Integration of EEG-based BCI Technology in IoT enabled Smart Home Environment: An in-depth comparative analysis on Human-Computer Interaction Techniques

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Abstract

The advent of smart home technology has revolutionized the way individuals communicate with their living spaces, offering efficiency, convenience, and comfort. The integration of brain-computer interface technology within smart home environments presents a promising avenue for transforming human-computer interaction paradigms. This review paper synthesizes current research findings on optimizing smart home user interfaces through human-computer interaction utilizing electroencephalography-based BCI technology. EEG-based BCIs offer a novel approach to interface design by directly interpreting users' neural signals, thereby enabling seamless interaction with smart home devices. By using EEG signals to figure out what people are thinking and feeling, BCI creates a direct way for people and machines to communicate naturally, without using traditional input methods. The paper examines a few explicit key components such as signal acquisition, feature extraction, feature selection, classification algorithms, and system integration. Furthermore, the review evaluates the effectiveness, challenges, and future prospects of EEG-based BCIs in optimizing human-computer interfaces within smart home ecosystems. Insights from this review contribute to the understanding of how EEG-based BCIs can revolutionize user interaction paradigms, leading to more intuitive, efficient, and personalized smart home environments. This work presents a comprehensive study on the proposed topic by consolidating useful information from various sources and exhibiting it in a single paper to provide quality data to the novice researchers to help them in this field of research.

Keywords: Internet of Things, Smart Home, Brain Computer Interface, Electroencephalogram, Ubiquitous computing.

1. Introduction

In this dynamically evolving era of modernized living, the incorporation of technology in our homes has reshaped the way we engage with our surrounding environment. As stated by some of the popular researchers, a home must have a minimum of multiple sensors and actuators, user interfaces (including visual displays and voice control), building services (like lighting, heating and ventilation) and various network appliances with a view to qualify as a smart home [1]. Smart homes are reforming the residential life of human

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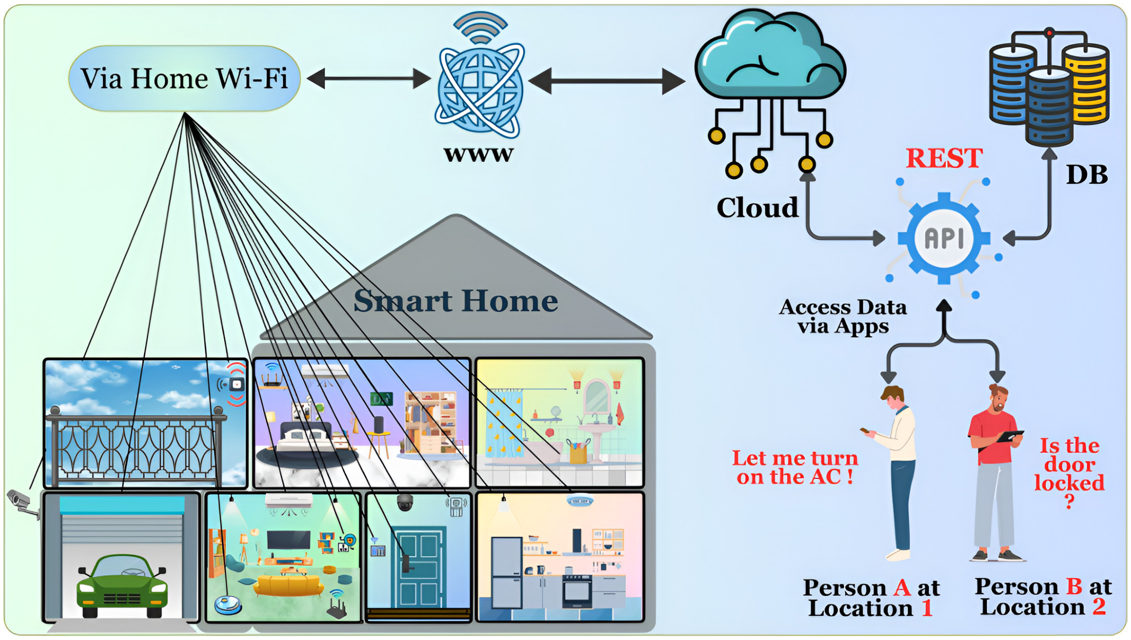
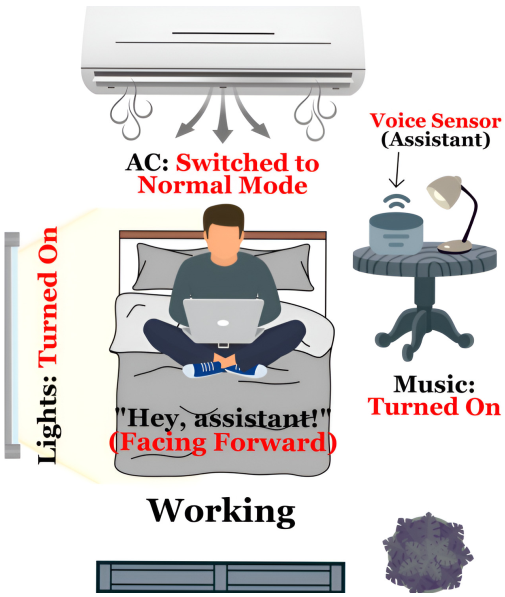


Figure 1: Ubiquitous computing: IOT Model Level 5

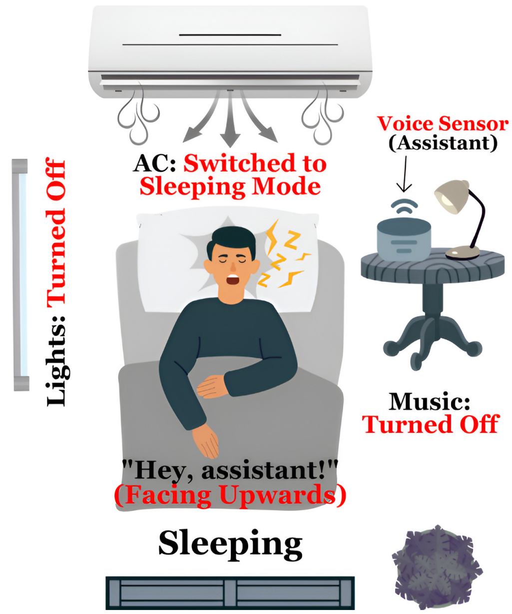
beings by harnessing sophisticated computing capabilities to enhance comfort, convenience and efficiency. The internal in-house networks are combined with the external networks (mobile phones and internet) [2] . Within this framework, a smart home is based on integrated communication services and centered around an automated structure by virtue of existing building infrastructure. Scholars generally agree that a smart home is fragmented into three components that are "Home Automation", "Internal Networks" and "Intelligent Controls"[3]. Human-Computer Interaction (HCI), a multidisciplinary field which studies the seamless interaction among humans and machines which plays a vital role in transforming the user experience within these smart home environments and in return it offers a bridge between human needs and the potential of intelligent devices. Residents may easily control, monitor, and customize their living spaces according to their preferences due to the dynamic ecosystem created by the collaboration of humans and machines.

1.1. Ubiquitous Computing

As computer technology progresses, Mark Weiser "The Father of Ubiquitous Computing" proposed that UbiComp has evolved from an innovation to a tangible reality in our everyday lives [**?**]. Recently, existing computing hardware (HW) embedded devices integrated with AI powered software (SW) are intended for enhancing human lives [4]. However, Ubicomp's internal modules must interact with themselves prior to engaging with end users. This kind of conception raises the significance of Human-Computer interaction in smart home environments [5]. Within this aspect, a smart home evolves into a Ubicomp-focused ecosystem fabricated of cooperative autonomous spaces each of which facilitates a service area provided with HW/SW to offer a range of services overseen by agents. One of the biggest benefits of Ubicomp-based smart home is its ability to execute numerous services with multiple configurations. Nevertheless, the most challenging task is figuring out the best configuration [5]. From the perspective of human-centric requirements, a home is typically thought of as offering services which fulfills "comfort", "security" & "convenience", which distinguishes a smart home from other UbiComp-based environments [5]. In specific terms, we illustrate "comfort" to be the Quality of services (QoS) and the method of providing these services are carried out by "convenience", which establishes a connection between the end user and the environment where these services are provided, and "security" be inspecting the issues of information privacy & security [5]. Additionally, every service interaction with end users needs to be adjusted with changing contexts of the environment [5].



(a) Proposed method for software cost estimation for: Triobj1



(b) Proposed method comparison with standard algorithm based on software cost estimation for: Triobj1

Figure 2: Smart bedroom scenario via voice recognition

1.2. *Voice Recognition and Orientation*

In contemporary Human-Computer Interaction (HCI), speech-based interaction stands out as a highly favored form, allowing individuals to engage in verbal communication with machines through technologies like speech recognition and speech synthesis [6]. Voice interaction has been recognized as one of the most preferred HCI techniques by virtue of its efficiency and humanized traits [7]. Intelligent voice technology is amplifying quickly and substituting people's earlier lifestyles due to advancements in Internet of things (IOT) and deep learning along with improved processing capability [8]. The necessity for human-machine speech interaction goes beyond recognition precision and a greater focus on user's experience elements [7]. Voice orientation primarily aims to the direction the head is looking at the time the speech signal is released [7]. Voice orientation and recognition is not just a mechanical speech recognition technique but it also inculcates the knowledge of people's states resulting from the understanding of voice orientation, which in further enhances the experience and enjoyment of speech-based HCI [7]. Despite being beneficial, voice recognition cannot always be determined only due it's acoustic characteristics [7]. The two major drawbacks in voice recognition are firstly, "The Multi path Effect ", which does not define the path of propagation and source of the voice signal and secondly, there is no specific spectrum for frequencies of various speech recognition [9]. Furthermore, we must execute comparatively better identification accuracy using minimal and basic equipments and reasonable hardware in a field of real-world occurrences [7].

1.3. *Brain Computer Interface (BCI)*

Brain-Computer interfaces (BCIs) have evolved as a valuable tool to facilitate daily life activities of elderly people and those with physical disabilities, over the past few decades [10]. BCIs establishes a direct communication pathway among the individual's brain impulses and various external kinds of actuation devices [11]. Lately, due to the various developments in augmented reality (AR) and Internet of things (IOT), smart homes have become an alternative option to enhance the daily activities of human beings [11]. The number of members engaged in BCI system testing were young even though the target were elderly. Hence, it was found that some evoked potentials such as P300 and steady-state visual evoked potential (SSVEP) was stimulated more in younger people than the elderly [12]. Regardless, the BCI system may

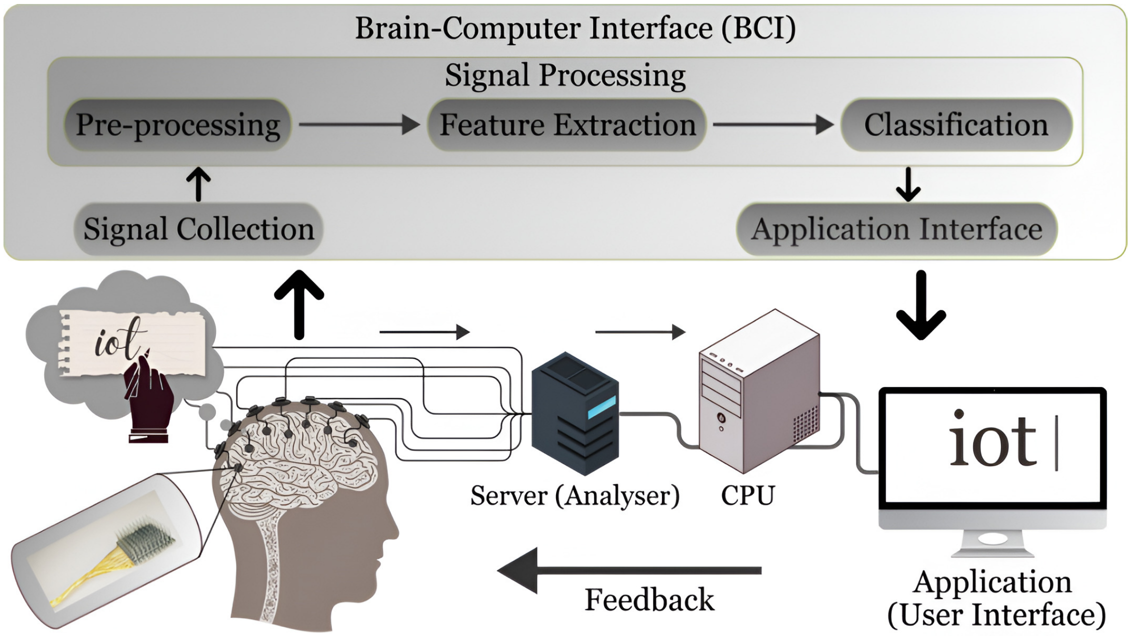


Figure 3: Outline for BCI methodology

be user-friendly for the youngsters but the elderly who are less acquainted with electronic devices may find it difficult to operate [13]. Therefore, by the integration of innovative electroencephalography (EEG)-based BCI and IOT, we can achieve a feasible system for people who are above the age of 65 [11].

1.4. ***Recognition Activities in an Intelligent Home***

In an intelligent home, to facilitate the identifying actions one must obey three major steps:

- Collect granual-level sensor data (collecting data from the sensors).
- Analyse data gathered (processing the collected data); and
- Reasoning learning or utilizing techniques to deduce activities from the analyzed data (activity recognition).

1.4.1. ***Acquiring Sensor Data***

The initial phase of data gathering involves employing sensors and actuators, compact and cost-effective devices positioned throughout the household, capable of detecting, observing, and relaying various human activities. There are a restricted number of sensors on the market tailored specifically for recognizing activities. Depending on their characteristics such as type, intended function, input and output signals, as well as technical setup, sensors can be categorized as follows:

- Dense sensors are further categorized into two broad classes as: vision-based sensors or obtrusive sensors and non-obtrusive sensors. Vision-based sensors, which utilize video cameras for activity recognition, fall under the category of obtrusive sensors, requiring no human intervention and thus are commonly favored for this purpose. Additionally, non-obtrusive sensors can be categorized into two further classes: dense-sensing environment sensors and wearable sensors.
- Wearable sensors are well-suited for tasks like tracking pulse, skin temperature, movement, and body position. However, they come with certain drawbacks such as limited battery life due to continuous operation and reliance on user willingness to wear them. As a result, they are being supplanted by dense-sensing sensors, which gather data without requiring physical contact with end-users.

- Within smart homes, the volume of generated data is constant, shaped by factors such as the quantity of sensors, the number of occupants, and the activities conducted within the premises. These sensors utilize either wireless or wired communication methods, necessitating Unique IDs, timestamps, and status signals. The precision of sensor data directly impacts the noise level within the smart home environment. Therefore, employing temporal-ordered random data processing becomes essential for accurate activity recognition.

1.4.2. ***Analysis and Processing of data***

Data analysis plays a crucial role in activity recognition within smart homes, primarily conducted using logical approaches and machine learning algorithms. However, as smart homes become increasingly complex, the collected data also becomes noisier, necessitating more extensive processing before it can be subjected to further analysis. Filtering raw data is essential to eliminate anomalies and remove outliers. Techniques such as median filters, low-pass filters, Kalman filters, Bayes, and particle filters can be deployed to refine the raw data. Following filtering and the removal of data gaps, the subsequent stage of data analysis involves formatting the data to align with established algorithms. Data segmentation also plays a vital role since sensor data collected in smart homes is recorded at frequent time intervals. During the segmentation process, the data collected is divided into three main smaller segments: activity-based,temporal-based and sensor-based.

1.4.3. ***Activity Recognition***

In the final phase depicted in Figure 4, activity recognition relies on two primary approaches: knowledge-driven, exemplified in [13][14] , and data-driven, demonstrated in [15]. Knowledge-driven methods leverage existing domain knowledge to characterize ongoing activities, encompassing knowledge acquisition, formal modeling with presentation of knowledge [16][17]. Within the domain of knowledge-driven models with the task involving logical resoning such as abduction, induction, and deduction play essential roles in activity recognition or prediction [2].These models display semantic clarity, logical elegance, and immediate and smooth applicability for users, effectively providing solutions to the cold-start problems [18].Nevertheless, they have limitations as static methods, offering less expertise in managing uncertainty and real time data. In contrast to driven by knowledge approaches, models driven by data extract insights from Pre-existing datasets containing user-generated behaviors,leveraging data mining and ml algorithms for learning process [2]. These models employ statistical or probabilistic methods to address temporal issues and data uncertainty. The models utilize probabilistic methods to address temporal issues and data uncertainty. Further classification of data-driven approaches reveals two main types: generative and discriminative [19].Within the generative approach, comprehensive representation of the input data is created using a probabilistic model [?]. For example, Conditional Random Fields (CRFs) yield satisfactory results for activity recognition as they integrate probability concepts [20]. Conversely, a discriminative approach utilizes past submissions to compile datasets containing both correct and incorrect data [2].As an illustration, the nearest-neighbor algorithm (KNN), which relies on an extensive array of training samples, expands exponentially in accordance with the targeted level of accuracy. Discriminative approaches are crucial in tackling the problems of classification, unlike the problem of representation in case of approach based on generation. To exemplify, one such approach is the nearest-neighbor method, which scrutinizes the dataset based on training groups together sequences that intimately match each other.Another instance of this method is decision trees, which are utilized to acquire descriptions of logical activities derived from sophisticated sensor data readings [2].

2. Literature Review

A brain-computer interface (BCI) is integration of brain and an external device which transmits brain signals in order to implement various external tasks without any foreign nerves and muscles [21]. BCI is primarily used by people with acute movement disorders, specifically patients with Motor neurone diseases, midbrain strokes, or other neuromuscular diseases [22]. BCI-based applications can be utilized to operate wheelchairs, orthics, assistive devices and multiple computer applications. In addition, BCI-based home

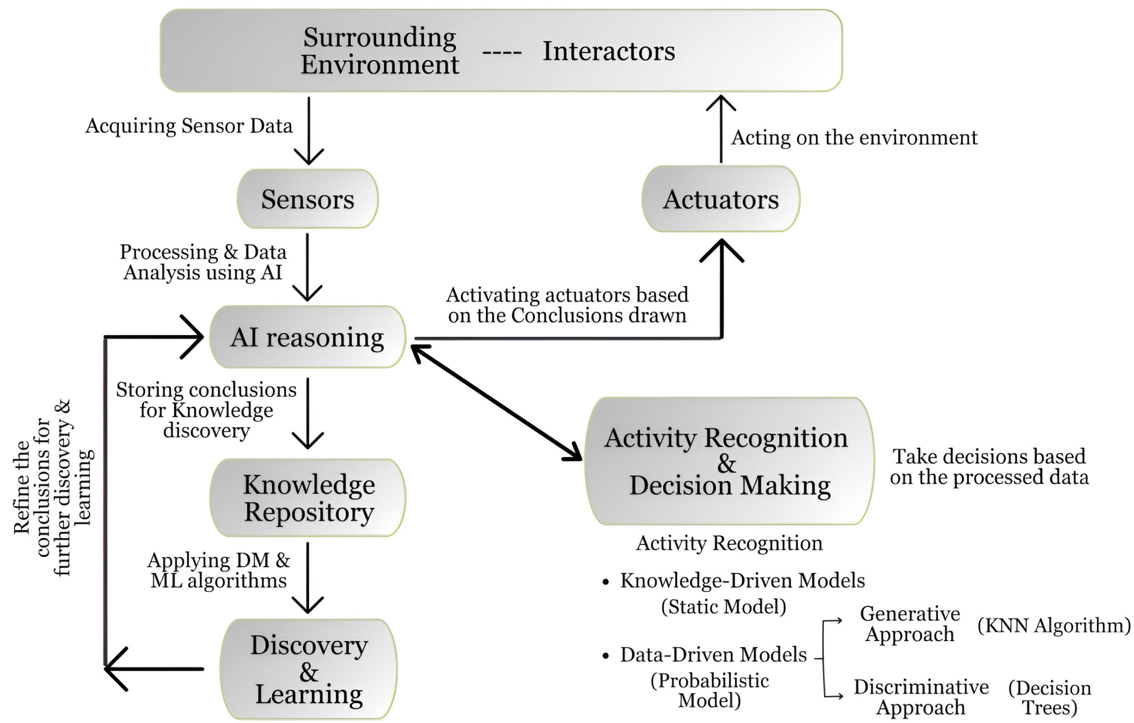


Figure 4: Data-flow illustration for activity recognition

automation control system was found advantageous in the domain of Artificial Intelligence (AI). Moreover, BCI-controlled home automation interfaces showcase independence with respect to illumination and audio spectrums[23]. Additionally, it allows a home automation interfaces to be controlled directly by the user's desired actions. In order to avoid surgical techniques, there are broadly four non-invasive measurement techniques which are implemented for collecting brain signals: electroencephalogram (EEG) [24], magnetoencephalography (MEG) [25], functional magnetic resonance imaging (fMRI) [26], and functional near-infrared spectroscopy (fNIRS) [27]. BCI-based control system is found beneficial over other type of brain techniques due to their good portability, temporal resolution, and less expensive.

Electroencephalograph(EEG) is the most prefered technology for reading signals from the brain. It's a kind of non-invasive BCI technique which involves intercommunication between the brain and an external equipment without any direct physical contact with brain tissue or implantation. It detects the potential fluctuation within the neurons whenever there are any external stimuli; basically, the variations in signals affect the location of synapses generating a potential difference which is then recorded [28]. The functioning of cerebral activity is most effectively observed in those areas where it is augmented [24]. The obstruction formed between the sensors and neurons often generates frequencies beyond 40Hz making it challenging for measuring accurate EEG signals [29]. Among brain activity measurement techniques, EEG stands out for its incomparable combination of affordability, portability, and compatibility. Moreover, it offers exceptional temporal resolution, capturing brain activity with millisecond precision. However, various research indicates that the EEG signals obtained after pre-processment are quite noisy due to their low signal-to-noise ratio, low spatial resolution, and several external factors such as artifacts and interfering frequencies. The EEG activity signals often exhibit a relatively low strength, typically measured within the theta and gamma frequency ranges. Considering EEG electrodes are positioned according to a standardized system on the scalp's surface which results in a low signal-to-noise ratio. Furthermore, it was observed that an extremly higher signal-to-noise ratio is obtained in the case of ECoG (Electrocorticography) since the sensor electrodes are explicitly placed on the brain. The noise must be processed to derive some meaningful insights from the

signal[30][31]. There are two major techniques for removal of noise from signals; one is filtering and other is artifact removal [23].Upon completion of the signal enhancement stage, the resulting noise-free EEG data undergoes feature extraction to isolate relevant characteristics of brain activity. Feature extraction from EEG signals is achieved through diverse techniques like Autoregressive models (AAR) for capturing signal dynamics, Principal Component Analysis (PCA) for dimensionality reduction, and Wavelet Packet Decomposition (WPD) for time-frequency analysis [28][32][33][34].
After the feature extraction phase, the brainwaves obtained are sorted into diverse classes using multiple classifiers. These classifiers are linear classifiers, Artificial Neural Networks (ANN) based classifiers, non-linear Bayesian classifiers and nearest neighbor classifiers [28][**?**]. As specified by [35], Support vector Machine (SVM) appears as a suitable algorithm for classifying Mind-control system powered by EEG data for increasing classification accuracy, as referred to by several research papers in their analysis. Multiple references suggest that a Gaussian classifier offers higher suitability for high-dimensional EEG-based robot controllers [36]. By implementing this classifier, along with threshold method by as proposed by [36], it not only offers reliable classification accuracy for BCIs but also filters out unrecognizable Motor Imagery (MI) tasks, reducing false positives in classification outcomes[28].A study on brain-computer interfaces using EEG [37] found success with k-Nearest Neighbor (k-NN) and Linear Discriminant Analysis (LDA) for classifying brain signals. The system achieved impressive accuracy, reaching up to 82%. To extract key characteristics from the brain signals, the researchers used techniques called Mean Derivative (MD) and Hilbert Transformation (HT). These findings encourage a potential interest in exploring alternative classification algorithms to enhance data utilization [23]. Another study [38] compared the performance of three classification algorithms: Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and Gaussian Naive Bayes (GNB). This comparison was conducted for a Brain-Computer Interface (BCI) controlled by motor imagery (MI). The study [35] found that the Gaussian Naive Bayes (GNB) method achieved higher classification accuracy compared to the other two (LDA and SVM) and argued that GNB is particularly well-suited for analyzing EEG data. Additionally, the researchers proposed that GNB's effectiveness could be further explored for developing real-time Brain-Computer Interfaces (BCIs) based on motor imagery (MI).

EEG and Brain-Computer Interface (BCI) are integrated along with smart home environments to facilitate a more innovative, efficient interface for controlling devices and enhanced functionalities for an interactive user experience. End users can control smart home devices with the help of brain signals which in return reduces the need of physical interaction or voice commands. This integration offers various benefits such as providing assistance to people with disabilities and hands-free operation for tasks in physically constrained environments. As suggested in [39], BCI technology acts as an useful device for HCI, it is capable of capturing ambient properties of human activities rather than performing active operations. Unlike traditional interfaces, EEG technology allows for user interaction without placing a burden on the user's mental focus. This makes it a valuable tool for various interactive devices. Furthermore, EEG driven by BCI are directed to encapsulate neural activities into smart wearables. This wearable device allows user's brain activities to be monitored even while free roaming, enabling the prototyping of ubiquitous computing. The prototype is demonstrated using EEG driven mobile BCI, which can be used as a novel form of human-computer interaction device. Highlighting the security benefits of eye gaze technology, we created a login system where users can authenticate by looking at the screen from a close distance. The functionality is achieved through the identification of characteristic EEG patterns elicited by user visual attention to the computer terminal's blinking display. Building on similar concepts, research by [39][40] explores eye sensors as an alternative for managing cell phone notifications. Their system leverages a user's gaze direction to infer their intent. This effectively merges eye tracking technology with Brain-Computer Interface (BCI) control. In simpler terms, imagine interacting with your phone by simply looking where you want to click – a truly intuitive approach that eliminates the need for physical touches or gestures.
As specified in [41], a potential framework for ubiquitous brain-aware computing (UBAC), characterizes the usage of wearable, ubiquitous BCI technology to facilitate cognitive state information to contextually aware and other HCI applications. The above mentioned paper analyzes the feasibility of using a cost-effective, single electrode, wireless-enabled, non-intrusive, gel-free, and battery-operated EEG recording device for ac-

curate identification of cognitive states. The preliminary outcomes of the above referred paper indicates that by using a straightforward single-electrode system, we can potentially distinguish among various categories of cognitive and emotional states. For instance, the states associated with reading "uninteresting" material, reading "interesting" material, listening to music, and engaging in relaxation is defined under this category. Numerous smart appliances and context-aware apps can become "smarter" if they have the access to mental models of their users.In future, one may imagine some certain brain-state information can be projected into real world enabling more seamless and smooth integration of people with their surroundings. A key feature of this data process decoupled, layered architecture is that it segregates different modules at different levels of processing (which includes feature extraction, selection,classification, high-level interpretation) [28][35][41]; developers working within one particular layer need not have in-depth knowledge regarding how other layers or processes (even within the same layer are implemented. This architecture is similar in nature to TCP/IP-based BCI platform BCI2000 [42].

According to a study [43], persons with disabilities and elderly people face difficulties in operating home appliances, hence this challenge can be tackled by using Neuro-control interface. Brain-computer interfaces (BCIs) employ non-invasive electrodes placed on the scalp to establish a communication channel between the external devices and the brain. Users connect and interact with the Brain sense headset through the Neuro view software. The electrodes detect brainwave activity. This information is then processed and transformed into a specific type of signal (blink wave) suitable for the Arduino board. Finally, the Bluetooth module wirelessly transmits this signal to the Arduino board. Once received by the Arduino board, the digital signal is processed to understand the user's intent. This information is then used to activate the corresponding appliances. An Arduino-based BCI-controlled home automation system for the physically disabled is presented in this paper. This paper suggests a BCI system specifically designed to empower individuals with paralysis or disabilities. The system allows for independent control of easy-to-build, cost-effective appliances. This scalable design can be adapted to manage any number of devices and has broad applications in various fields, including automobiles, industrial settings, remote control operations, and beyond.

The paper proposed in [44] discusses the development of a Mind Controlled Robot utilizing BCI technology, which analyzes brain waves using LabVIEW software.BCI technology facilitates a direct link between the brain and physical devices. By analyzing different brain activity patterns instantaneously, BCIs allow for the control of mobile robots. It focuses on analyzing brain wave signals, which represent the complex interactions between neurons in the human brain and manifest them as thoughts and emotional states. As human thoughts evolve, these patterns change, resulting in the production of different electrical waves which are further transmitted to the robotic hardware system (often used with Arduino) by using Bluetooth transmission protocol.

The research performed in [45] involves the decoding and interpreting of EEG signals to recognize Hook and Span hand gestures. This model utilizes various signal processing methods alongside supervised machine learning algorithms like SVM, Decision Tree, Adaboost, and Random Forest to achieve classification. The system begins by processing the EEG signal. It first removes unwanted noise using band-pass (14-30Hz) and notch (49-51Hz) filters. Then, it extracts relevant features from the cleaned signal and finally classifies it as either a hook or span hand gesture. The objective of this work is to offer assistance to individuals with nerve damage by equipping users with the ability to interact with the automated features of their wheelchairs. The significance in the above research lies in it's specific focus on operating wheelchair gear control and release, just by using hand gestures.

Conventionally, the EEG system driven by BCI is segmented into four different patterns, that are Steady-state visual evoked potential (SSVEP), Motor Imagery (MI), P300 potentials, and slow cortical potentials. Each signal pattern has its own pros and cons [46]. While reference [47] demonstrated controlling a system with MI signals based on hand grasps, it suffered from a restricted set of available commands. Research by [48] investigated eye blinks and eye movements for controlling a home lighting system. They concluded that eye blinks offered greater accuracy. Eye movements, they found, could be influenced by involuntary factors or slight head movements, introducing errors and potentially causing unintended light activations. When MI signals are compared with eye-blink signals, it is observed that P300 and SSVEP signals exhibit exceptional accuracy and rapid response times. As a result of which, the majority of the existing home automation systems based on BCI technology rely on P300, alpha rhythm and SSVEP signals to achieve faster and more precise control. Both P300 and SSVEP signals require external triggers for operation. P300 signals are particularly well-suited for recognizing a wider variety of triggers (typically more than six). In contrast, SSVEP signals demonstrate optimal performance when dealing with a limited number of triggers (under six). A person whose entire body is completely paralyzed can still communicate using eye signals to execute gestures through the hook and span method described in the aforementioned paper [45].

In accordance with the study made in [49] a multimodel BCI system for home automation control was proposed. This study investigated the use of electrodes to record two specific brain signals. Participants focused solely on a stimulus and used eye blinks to interact. The user sees a specific visual pattern (stimulus) that triggers the desired commands through SSVEP brain signals. Single eye blinks indicates selection confirmation, while two consecutive eye blinks signify denial and prompts reselection, thereby calibrating the SSVEP command. The study concludes that the proposed model provides 38 navigation commands with a duration of 2s with an accuracy of 96.92%, leveraging a single bipolar EEG channel for data acquisition. his research proposes a groundbreaking brain-computer interface (BCI) system specifically designed for automation of home applications. The system utilizes eye blink signals, SSVEP, aiming to empower individuals with disabilities.

The use of EEG for UAV control is limited due to the demanding nature of drone piloting, which requires precise control and sustained mental focus. While EEG shows promise for UAV control, using it alone might be challenging due to the limitations in accurately translating complex user intentions into precise flight commands. However, a hybrid BCI system that incorporates EOG signals alongside EEG can address this limitation by offering a more robust and intuitive control interface [49][50]. By implementing an obstacle avoidance algorithm, we can effectively prevent collisions and navigate around dead ends in any given environment. The integration of eye-tracking zones empowers users to navigate more effectively by leveraging real-time video from the UAV camera. By fixating their gaze on specific areas of the live feed, users can direct the drone's movement. This system incorporates an additional control layer through visual attention. Users can control the drone's ascent, descent, and forward/backward velocity by directing their gaze on the live video feed. Meanwhile, motor imagery (MI) signals are employed for precise control over the drone's tilt (roll), sideways movement (pitch), and turning (yaw). A novel application of a hybrid autogenous BCI was demonstrated in [51] for controlling a drone swarm. The control system leveraged different brain signals: visual imagery (VI) for specifying high-level goals, motor imagery (MI) for directional control, and speech imagery for commanding specific swarm configurations.

The study of attention, a critical aspect of brain function, represents a highly valuable domain in the field of neuroscience. It has a significant impact on some crucial cognitive processes like learning, driving vehicles, etc. Artificial Intelligence (AI) has accelerated the growth of brain-computer interfaces (BCIs), enhancing interpretation and understanding of brain activity. Another study [52], detected and measured the cognitive load of a person by using BCI and EEG Signals. This model could help ensure the alertness of drivers and pilots by monitoring their brain activity and identifying potential fatigue or distraction. This could lead to safer roads and skies. This paper explores the use of electroencephalography (EEG) and machine learning to classify different mental attention states in humans. This research focuses on its potential application in diagnosing Attention Deficit Hyperactivity Disorder (ADHD), where attention difficulties are a core symptom. The study recruited five volunteers to assess their mental focus levels. Researchers employed a technique called Short-Time Fourier Transform (STFT) to extract relevant features from their brain activity data recorded through EEG. These features were then fed into a Support Vector Machine (SVM) classification algorithm, which categorized the volunteers' mental states into three main categories: focused, unfocused, and drowsy [53].As more features are included during model training, the accuracy of predicting human mental states can be significantly improved. This allows for more precise classification of focus levels, leading to potentially better applications. More accurate prediction of drivers' mental states could reduce accidents, while monitoring students' brain activity could assess their engagement during learning [52].

Employing EEG technology for security purposes will unlock innovative methods in enhancing safety of individuals. Addressing occupational safety through strategies for managing IoT networks is yet a persistent

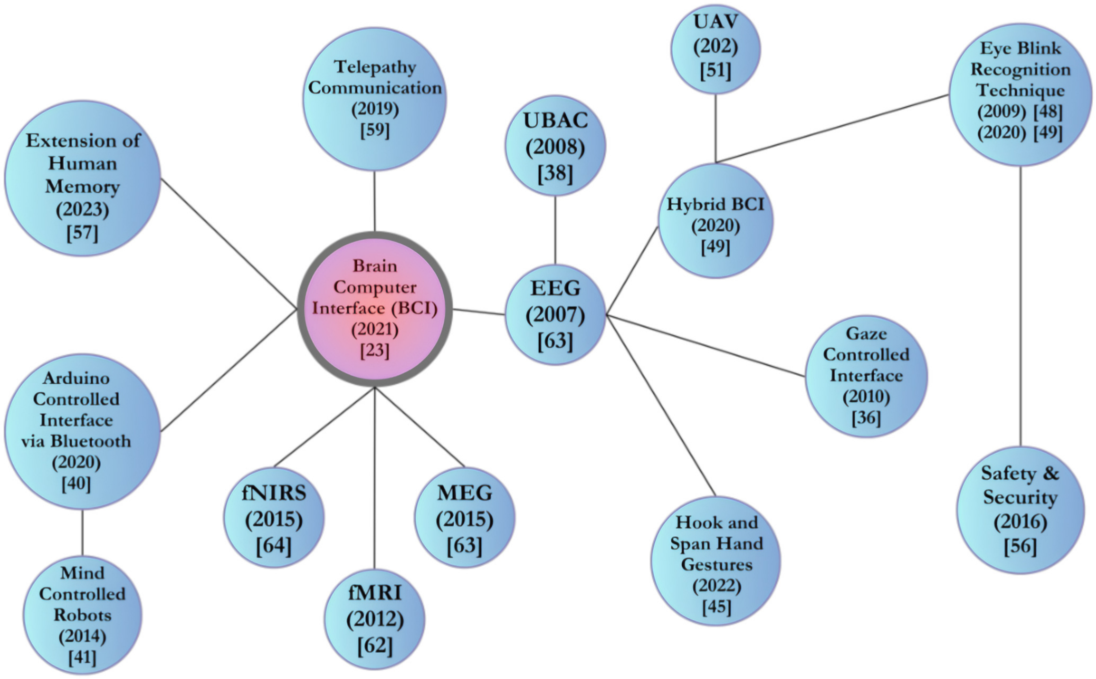


Figure 5: Visual Representation depicting different studies in the field of BCI

challenge. A paper [54] suggested the use of UAVs to monitor mine workers' exposure to harmful conditions. Another paper [55] proposed a smart helmet equipped with EEG sensors, enabling constant monitoring of the user's health condition via IMU and EEG sensors [56]. To promote worker well-being, sensors monitor for signs of fatigue or stress and send alerts to connected devices or apps. Exploration teams working in remote locations, often beyond the reach of traditional communication, could benefit from EEG technology. This allows for emergency alerts to be sent directly from a worker's brain activity. However, whether utilized independently or in conjunction with other physiological indicators, EEG presents an opportunity for enhancing security systems, contributing to the detection of hidden targets that would be difficult to find using traditional methods [28].

Table 1: Summarizing the objectives and models used in different studies of BCI along with their citations.

Title/Author's Name	**Objectives**	**Models/Algorithm /Technology used**	**EEG Control Signals**
An Overview of the Use and Applications of Brain-Computer Interfaces Based on Electroencephalographs (EEG) [28]	• This paper aims at demonstrating various methods for collecting brain signals. • It provides a clear and concise examination of each approach, including the benefits and drawbacks of each.	• EEG-based BCI Technology. • fMRI, MEG, fNIRS ECoG methods are used for signal acquisition. • FFT, ICA, PCA, WT, AAR are mostly used for feature selection. • SVM, k-NN, ANN, LDA are some the classification algorithms used.	• Desynchronization/Synchronization (ERD/ERS). • Steady-State Visual Evoked Potentials (SSVEP). • P300 • Visual Evoked Potentials (VEP). • Slow Cortical Potentials (SCP).
A review of classification algorithms for EEG-based brain–computer interfaces [57]	• This research paper provides an overview of some of the classification algorithms used in EEG-based BCI systems. • It outlines their key attributes, and compares their performance based on the existing literature.	• SVM, Random Forest, k-NN, LDA and ANN are few classification algorithms used in this paper.	• SSVEP. • P300 • ERD/ERS.
EEG-Based BCI Control Schemes for Lower-Limb Assistive-Robots [58]	• The objective of this research is to explore Applications of EEG-based BCI for mobility rehabilitation and locomotion, highlighting advancements and challenges in controlling wearable lower-limb devices and assistive-robots.	• TCP/IP Protocol suite is used for transmission purposes. • SVM, LDA, ANN and Gaussian classifiers are used for classification.	• P300 • SCP • VEP • ERD/ERS • MI
Quaternion-Based Signal Processing for Electroencephalographic Signals-Based Motor Imagery Classification [37]	• The purpose of this work is to extract features from EEG data and use the QSA approach to represent motor commands.	• k-NN , LDA, SVM and DT classification algorithms are used. • To represent the signals, features are extracted using Mean Derivative (MD) and Hilbert Transformation (HT).	• P300 • SSVEP

Towards Ubiquitous Brain-Aware Computing: A Preliminary EEG Study [41]	• This paper suggests a potential framework for ubiquitous brain-aware computing (UBAC), characterizing the usage of wearable, ubiquitous BCI technology to facilitate the identification of cognitive states and other HCI applications.	• Ubiquitous Brain-aware Computing (UBAC) framework is implemented. • Fisher Linear Discriminant Analysis (FLDA) is performed for task classification.	• ERP/ERD/ERS • P300
An Arduino Home Automation System with Brain-Computer Interface for People with Physical Disabilities [43]	• This paper aims at utilizing Bluetooth (for communication) and Arduino (for controlling) to interpret brain signals and convert them into real life actions by integrating BCI with IoT so as to facilitate home automation for paralyzed and disabled ones.	• MATLAB Software is used to visualize and sense the brain signals.	• Eye Blink
An Electroencephalogram Based Detection of Hook and Span Hand Gestures [45]	• This work analyzes and classifies the EEG signals to recognize Hook and Span Hand Gestures. Its objective is to offer assistance to individuals with nerve damage by enabling them to independently operate automated wheelchair controls.	• SVM, Decision Tree, Adaboost, and Random Forest classification algorithms are implemented. item[•] A notch filter of 49-51 Hz and a band pass filter of 14 -30Hz is used during preprocessment.	• SSVEP • Alpha Rhythm
Eye blinks detection from EEG data for home lighting activation systems [48]	• This study investigates an optimal eye activity to trigger home lighting systems and subsequently identifies this activity from EEG signals.	• The technique of Short-time Fourier transform (STFT) is utilized to extract features. item[•] Convolutional neural network (CNN) is used as a classification algorithm.	• Motor Imagery (MI) • Eye Blink • Eye Movement • SSVEP • P300 • Alpha Rhythm

A Hybrid Brain-Computer Interface System for Home Automation Control Based on Bipolar-Channel using Eye-Blink signals and Steady-State Visually Evoked Potential [49]	• The aim of this study was to create and authenticate a hybrid BCI system designed for controlling home automation and leveraging SSVEP and eye blink signals, with potential benefits for individuals with disabilities (esp. full-body paralysis).	• Short-time Fourier transform (STFT) is applied for feature extraction. item[•] Convolutional neural network (CNN) is used as a classification algorithm.	• SSVEP • Eye Blink
Design of an Endogenous BCI-based Drone Swarm Control System Using EEG [51]	• This study focuses on an endogenous model with an emphasis on EEG-based Unmanned Aerial Vehicle (UAV) deployment and drone swarm control.	• Common spatial pattern (CSP) is used for extracting spacial features. • CSP-LDA algorithm is used to classify the model. • Robotic Operating System (ROS) is used to interact with MATLAB for controlling the UAV device remotely.	• Motor Imagery (MI) • Visual Imagery (VI) • Speech Imagery (SI)
Bluetooth-Based Brain-Computer Interface System for Mind-Controlled Robot [44]	• The paper discusses the development of a Mind Controlled Robot utilizing BCI technology, which analyses brain waves using LabVIEW software. It facilitates people with severe organ disorders and help them improve their quality of life.	• XBee and XBee-PRO modules along with Zigbee are used to transmit data to Robot module. • Think-gear is another technology that is used to empower and enable devices to interact with the user's brainwaves.	• P300 • SSVEP • Eye Blink
Human Attention Detection using Artificial Intelligence via Brain-Computer Interface for Health Care Monitoring [52]	• This paper focusses on detecting and measuring the attention of a person by using EEG-based BCI to avoid problems associated with lack of consciousness of a human mind (ADHD).	• Fast Fourier transform (FFT) is used in preprocessement. • k-NN classification algorithm is used.	• SSVEP
An intelligent safety helmet that uses IMU and EEG sensors to identify worker tiredness [55]	• This study describes the use of a Smart Safety Helmet (SSH) to monitor miners' head motions and brain activity with the aim to detect abnormal behaviors.	• Inertial Measurement Unit (IMU) is used to recognize human head gestures.	• P300

Following the idea of Stephen Hawking to expand human memory by transferring the mind to a computer system [58], advancements in Brain-Computer Interfaces (BCI) suggest a potential future where scientists can accurately extract and store sensitive brain information in external physical memory devices, such as portable flash drives. It's working can be beneficial in many possible ways for instance, a counseling psychologist is equipped with precise insights acquired through a BCI device regarding an individual's behaviors and traits. Naturally, such an expert would be anticipated to offer insightful guidance and conclusions, significantly impacting the individual undergoing counseling. This scientific endeavor demands rigorous multidisciplinary research to gain maximum excellence. A prominent researcher suggests that Brain-Computer Interfaces (BCI) combined with computer-brain interfaces (CBI) [59] could enable a form of telepathic communication, bypassing physical interaction and sensory channels. While Brain-Computer Interfaces (BCI) combined with other Brain-Computer Interfaces (CBIs) create a "brain-brain interface" technology still in its early stages [60], further research is needed. Integrating BCI with the Internet of Things (IoT) and other communication methods like mind-to-mind and mind-to-machine interfaces holds promise. Exploring these possibilities could unlock new functionalities in human-machine-human communication [61].

3. Proposed Review and Comparative Analysis

A variety of comprehensive review papers have been published on EEG-based BCI in smart home environment [62] [63] [64]. But very few of these papers have intensively focused on the processes involved in extracting, pre-processing, and classifying the brain signals with respect to their applications. In this paper, we perform an explicit review on various pre-processing, feature extraction and classification techniques on EEG signals over the last few decades and provide an overview of integrating smart home environment with EEG-based brain computer interface (BCI) along with their features. This paper derives from an extensive study of diverse models proposed across a wide range of papers and perform an in-depth comparative analysis of these models based on different process criteria and demonstrate them in a tabular structure. The annual trajectory of research publications with reference to EEG-based BCI in smart home environment highlights the encouraging outcomes of BCI systems in the domain of IoT. Moreover, the limited presence of review papers signifies a deficiency of comprehensive analyses that could aid novice researchers in gaining deeper insights into the domain and better understand the field of research while keeping up with the new and emerging trends and advancements in the field.

3.1. ***EEG signal processing methodologies***

The implementation of EEG paradigms involves a series of sequential steps for deployment. According to a study [65], there exist five steps in this process, these include: we start by acquiring and segmenting signals. Pre-processing cleans them, then features are extracted and fed to models for predictions. These predictions are then put to use.

3.1.1. ***Signal Acquisition and Partitioning***

Understanding the brain's structure is crucial for acquiring meaningful EEG signals. The brain is divided into two main regions: the cerebral cortex and subcortical regions. While subcortical areas manage vital functions like body temperature and reflexes, the cerebral cortex is responsible for higher functions like sensory processing and decision-making. Further divided into lobes with specialized functionalities [66], the cerebral cortex offers a map for interpreting EEG signals based on their origin. This knowledge is essential for developing effective Brain-Computer Interfaces (BCI).

- *Frontal lobe:* It spans across the frontal and upper regions of the cortex particularly in front of the brain's central sulcus. The prefrontal lobe, frontal motion area, and primary motion area all constitute this region. Its functions encompass a wide range, such as cognition, decision-making, planning, speech, memory, judgement, problem-solving, social skills, consciousness, personality traits, emotional and behavioral control, intellectual capabilities, and self-awareness. It serves as the highest-level sensory center.

- *Parietal lobe:* Located in the back upper area of the cerebral cortex, specifically behind the central sulcus and bordering the front of the occipital fissure. It is responsible for a wide range of functions, including sensation, touch, pain, temperature, taste, pressure, reading comprehension, spelling, differentiating left-right, spatial orientation, visual attention, perception, language interpretation and word recognition. This region is also associated with logical and mathematical reasoning.

- *Temporal lobe:* It is located at the bottom central region of the cortex, just behind the temples particularly beneath the lateral fissure, sandwiched between the frontal lobe at the front and the occipital lobe at the back, the parietal lobe occupies the upper region of the brain. Its functions include smell, hearing (interpreting auditory signals from the ears), object categorization, recognizing faces, and generating emotions.

- *Occipital lobe:* It is situated at the lower, posterior region of the cortex particularly behind the occipital sulcus. Its primary functions include visual perception, color identification, tracking object motion, perception of behavior and abstract concepts [23].

The most widely used system for non-invasive electrode placement is the 10-20 system, endorsed by the American Electroencephalographic Society. This system ensures standardized electrode positioning across individuals, facilitating the gathering and processing of EEG data in a consistent and comparable manner. As illustrated in Figure 6, the 10-20 system relies on specific distances for electrode placement. These distances are derived from measurements of the head: 10% of the total distance from the nasion (bridge of the nose) to the vertex (top of the head) and 10% of the total distance from the inion (bony bump at the back of the head) to the preauricular point (just in front of the ear). The remaining electrode positions are spaced at intervals of 20% along these total lengths. Following this approach, the 10-20 system assigns a total of 21 specific electrode positions across the scalp. Each position is denoted using a letter-number combination. The letter corresponds to the underlying cortical region the electrode is closest to (Fp: pre-frontal, F: frontal, C: central, etc.), while the number indicates the hemisphere (odd for left, even for right). Numbers also specify position within a hemisphere, which is important because brain functions can differ between the left and right sides. The "z" designation is used for midline positions, particularly for baseline measurements [67][68].

The brain is a constantly buzzing hive of electrical activity! These electrical signals can be categorized into distinct frequency bands based on their speed (measured in Hertz, Hz). The five main bands are delta (slowest, 0.5-3.5 Hz), theta, alpha, beta (fastest), and gamma. There's also a sub-band within alpha called mu (7-11 Hz). The strength of these signals, measured in microvolts (μV), is typically quite weak, ranging from 0.5 to 100 μV [68][69][70]. The brain emits a variety of rhythmic signals across different frequency ranges, as discussed below:

- Delta Wave (0.5-3.5 Hz): These waves usually manifest in the frontal cortex of the brain with amplitudes ranging from 20 μV to 200 μV. They are commonly observed during the state of unconsciousness due to oxygen deficiency, deep sleep without dreams, or under anesthesia. When we enter the deepest stages of sleep, our brain activity slows down, and the electrical waves measured by EEG machines become larger in amplitude. Variatioin the depth are caused by several neurological and physiological conditions. Disrupted sleep, often associated with depression, anxiety, and ADHD are frequently observed in adults and, posteriorly, in children. These waves disappear in adults who tend to be in awake or alert situation [71][72].

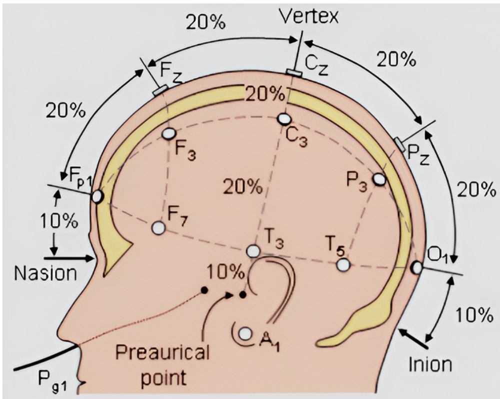
- Theta waves, pulsing between 4 and 7 cycles per second (Hz), are most active in the brain's parietal and temporal regions. These waves are relatively strong, with electrical activity reaching between 100 and 150 microvolts (μV). They are associated to a state of relaxation and cognitive tasks involving working memory. Theta waves are like the brain's in-between gear. They're present when you're alert and engaged, actively learning or remembering things, meditating, or even entering lighter sleep stages (not the deepest snooze!). They are frequently observed in both young and older children, as well as in adults. Theta waves are specifically observed along the frontal midline when positive emotions are elicited [73][74].

- Alpha waves take center stage when you're relaxed and your mind is wandering. These calming signals, ranging from 20 to 100 microvolts (μV), are strongest in the back (occipital lobe) and upper (parietal lobe) parts of your brain. They are typically observed during states of relaxation with eyes closed. This frequency band is mostly detected during tasks involving mental arithmetic, visualization of images, and performing short-term memory activities. Within this band, various small and large alpha waves are accounted, signifying the dynamic involvement and disengagement in the specific task at hand. Alpha waves (relaxation) fade with sight, sound, or mental effort. Moreover, these waves get suppressed when the eyes are open or when the individual experiences drowsiness and sleepiness. Interestingly, they exhibit higher oscillatory energy as compared to beta and gamma waves during both positive and negative emotional states [75][76].
- Mu Wave (7-11 Hz): These waves are typically detected in the sensorimotor cortex, particularly in the central region of the brain with amplitudes roughly ranging from 30 μV to 120 μV. They are often associated with states of relaxation and immobility, and can be suppressed during voluntary movement or motor tasks. This rhythm is specifically studied in the context of motor planning, imitation, and mirror neuron activity and is thought to play an essential role in social cognition, modulating motor functions and understanding others' actions. These waves are of key interest in various fields, including neuroscience, psychology, and neuro-rehabilitation, for their potential involvement in motor control and social interaction research [68].
- Beta Wave (13-30 Hz): They are typically observed primarily in the frontal lobe of the brain; however, during contemplation, these waves may arise in various brain regions with amplitudes ranging from 5 μV to 20 μV. This rhythm is associated with high mental activity, active cognition processing, focused mindset, alertness in brain activity, and the perception of an individual. These waves signify a re-synchronization that occurs in response to an external stimulus and serve as a measure of movement preparation. They exhibit symmetrical distribution on both sides of the brain. The beta rhythm eventually disappears as emotional activity increases, whereas alpha waves predominate in the cerebral cortex when the body is at rest. The amplitude of alpha waves diminishes and the frequency of beta waves increases in conditions when the central nervous system is tense, stressed, or straining, resulting in a gradual shift from alpha to beta waves. When the cerebral cortex seems to be in the beta state, an excited state is detected [73][77].
- Gamma Wave (>30 Hz): The EEG signal originates from widespread cortical networks, encompassing both sensory and non-sensory processing areas. These electrical waves exhibit low amplitudes, usually below 2 μV. Among all EEG rhythms, this frequency band exhibits the highest value, corresponding to a state of peak focus. These waves, prominent during multimodal sensory processing [73][77], are implicated in high-level cognitive functions like information processing, integration, and feedback within the brainstem. Additionally, they are associated with states of intense focus and represent the optimal brain frequency for cognitive performance.

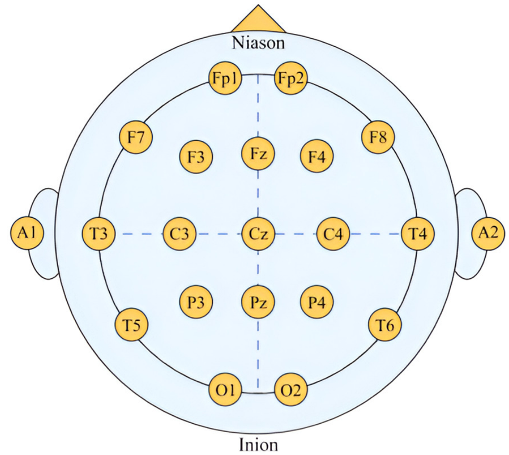
EEG acquisition can be achieved through wired or wireless methods [78]. Wired systems utilize an elastic cap with electrodes (1-256) attached to the scalp, often requiring conductive gels for optimal signal quality [68]. However, this approach can be time-consuming and cumbersome. Dry electrodes offer a faster alternative but suffer from reduced signal fidelity (30% lower information rate) compared to gel-based systems [78]. While wired EEG is well-established, limitations include complex setup and restricted user mobility due to cables. To address these issues, wireless EEG systems have gained popularity due to their non-invasive nature and unrestricted movement. Headset selection hinges on application; research-oriented models offer higher channel counts and resolution for advanced studies, while lower-cost options cater to non-research purposes like meditation or home therapy. Ultimately, the optimal acquisition method depends on the specific BCI application.

3.2. ***EEG Signal Preprocessing***

EEG preprocessing tackles unwanted noise from muscles, blinks, or even the environment, leaving a clearer picture of the brain's electrical activity. EEG signals, despite originating from the brain itself, are easily



(a) Proposed method for software cost estimation for: Triobj1



(b) International 10-20 EEG electrode placement system on the scalp and letter-number-denotation

Figure 6: Smart bedroom scenario via voice recognition

corrupted by electrical noise from both biological sources (muscle activity, eye blinks) and environmental sources (power lines). This noise can originate from the electrodes or from the body itself and is commonly referred to as "artifact" or "interference". EEG recordings, while offering a window into brain activity, are vulnerable to electrical noise from the environment. This includes the constant hum of power lines (50/60 Hz), flickering lights, and even the buzz of nearby electronics like computers, phones, and tablets. EEG electrodes may capture unwanted physiological signals, during signal recording leading to the rise of physiological noise which derives from various bodily activities, including movement, other bio-electrical potentials, and fluctuations in skin resistance. ey sources of physiological noise include activity from electrooculography (EOG, related to eye movements), electrocardiography (ECG, heart signals), scalp electromyography (EMG, muscle activity), ballistocardiography (motion related to heartbeats), and breathing. Physiological artifacts pose a challenge in EEG-based state recognition. Eye movements (EOG) and muscle activity (EMG) generate electrical signals that contaminate the EEG. Cardiac activity, particularly the QRS complex (ECG), can also introduce noise via volume conduction through cerebrospinal fluid. Additionally, motion artifacts arise from cable movement and electrode displacement during subject movement. While artifact removal is common, caution is necessary, as some artifacts may contain valuable information about brain states relevant to recognition algorithms. Therefore, this pre-processing phase is crucial to prevent and minimize the noise contamination in raw EEG data that could potentially effect subsequent classification phase. There are two main techniques through which we can reduce the noise or artifacts present in the acquired EEG signals. These techniques are discussed as follows:

3.2.1. ***Filtering***

Extracting meaningful information from raw EEG necessitates amplification. The digitization process amplifies these weak signals by a factor of 500 to 2000. Various pre-processing techniques are employed while interpreting the raw EEG data. One of the techniques to do so is filtering, which reduces artifacts in the collected EEG signals by applying various types of filters on them. The three frequently used filters in the domain of EEG include: low-frequency filters, high-frequency filters, and notch filters. The initial filtering stage employs two distinct filters to isolate the desired frequency band (1-50/60 Hz). These filters, known as low-pass and high-pass filters, respectively remove electrical noise below 1 Hz and above 50/60 Hz. For even more targeted noise removal, notch filters are employed. Unlike low-pass and high-pass filters that eliminate a range of frequencies, notch filters focus on a very specific frequency and suppress it. In EEG recordings, this technique is commonly used to eliminate the electrical noise from power lines, which typically oscillate in the range of 50 to 60 Hz depending on the regional electricity standard [75]. EEG signal processing often

Table 2: Comparative Analysis on various EEG-based Preprocessing Methods on some additional Parameters

Preprocessing Algorithms/ Artifact Removal Techniques	Automatic	Single Channel Usability	Percentage of Literature Usage (2010-2020)
ICA	NO	YES	26.8
CAR	YES	NO	5.0
SL	YES	NO	0.4
PCA	NO	YES	50.1
CSPS	YES	NO	17.7

utilizes frequency domain filters to refine the bandwidth of interest. Specific filter types, like Butterworth, Chebyshev, and inverse Chebyshev, are favored due to their desirable characteristics in this application [79]. There exist some unique characteristics in each of them that require thorough analysis. The filtering toolbox proves to be a powerful weapon against EEG artifacts. Various filter types, including those mentioned previously, effectively remove unwanted noise and enhance the signal of interest [77].However, caution must be exercised when applying filters. Generally, in the time domain, the EEG signal's waveform and structure is distorted using filters. Hence, filtering should be used sparingly to prevent loss of EEG signal information. This processing step also tackles low-frequency noise, like the hum from power lines, that sneaks into EEG recordings from external sources [80].

3.2.2. ***Artifact Removal***

While band-pass filtering effectively mitigates EMG and EOG artifacts by removing frequencies outside the desired EEG range (typically 1-50/60 Hz), other sources like blinks and facial movements can remain prominent due to their spectral overlap with neural activity. These residual artifacts necessitate further processing techniques for optimal signal quality [81].EEG recordings are susceptible to contamination from two primary artifact categories: extrinsic and intrinsic. Extrinsic artifacts originate from external sources, including power line interference (DC line noise) and electromagnetic interference from wireless signals. Band-pass filtering proves to be a valuable tool in mitigating these artifacts by attenuating frequencies associated with device drift and power line noise (typically 50/60 Hz depending on the region) [82]. Intrinsic artifacts, in contrast, arise from physiological processes within the subject's brain. These include electrical activity generated by eye movements (EOG), blinking, and muscle contractions (EMG) [83]. Addressing these intrinsic artifacts requires more sophisticated techniques compared to band-pass filtering. Common approaches include adaptive filtering, which dynamically adjusts to suppress noise, spatial filtering that utilizes electrode placement to isolate desired brain regions, and blind source separation techniques like independent component analysis (ICA) to separate the underlying brain signals from the contaminating artifacts [83]. Preprocessing is a complex process aimed at eliminating unwanted components present in the EEG signal. Effective pre-processing enhances signal quality, thereby improving feature distinguishability and classification performance. Nevertheless, pre-processing helps to distinguish between various signals and their sources. Table 2(a) and 2(b) presents some of the popular methods of artifact removal used in pre-processing of EEG signals, along with their characteristics, advantages, limitations, literature usage statistics (in %) for last one decade and many other attributes [84].

Table 3: Comparative Analysis on various EEG-based Preprocessing Methods

Preprocessing Algorithms/ Artifact Removal Techniques	**Characteristics**	**Advantages**	**Limitations**
Independent component analysis (ICA) [85][86][87]	Without the use of reference channels, it analyzes the properties of the data to extract artifacts from EEG signals. Effective in eliminating ocular artifacts, it separates multi-channel EEG data into discrete components that are both temporally unique and spatially fixed.	It breaks down signals into temporally autonomous and spatially consistent elements, which efficiently distinguishes artifacts from noise components.	The success of ICA depends on specific conditions where one signal surpasses the others in magnitude. The effectiveness of the corrected signals is heavily influenced by the quality of the artifacts.
Common Average Reference (CAR) [88][89][90][91]	It is employed to create a reference for individual channels by averaging all recordings across each electrode, enhancing the Signal-to-Noise Ratio quality.	It surpasses traditional electrical referencing methods, achieving a noise reduction of over 30	Calculating the average may pose challenges with incomplete head coverage, and limited sample density.
Surface Laplacian (SL) [92][93][94][95]	It provides high spatial resolution when viewing EEG data. Without requiring precise information regarding volume conduction, it calculates the current density entering or leaving the scalp through the skull while considering the external shape of the volume conductor.	Since its estimates are not influenced by references, they produce identical SL estimates regardless of the EEG recording reference scheme. It improves the EEG signal's spatial resolution without demanding further functional neuroanatomy assumptions.	Spline patterns and artifacts influence it.
Principal Component Analysis (PCA) [96][97][98][99]	It identifies patterns within data by rotating the coordinate axes, thereby aligning them with linear combinations of sets of time points, collectively representing patterns within the signal. This rotation aims to maximize the variance along the first axis while keeping the axes orthogonal.	It contributes to reducing feature dimensions and facilitates data classification through ranking.	It does not entirely eliminate noise, but it can diminish its presence. Compared to ICA, PCA compresses data and enables data separation.
Common Spatial Patterns (CSP) [100][101][102]	It utilizes spatial filters to differentiate between various classes of EEG signals, such as those associated with different types of motor activity.	It does not necessitate pre-selection of specific frequency bands or prior knowledge about them.	It relies on a large number of electrodes, and alterations in electrode placement can impact classification accuracies.

3.3. ***EEG Feature Extraction Methods***

After acquiring the noise-free signals from the signal enhancement phase (i.e., preprocessing and artifact removal), essential features were extracted from the brain signals which will be fed to the classifier in the next phase. Its main distinguishing characteristics include its structure, frequency, rhythmic variations, phase variations, power, latency, and reactivity [103]. This prompts the question: how does one determine which feature(s) to select for a specific task? Considering all the features are both computationally expensive and time consuming. Therefore, the objective of this phase is to capture one of the three types of features, they are: (a) time domain features (describing the shape and peak values of the waveforms), (b) frequency domain features (describing the spectrum of the EEG data during rhythm variations), (c) spatial domain features.

Time-domain features incorporate various metrics such as Hjorth features, higher-order crossing (HOC), event-related potential (ERP), principal component analysis (PCA), and Higuchi's fractal dimensions (FD), independent component analysis (ICA), which serve as an indicator of self-similarity and signal complexity within the domain. This kind of analysis is particularly relevant for applications that primarily deal with Event-Related Potentials (ERPs) and the shape and latencies of waveforms [104][105][106]. In order to extract and assess frequency domain characteristics, frequency domain analysis algorithms convert time-domain EEG data into frequency-domain signals. Typically, the EEG signal is split up into several sub-bands from which features are extracted for analysis. These features include logarithmic energy spectrum, power spectral density (PSD), differential entropy (DE), higher-order spectrum (HOS) [107][108]. The fast Fourier transform (FFT) is widely recognized as the most popular frequency-domain method. AR (Auto recessive) models serves as a replacement for Fourier-based techniques for analysing frequency spectrum of signal [109][110]. Frequency-Time domain analysis techniques are founded on the assumption that signals based on EEG are linear and quasi-stationary, meaning the frequency content of the EEG signals remains constant throughout the analysis window.Conventional time-domain analysis techniques, which depend on features such as duration,amplitude, variance and auto-correlation, not suitable for analyzing signals that are non stationary such as EEG based signals in adults.Examining non-stationary signals necessitates insight into energy distribution across frequencies and fluctuations in frequency over time, aspects not addressed by either time-domain or frequency-domain analysis techniques. Frequency-domain representation sacrifices temporal information during spectrum construction, thereby imposing constraints.In response to these limitations, alternative tools have emerged for representing signals, referred to as time-frequency domain analysis techniques. This approach integrates information from both the time and frequency domains, facilitating localized analysis within the frequency-Time domain.

Results of which Features in the frequency domain are adept at capturing time-varying and non-stationary signals, enabling the characterization of diverse emotional states [69]. Among time-frequency analysis methods, the Wavelet transform emerges as the predominant approach.The Short-time Fourier transform (STFT) [74], Hilbert Huang transform (HHT) [111], and wavelet packet transform (WPT) [112] represent key methods in time-frequency domain analysis.The time-frequency domain capitalizes on variations in both time and frequency, delivering detailed descriptions of neural activities. To accomplish this, techniques such as wavelet transform (WT) and wavelet packet decomposition (WPD) are utilized [113]. Spatial-frequency domain analysis techniques are employed to analyze brain activity across various brain regions. Spatially localized features can be used when information from specific electrode positions needs to be isolated, extracted, and utilized exclusively [83].Table 3 illustrates some of the commonly used algorithms in the feature extraction method along with their characteristics, advantages, limitations, literature usage statistics (in%) over the last decade, and several other attributes.

Table 4: Comparative Analysis on various EEG-based Feature Extraction Methods

Feature Extraction Algorithms	**Characteristics**	**Advantages**	**Limitations**	**Feature Extraction Domain**	**Literature's Usage Statistics % (2010-2020)**
Independent Component Analysis (ICA) [77][114][115][116]	ICA functions as an algorithm for feature extraction as well as a signal enhancement technique. It isolates independent elements by leveraging the principle of statistical independence.	Offers computational efficiency. Demonstrates exceptional performance with large datasets. Dissects signals into temporally independent and spatially fixed components.	Not suitable for situations with low clarity. Demands additional calculations to be made for the breakdown.	Time. In the frequency domain, there is exists a FastICA.	11.3
Principal Component Analysis (PCA) [117][118][119][120]	Even though dimensionality reduction is one of the functions for the PCA technique, feature extraction is its primary objective. It diminishes signal extent by generating new, uncorrelated variables.	An effective tool for data analysis and dimensionality reduction with minimal information loss.	Struggles to handle complex manifold structures in data processing. Relies on data being linear and continuous.	Time	19.7
Wavelet Transform (WT) [121][122][123]	The WT approach uses discrete or continuous wavelets, which are safe and straightforward building blocks, to represent the actual EEG signal.	Able to analyze signals with discontinuities by adjusting window size dynamically. Able to extract features such as energy, distances, or clusters.	Lack of a well-defined approach for applying Wavelet Transform to widespread noise. Heisenberg Uncertainty Principle limits the performance.	Time-frequency	26.0
Auto Regressive (AR) [109][110]	It utilizes a parametric approach to estimate the power spectrum density (PSD) of EEG signals. The process of PSD estimation includes determining the parameters or coefficients of the linear system under examination.	Needs shorter data record durations. Enhances frequency resolution and minimizes spectral loss issues.	Not suitable for non-stationary signals. Challenges arise in determining the model properties of EEG signals.	Frequency	1.6

Wavelet Packet Decomposition (WPD) [124][125][126]	To demonstrate the breakdown procedure, it makes use of a sub-band tree structure facilitated by a complete binary tree. It independently breaks down the original signals in an orthogonal manner, adhering to the conservation of energy principle. Feature extraction involves extracting the energy distribution.	Capable of analyzing non-stationary signals.	Extended computation duration.	Time-frequency	1.6
Fast Fourier Transformations (FFT)	Power spectral density (PSD) estimation is used to evaluate and calculate features of EEG signals in order to represent EEG sample signals selectively.	Effective technique for frequency analysis.	Highly sensitive to noise, resulting in decreased performance. Only suitable for stationary signals and linear random processes.	Frequency	2.2
Hjorth Features [104][105][106]	These statistical indicators use normalized slope descriptors. They include activity, which measures the variance of a time function; mobility and complexity, which evaluates how close the signal is to a pure sine wave in relation to the frequency change.	Suitable for real-time analysis due to their low computational expense.	Potential bias may occur when calculating signal parameters statistically.	Time	17.0
Differential Entropy (DE)	Entropy indicates the scattering within data, while DE can capture spatial [107][108][127][128]variations in signals.	Entropy and related measures show how information moves around inside the brain.	Entropy-based measures can be sensitive to noise in the data, potentially leading to inaccurate assessments of information flow within the cortex	Time–spatial	4.9

3.4. EEG Feature Selection and Dimensionality Reduction Methods

The process of feature selection is one of the most crucial phases as it identifies the signal characteristics that most accurately characterize the EEG parameters to be classified. The feature vector in BCI systems typically has a large dimensionality [129]. Feature selection aims to reduce the number of input variables for the classifier, distinct from dimensionality reduction, which merges features to decrease their amount. Feature selection methods do not alter the fundamental properties but rather exclude some based on specific criteria of usefulness. These methods strive to achieve optimal results by processing minimal data. They

eliminate features that are unecessary, reduntant and do not participate in the classification for simpler, faster, and more effective classification models. Moreover, feature selection methods help to reduce the risk of over-fitting in standard datasets, flexible models, or datasets with numerous features but lacks sufficient observations. Feature selection methods can be classified into two categories based on the number of variables, these include: (1) Uni-variate and (2) Multi-variate. Uni-variate methods evaluate the input features individually, whereas multi-variate methods analyze the entire group of characteristics simultaneously. Another type of classification categorizes feature selection methodology into filtering, wrapper, and built-in algorithms.
Filtering methods access features based on the inherent characteristics of the data. Moreover, majority of these methods are uni-variate, as each attribute is independently assessed. These techniques are less computationally intensive, making them suitable for huge datasets. Depending on the type of classifier, wrapping techniques select additional features based on their ability to affect previously chosen characteristics, with only attributes that raise accuracy are maintained. Built-in techniques operate internally within the classification methods, like those used in deep learning techniques. It generally requires less computational resources as compared to wrapper techniques. Some of the popular feature selection algorithms include Stepwise discriminant analysis (SDA), Genetic Algorithms (GA), Fisher score and many more as described in Table 4 [83]. Genetic algorithms employ evolutionary methods to lower the size of the feature vector, retaining only the most informative features [130][130][130]. By introducing the stepwise function, the stepwise discriminant analysis algorithm enhances the statistical tool used for discriminant analysis [131]. Another feature selection technique that employs statistical metrics to determine the relationship between each feature and the output classes is Fisher score. Table 4 presents some of the widely used feature selection algorithms along with their literature usage statistics (in%) in last one decade [132].

Table 5: Comparative Analysis on various EEG-based Feature Selection and Dimensionality Reduction Methods

Feature Extraction Algorithms	**Properties**	**Advantages**	**Limitations**	**Percentage of Literature Usage (2010-2021)**
Uni-variate [77]	This method evaluates the input features one-by-one.	It is simple to implement and computationally efficient.	It ignores interactions between features and could discard some relevant features.	6.3
Multi-variate [77]	This method examines the entire group of features simultaneously.	It considers relationships between features and can be more effective than uni-variate methods.	It can be computationally expensive and may be sensitive to irrelevant features.	6.3
Genetic Algorithm [130][133][134]	This method uses evolutionary techniques to reduce dimensionality of a feature vector, retaining only the most informative features.	It can handle complex feature interactions and works well for non-linear relationships.	It can be computationally expensive and parameter tuning can be challenging.	32.3

min-Redundancy Max-Relevance (mRMR) [135][136]	This algorithm assesses the common data between every feature and every class at the output for comparison.	It reduces computational cost by selecting a small subset of non-redundant and relevant features. This improves model performance and enhances interpretability.	It may not be suitable for problems with highly non-linear relationships between features and target.	11.5
Stepwise Discriminant Analysis (SDA) [131]	This algorithm enhances the statistical tool for discriminant analysis by integrating it with the stepwise function.	It is efficient for feature selection in classification and considers class labels.	It may be biased towards features that separate initial classes well and not suitable for high-dimensional data.	17.7
Fisher score [136]	It is a feature selection technique that employs statistical metrics to determine the relationship between each feature and the output classes.	It is simple to implement and works well for linear relationships.	It ignores feature interactions and may not be suitable for non-linear relationships.	7.3
Wrapper method [77][136]	Only features that improve accuracy are kept in this strategy, which depends on the type of classifier that selects new features based on their influence on previously selected features.	It can be very effective in finding optimal subsets and handle complex interactions.	They can be computationally very expensive, especially for high-dimensional data.	15.6
Built-in methods [77]	This method operates internally within the classifier algorithms, such as those used in deep learning.	They are efficient, promote sparsity, and some can be interpretable. Ex: Lasso Regression Algorithm.	Their performance depends on the specific algorithm and may not be suitable for all data types.	3.1

3.5. *EEG Signal Classification Methods*

After acquiring the features, they can undergo post-processing analysis to derive meaningful insights. Typically, this involves training a classifier on these features. The classifier establishes a mapping between the EEG feature vectors and a classification scheme it acquires during training. Small variations can significantly influence the intricate patterns of EEG signals related to human cognition, highlighting the need for a highly efficient and resilient classifier. In a BCI system, this phase takes the feature vector, a summary of brain activity extracted earlier, and aims to decode the user's intentions based on those features. This objective can be accomplished through classification and regression techniques, with classification algorithms currently being the most preferred choice. Regression analysis predicts user intents by using features obtained from EEG signals as distinct variables. Conversely, classification algorithms define boundaries between various targets in the feature space by using the retrieved features as distinct variables [137]. According to a study [138], the selection of classifiers is influenced by three key factors: (a) the likelihood of features being affected by noise, (b) feature dimensionality, and (c) whether the features exhibit non-stationary characteristics. A research proposed [139], categorizes EEG based BCI classifiers into five major groups: (a) linear classifiers, (b) nearest neighbor classifiers (NN), (c) hybrid classifiers (or ensemble learners), (d) non-linear Bayesian classifiers, and (e) artificial neural networks (ANN), as described in Table 5, specifying their advantages and disadvantages along with the citations. Among these, linear classifiers are not commonly utilized in practical applications due to their limited learning capability. Classification methods transform the data extracted into specific motor oriented tasks, such as foot movements, hand gestures, word production, and so on in MI based BCIs [140]. Accurate classification of the same brain activity can be improved by combining distinct signal properties from different sources or devices. For example, finger-tapping and hand/arm movement have been successfully identified using a combination of fNIRS and EEG techniques[141]. ML and DL techniques are utilized to recognize and detect EEG-based BCI signals. ML algorithms are typically categorized into three classes based on their outcomes, these include: supervised, unsupervised, and reinforcement learning [140]. Additionally, DL methodologies signified enhancements in classification accuracy. Table 5 showcases a range of classification algorithms, detailing their categories, characteristics, advantages, limitations, literature usage statistics (in %) in last one decade, examples and various other attributes.

Some of the well-known classification algorithms include linear discriminant analysis (LDA), multilayer perceptron (MLP), convolutional neural network (CNN) [142], k-nearest neighbors (k-NN), support vector machine (SVM) [113], and decision trees [143]. Notably, the SVM classifier demonstrates superior performance compared to other classification algorithms like k-NN, MLP, LDA, etc. A comprehensive comparative analysis [144] was conducted to study three classification models for their accuracies, namely: k-NN, MLP, and SVM classifiers, with the objective to identify the optimal features based on wavelets. In general, all the three models performed very well, achieving accuracy above 98%. SVM took the top spot with 98.75% accuracy for approximate coefficients (A4) related to delta waves (0.53–3.06 Hz) while the Multi-Layer Model (MLM) reached 98.57% accuracy for detailed coefficients (D4) associated with theta waves (3.06–6.12 Hz). Moreover, both of these classifiers come under the category of non-linear classification method. During the assessment of classification accuracies for SVM, backpropagation neural network (BPNN), and SVM, it was observed that both LDA and SVM classifiers exhibited comparable high accuracies, surpassing those of BPNN [145]. Deep Learning models (DL) bypass the need for an explicit feature extraction phase as they can learn directly from EEG data over a period of time [146][147][148]. Deep learning streamlines the process by automatically identifying relevant features and incorporating them directly into the classification model [90], removing the separate feature extraction and selection stage. However, deep learning models exhibit high computational complexity, necessitating extensive training periods.

In EEG-based BCI research, popular DL models include Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), General Adversarial Networks (GANs), and Auto-encoders. Among these, CNNs are frequently favored and often demonstrate superior performance compared to other algorithms [149]. However, GANs tackle a crucial issue in EEG applications. By employing generative classifiers, GANs can mimic EEG signals, thereby expanding the training dataset, potentially improving the functioning of various DL classifiers. In a comparative study between Principal Component Analysis (PCA) and Recurrent Neural Network (RNN), RNN attained a control accuracy of 94.5% within a time expenditure of 0.61 ms, whereas PCA achieved a control accuracy of 93.1% with a time overhead of 0.48 ms [150]. Table 6 provides a comparative analysis of different classifiers utilized in EEG systems.
In [117], it was found that Artificial Neural Networks (ANNs) outperform SVM classifiers when dealing with limited data. A deep learning framework based on Convolutional Neural Networks (CNNs) is employed for continuous decoding of EEG signals related to motor imagery (MI) across various individuals. Results from the publicly accessible BCI competition IV-2b dataset reveal that employing stochastic gradient descent and adaptive moment estimation as training methods produce average decoding accuracies of 71.49% (with variance of 0.42) and 70.84% (with a variance of 0.42), respectively [151][152].

Table 6: Comparative Analysis on various general Classification Methods

Types of Classifier	Characteristics	Advantages	Limitations	Classification Algorithms(with citations)	Percentage of Literature Usage (2010-2021)
Linear Classifiers	These algorithms create decision boundaries, like straight lines or flat planes, using simple equations to divide data points into different categories.	These algorithms exhibit a desirable balance between classification accuracy and the ability to generalize to unseen data.	These algorithms often exhibit sub optimal performance when processing complex nonlinear EEG signal data.	Discriminant Analysis, Bayesian Linear, Graph Regularized Sparse Linear Regularized GRSLR [30], Linear Discriminant Analysis LDA, Support Vector Machine SVM [105,106], Long Short-term Memory Recurrent Neural Network LSTM-RNN [66–69], Multilayer Perceptron MLP [107].	5.50 1.40 30.30 0.02
Nearest Neighbor Classifiers (NN)	These algorithms make predictions by comparing new data to known categories based on similarity.	kNN shines in asynchronous BCI due to its effectiveness with low-dimensional data, a common characteristic of BCI feature vectors.	High dimensionality and noisy features can weaken the effectiveness of kNN for classification tasks.	Mahalanobis Distance [114], k-Nearest Neighbors kNN [113].	4.5 0.1
Nonlinear-Bayesian Classifiers	Unlike some classifiers, generative models can create flexible decision boundaries to separate data classes.	Generative classifiers effectively identify and discard uncertain samples.	In the case of Bayes quadratic, accurately estimating the covariance matrix becomes challenging when dealing with high dimensionality and insufficient training sample patterns.	Hidden Markov Model HMM [50,112], Bayes quadratic [110].	0.10 0.30
Artificial Neural Networks (ANN)	NNs are discriminant algorithms specifically designed to identify root causes within a dataset, copying the operations of the human brain.	Neural Networks typically achieve high classification accuracy.	EEG signals are noisy and constantly changing, making it difficult for models to learn without overfitting.	Convolutional Neural Network (CNN) [68, 70–73, 109–111], Complex-Valued Convolutional Neural Network (CVCNN) [105], are among the models employed.	1.60 1.10 0.20 46.16 0.40 0.40

Table 7: Comparative Analysis on various EEG-based Classification Methods

Classification Algorithm Applied	Advantages	Disadvantages
Linear Discriminant Analysis (LDA) [153]	• It requires minimal computational resources. • Easy to operate. • Yields effective outcomes.	• It struggles when the discriminatory function is based on variance rather than mean of the features. • Additionally, it may not adequately capture complex structures in non-Gaussian distributions.
Support Vector Machine (SVM) [154]	• It demonstrates robust generalization capabilities • Outperforms other linear classifiers in terms of performance.	• It exhibits significant computational complexity.
Artificial Neural Network (ANN) [155]	• Simplicity in application. • Robust in nature. • Involves straight forward computations. • Demands minimal training data.	• Challenging to construct. • Performance linked to hidden layer neuron count.
Naive Based Classifier (NBC) [156]	• Only a small training dataset is needed for parameter estimation. • Only the variance of class variables needs computation, without the necessity of computing the entire covariance matrix.	• Struggles to provide accurate estimates for the probabilities of correct classes.
k-Neural Network (KNN) [28]	• Highly understandable. • Straightforward to implement and troubleshoot.	• Runtime performance suffers with large training sets. • Prone to the influence of irrelevant and redundant features. • Under performs when compared to alternative classification methods on challenging tasks.

Hybrid Classifiers (ensemble-learners)	Hybrid classifiers employ techniques like boosting, voting, and stacking. Boosting involves a series of cascading classifiers. In voting, classifiers assign scores to each class, resulting in a combined score and final class label.	Reduction in variance resulting in improved classification accuracy.	The quality measures vary depending on the context of the application.	Ensemble methods have the capability to amalgamate various types of classifiers [115]. Examples include Random Forest [10, 116], Bagging Tree [111, 115], XG-Boost [117], and AdaBoost [118].	12.1 1.1 0.2 0.4 3.9

4. Conclusion

Over the past four decades, a multitude of Brain-Computer Interface (BCI) applications have emerged across diverse fields, spanning entertainment to medicine and even data security frameworks. While BCI systems have primarily prioritized improving their precision, reliability, and user-friendliness, insufficient attention has been devoted to safeguarding these devices and the sensitive data they gather.Several studies have highlighted regarding rapid interest in BCI applications across various fields including medicine, organizational management, transportation, gaming, entertainment, security and authentication.Additionally, it showcases the diverse range of devices employed for capturing brain signals.Till now, BCI systems have primarily concentrated on improving their accuracy, dependability, and user accessibility, with insufficient emphasis placed on securing these devices and the confidential data they gather.This article presents a comprehensive review analysis focusing on EEG-based Brain-Computer Interface (BCI), with particular emphasis on examining its methodological strengths and weaknesses.The field of EEG-based BCI in smart home environment has gained considerable attention within the computing domain. Substantial progress in creating affordable BCI devices with improved usability has spurred numerous research endeavors. This work performs an extensive analysis on different algorithms and methods that can be part of EEG-based BCI in Smart Home Environment. These include: (1) EEG signal acquisition and segmentation, (2) EEG signal pre-processing, (3) EEG feature extraction, (4) EEG feature selection and dimensionality reduction, and (5) EEG signal classification methods. As observed in this review, computational methods lack standardized approaches across various applications, prompting researchers to persist in their quest for new solutions in an ongoing endeavor. Exploring the relationship between brain signals and emotions proves to be a complex challenge, with continuous presentation of innovative methods and implementations. We anticipate that many existing challenges will soon find resolution, thereby opening up a wide array of potential applications using EEG-based BCI systems.

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