one research to the next.

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