NEUROSYNC: A HYBRID BRAINWAVE–GESTURE CONTROL SYSTEM

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Abstract—Today, automation technology is becoming increasingly accessible, user friendly, and efficient, enabling novel solutions for improving the quality of life. This project explores the integration of brain-computer interfaces (BCI) with the Internet of Things (IoT) to provide a smart assistive system for individuals with limited physical mobility. The system employs an EEG headset to capture real-time brain signals, which are transmitted via Bluetooth to an ESP32 microcontroller for processing. Based on the interpreted brain signals, the system can control electrical appliances such as lights and fans by switching a relay module ON or OFF. The system also supports hand gesture control as a backup input method, ensuring reliable operation even when brain signals are unstable. Additionally, the system is designed to detect abnormal brain activity, automatically triggering alerts through an application, and activating a buzzer to notify caregivers or family members. The application also provides a real-time display of appliance status, ensuring users are always aware of the current system state. The expected outcome of this project is a reliable and user-friendly brain-controlled automation system that enhances safety, and convenience for physically challenged individuals.

Keywords—Brain–Computer Interface (BCI), Internet of Things (IoT), EEG Signals, Assistive Technology.

How to cite this article: Cyriac M, Kanjana G, Roy RM, Ravi K S, Smitha KS, Hema S. NEUROSYNC: A Hybrid Brainwave–Gesture Control System. Int J Drug Deliv Technol. 2026;16(72s): 1598-1607. DOI: 10.25258/ijddt.16.72s.179

1. Introduction

The evolution of automation technologies over the past decade has significantly transformed modern living by enabling intelligent and responsive environments. The integration of the Internet of Things (IoT) has played a crucial role in this transformation by connecting physical devices to the internet, allowing them to communicate, monitor, and operate autonomously. Smart home automation systems, in particular, have gained widespread attention due to their ability to enhance comfort, energy efficiency, and convenience. These systems typically rely on conventional control methods such as manual switches, mobile applications, and voice assistants. However, despite their advantages, such methods are not universally accessible, especially for individuals with severe physical disabilities or mobility impairments.

A large section of the population, including paralyzed patients, elderly individuals, and people suffering from neurological disorders, faces significant challenges in interacting with traditional automation systems. These users often depend on caregivers for performing even simple daily tasks such as switching ON/OFF appliances. This dependency not only reduces their independence but also introduces delays in response during critical situations. In addition, voice-based systems may not function effectively for users with speech impairments, while mobile-based interfaces require a certain level of motor control and familiarity with technology, further limiting accessibility. Brain–Computer Interface (BCI) technology has emerged as a promising solution to address these limitations by enabling direct communication between the human brain and external electronic systems. BCI systems operate by capturing electroencephalogram (EEG) signals, which represent the electrical activity generated by neurons in the brain. These signals are processed and interpreted to identify patterns corresponding to different mental states such as attention, relaxation, or intentional focus. By mapping these patterns to control commands, users can interact with devices without requiring any physical movement, making BCI a powerful tool in assistive and rehabilitation technologies.

Despite its advantages, the implementation of EEG-based control systems presents several technical and practical challenges. EEG signals are extremely low in amplitude and are highly sensitive to noise and interference. External factors such as muscle movements, blinking, environmental electrical noise, and emotional fluctuations can introduce distortions in the signal. Moreover, different users exhibit variations in brain signal patterns, making it difficult to design a one-size-fits-all solution. These challenges necessitate the use of robust signal processing techniques and reliable decision-making mechanisms to ensure accurate interpretation of user intent.

Another major concern in brainwave-controlled systems is the issue of false triggering. Situations such as increased attention due to unrelated thoughts or emotional responses can generate signal patterns similar to intentional control signals. Without proper filtering and threshold mechanisms, this can lead to unintended switching of appliances. Therefore, it becomes essential to implement threshold-based validation, continuous monitoring, and stability checks before executing control actions. These mechanisms help in improving the reliability and safety of the system during real-time operation.

The integration of IoT further enhances the system by enabling real-time data visualization, remote monitoring, and control. Users and caregivers can access system status, appliance states, and alert notifications through a connected interface, ensuring transparency and ease of use. The use of an LCD within the system provides immediate local feedback, displaying parameters such as control mode, signal values, and appliance status, thereby improving interaction and usability. From a system design perspective, the combination of wireless communication, embedded processing, and real-time decision-making creates a compact and efficient architecture suitable for practical deployment. The use of cost-effective components such as ESP32 and commercially available EEG headsets makes the system economically viable, which is an important factor for large-scale adoption. Additionally, the modular nature of the design allows for future enhancements, such as integration with machine learning algorithms for improved signal classification or expansion to control a wider range of devices. The inclusion of a gesture-based fallback system significantly enhances the robustness of the overall design. In cases where brain signals are unstable, inconsistent, or unavailable, the system can switch to gesture mode, allowing the user to control appliances using hand movements detected by sensors . This multi-input approach ensures uninterrupted functionality and reduces the dependency on a single mode of interaction. It also improves user confidence, as the system remains responsive even under varying conditions. In addition to control functionality, the system incorporates continuous monitoring of brain signal patterns to identify abnormal conditions. Sudden or irregular variations in EEG signals may indicate stress, discomfort, or other neurological anomalies. The system is designed to detect such patterns and trigger an alert mechanism, which includes activating a buzzer and sending notifications through an IoT platform. This feature introduces an additional dimension of safety, enabling timely intervention in critical situations.

Fig 1: FT&S Mind Link Head Band

To address these limitations, the proposed system adopts a hybrid control architecture that combines brainwave-based input with an alternative gesture-based control mechanism [14]. The system utilizes an EEG headband to acquire real-time brain signals, which are transmitted wirelessly via Bluetooth to an ESP32 microcontroller. The microcontroller processes the incoming data and applies threshold-based logic to determine whether a valid control condition has been satisfied. Once validated, the system generates control signals to operate electrical appliances through a relay module. Another major concern in brainwave-controlled systems is false triggering. Situations such as increased attention due to unrelated thoughts or emotional responses can generate signal patterns similar to intentional control signals. Without proper filtering and threshold mechanisms, this can lead to unintended switching of appliances. Therefore, it becomes essential to implement threshold-based validation, continuous monitoring, and stability checks before executing control actions.

2. LITERATURE REVIEW

Brain–Computer Interface (BCI) technology has been recognized as a potential solution for establishing communication between the human brain and external devices. Recent developments in electroencephalography (EEG), machine learning, and deep learning have improved the applications of EEG-based brain–computer interfaces in healthcare, rehabilitation, smart homes, and other fields.

Zhang et al. [1] proposed a unified deep learning framework for Brain–Computer Interface and Internet of Things (IoT). The study introduced the concept of human–thing cognitive interaction and demonstrated the feasibility of using EEG signals to control IoT devices. The framework showed improved reliability and scalability for cognitive IoT applications compared to conventional approaches.

Bang et al. [2] introduced a novel multimodal human–computer interface that utilizes gaze and EEG signals for improved accuracy. The approach demonstrated better performance than conventional EEG-based interfaces by minimizing false triggering and increasing the accuracy of control commands.

Recent developments in computational intelligence have significantly improved the processing of EEG signals. Gu et al. [3] presented a comprehensive survey of EEG-based brain–computer interface technologies that have been widely applied in signal acquisition, preprocessing, feature extraction, classification, and applications. The review highlighted the superior performance of deep learning algorithms in EEG decoding while presenting limitations in signal-to-noise ratio and inter-subject variability. The application of transfer learning in EEG-based brain-computer interface has gained significant research interest due to its ability to improve the performance of classification models while reducing training time.

Wu et al. [4] presented a review of recent advances in transfer learning for EEG-based brain–computer interface applications. The study demonstrated the effectiveness of transfer learning in minimizing the calibration burden and improving classification accuracy across different subjects and tasks. The review highlighted the importance of domain adaptation and deep transfer learning techniques in improving the performance of BCI systems.

The application of BCI in smart home automation has been widely investigated as a potential solution for controlling home appliances using EEG signals. Maleki et al. [5] presented a review of BCI-based smart home technologies that have been widely explored in the literature. The study highlighted different signal acquisition and processing techniques used in the development of smart home systems and control strategies for managing home appliances. The review demonstrated that BCI-based smart home systems could be used to improve the quality of life for the elderly and physically challenged individuals.

Ajmeria et al. [6] presented a comprehensive survey of EEG-based brain–computer interface technologies for Industrial Internet of Things (IIoT) applications. The study highlighted the significance of artificial intelligence and cloud computing technologies in processing large volumes of EEG data while ensuring minimal latency and reliable communication. The review also identified several research challenges in the application of BCI in IIoT, including cybersecurity concerns and the need for scalable solutions.

The increasing popularity of smart home technologies has prompted researchers to design intelligent systems that can support individuals with minimal manual effort. Zielonka et al. [7] presented a review of recent advances in smart home technologies that have been widely explored in the literature. The study highlighted the significance of artificial intelligence, IoT, wireless communication, and human–computer interaction technologies in the development of smart home systems. The review demonstrated that BCI technologies could be incorporated into smart home systems to support individuals with severe motor disabilities.

The application of visual stimuli in BCI systems has been widely investigated due to their high information transfer rate and improved control capabilities. Park et al. [8] presented an augmented reality-based home appliance control system that utilizes steady-state visual evoked potentials for improved performance. The study demonstrated the feasibility of using visual stimuli to operate home appliances while incorporating augmented reality for enhanced user experience.

Similarly, the integration of eye gaze and steady-state visual evoked potential (SSVEP) has been demonstrated as an effective method for operating smart home appliances. Putze et al. [9] presented a novel approach for smart home control using eye gaze and SSVEP-based brain–computer interface. The multimodal interface demonstrated improved accuracy and reduced cognitive workload compared to conventional approaches.

Deep learning algorithms have gained significant research interest in the field of EEG-based brain–computer interface due to their ability to automatically extract discriminative features from EEG signals. Gu et al. [10] demonstrated that convolutional neural networks, recurrent neural networks, and hybrid deep learning approaches have shown superior performance in EEG classification tasks. The review highlighted the importance of large-scale EEG datasets and optimized neural network architectures for improved performance. Al-Saegh et al. [11] presented a review of deep learning algorithms for motor imagery EEG classification. The study compared the performance of convolutional neural networks, long short-term memory networks, and other deep learning approaches in decoding motor imagery EEG signals. The review concluded that hybrid deep learning approaches could offer better performance in motor imagery classification tasks.

Aggarwal and Chugh [12] presented a review of machine learning algorithms for EEG-based brain–computer interface applications. The study highlighted the significance of feature extraction and selection methods in improving the performance of machine learning classifiers such as support vector machines, random forests, k-nearest neighbors, artificial neural networks, and deep learning approaches. Al-Qaysi et al. [13] conducted a systematic review of non-invasive EEG acquisition equipment for assistive and rehabilitation applications. The study compared the performance of different EEG acquisition systems, including electrodes and signal processing techniques, to identify the most effective and cost-effective solutions for BCI applications.

Flores Vega et al. [14] presented a novel fuzzy temporal convolutional neural network approach for P300-based smart home control applications. The study demonstrated the effectiveness of incorporating fuzzy logic and temporal convolutional neural networks in improving the accuracy of P300-based brain–computer interface systems. Hsu [15] introduced a new approach for motor imagery classification based on wavelet fractal features and neuro-fuzzy prediction. The study demonstrated the effectiveness of the proposed method in extracting discriminative features from EEG signals while improving classification accuracy.

Abd Rani et al. [16] presented an EEG-based eye blink detection system for controlling home lighting systems. The study demonstrated that simple EEG-based commands could be used to operate home appliances, providing a low-cost solution for individuals with limited mobility. Abdulwahab et al. [17] presented a comprehensive survey of EEG-based brain–computer interface applications and implementations in different fields, including healthcare, gaming, robotics, rehabilitation, education, and assistive technologies. The study highlighted the current challenges and future research directions for EEG-based BCI technologies.

Abhang et al. [18] discussed EEG signal analysis methods and their application in emotion recognition. The study demonstrated the significance of EEG-based brain–computer interface in understanding human emotions and cognitive states. Al-Fahoum and Al-Fraihat [19] presented a review of different feature extraction methods for EEG signals in time and frequency domains. The study highlighted the importance of using hybrid feature extraction methods for improved classification performance.

Gouda et al. [20] presented a comprehensive review of EEG-based brain–computer interface applications in smart home environments. The study evaluated different human–computer interaction methods, communication protocols, and machine learning algorithms used in smart home automation systems. The review concluded that hybrid brain–computer interface approaches that incorporate deep learning, IoT, and multimodal interaction offer the best performance in smart home applications.

In general, the reviewed studies demonstrate that EEG-based brain–computer interface technologies have been significantly improved by recent advances in deep learning, transfer learning, and IoT technologies. However, several challenges, including signal noise, inter-subject variability, calibration time, and cybersecurity concerns, still hinder the widespread adoption of BCI technologies. Future research should focus on developing efficient deep learning algorithms, hybrid multimodal approaches, and secure communication protocols to improve the performance and reliability of EEG-based brain–computer interface systems.

3. PROBLEM STATEMENT

The rapid advancement of home automation technologies has significantly improved convenience and efficiency in modern households. However, most existing systems are designed with conventional interaction methods such as manual switches, smartphone applications, or voice-controlled assistants. While these approaches are effective for the general population, they present serious limitations for individuals with physical disabilities, elderly users, and patients with restricted mobility. Such users often face difficulties in performing even basic tasks like controlling household appliances, leading to increased dependency on caregivers and reduced independence in daily life.

In addition to accessibility challenges, traditional automation systems lack alternative interaction mechanisms that can function reliably across different conditions. Voice-controlled systems may fail in noisy environments or for users with speech impairments, while mobile-based applications require precise motor control and continuous engagement. These constraints highlight the absence of inclusive design in many existing solutions. There is a clear need for systems that can interpret user intent without relying on physical movement or verbal communication, thereby enabling seamless and hands-free interaction. Brain–Computer Interface (BCI) technology provides a promising approach by enabling direct control through brain signal.

However, the practical implementation of EEG-based systems introduces several challenges related to signal reliability and accuracy. EEG signals are inherently weak, highly variable, and susceptible to noise caused by environmental interference, muscle activity, and emotional fluctuations. This makes it difficult to consistently distinguish intentional commands from unintentional variations, often resulting in false triggering or failure in executing desired actions, thereby reducing system reliability in real-time applications. Another critical limitation is the lack of robustness in systems that rely on a single mode of input. Purely brainwave-based systems do not provide a fallback mechanism when signal acquisition becomes unstable or inconsistent, leading to system inoperability under certain conditions. Furthermore, many existing solutions do not incorporate mechanisms to monitor abnormal brain activity, which is particularly important in assistive systems where user safety is a priority. The absence of such features limits the applicability of these systems in real-world scenarios.

Additionally, current automation solutions often lack effective real-time feedback and monitoring capabilities. Users are not always provided with clear information regarding system status, signal interpretation, or appliance conditions, making it difficult to verify whether their input has been correctly recognized. The absence of integrated alert mechanisms further reduces system effectiveness in critical situations. These limitations collectively indicate the need for a reliable, multi-modal automation system that ensures accurate control, continuous monitoring, and enhanced safety through integrated feedback and alert features.

4. METHODOLOGY

The proposed Brainwave-Based IoT Home Automation System is designed as a multi-layered, real-time control framework that integrates brain signal acquisition, data processing, intelligent decision-making, and device actuation. The system follows a modular and scalable architecture in which each layer performs a dedicated function while maintaining continuous interaction with other layers. This structured design ensures efficient handling of noisy EEG signals, accurate interpretation of user intent, and reliable execution of control actions. The workflow operates in a closed-loop manner, allowing continuous monitoring, validation, and feedback for improved system performance.

1. Signal Acquisition Layer

The signal acquisition layer is responsible for capturing real-time brainwave data from the user using an EEG headband. The headset measures electrical activity generated by neurons and internally processes raw EEG signals to extract parameters such as attention and meditation levels. These values are transmitted wirelessly via Bluetooth to the ESP32 microcontroller at regular intervals. Since EEG signals are highly sensitive and prone to fluctuations, maintaining stable sensor contact and minimizing motion artefacts is essential. The continuous and real-time nature of this layer ensures that the system always has updated input data for further processing and control.

2. Data Processing and Filtering Layer

After acquisition, the EEG data is received by the ESP32 and subjected to preprocessing and filtering. This layer focuses on improving signal quality by reducing noise and eliminating sudden fluctuations that may arise due to external disturbances or unintended cognitive activity. Threshold-based filtering is applied to identify stable signal regions, while temporal consistency checks are used to ensure that the signal remains above a threshold for a specific duration before being considered valid. This prevents rapid switching and enhances the stability of the system. The processing is performed in real time, ensuring minimal latency between input and response. Decision-Making and Control Logic Layer.

The decision-making layer interprets the filtered EEG data and maps it to corresponding control actions. The system uses predefined threshold values and logical conditions to determine whether a signal represents an intentional command. For instance, a sustained attention level above a certain threshold is treated as a trigger to toggle an appliance. Additional logic is implemented to avoid repeated triggering from continuous high signals by introducing state-based control and delay mechanisms. This layer also manages mode selection, allowing the system to dynamically prioritize brainwave input or gesture input depending on signal reliability.

3. Gesture-Based Fallback Mechanism

To address the limitations of EEG signal instability, a gesture-based fallback mechanism is integrated into the system. This subsystem utilizes motion sensing components to detect hand gestures, which are then mapped to predefined control actions such as turning appliances ON or OFF. The system continuously evaluates the quality of EEG signals, and when instability or inconsistency is detected, it shifts control to gesture mode. This transition is handled seamlessly without interrupting system operation. The presence of this fallback mechanism significantly improves robustness and ensures that the system remains functional under all conditions.

4. Actuation and Device Control Layer

The actuation layer is responsible for executing control decisions through hardware components. The ESP32 microcontroller sends digital control signals to a relay module, which acts as a switching interface between low-voltage control circuitry and high-voltage electrical appliances. Based on the received signals, the relay activates or deactivates connected devices such as lights and fans. Proper electrical isolation is maintained to ensure user safety and protect the microcontroller from high-voltage exposure. The switching process is designed to be fast and reliable, ensuring immediate response to user commands.

5. Monitoring System Layer

This layer continuously monitors EEG signal patterns to detect abnormal or irregular activity. The system analyzes variations in signal values and identifies patterns that deviate significantly from normal ranges. This feature is particularly useful in assistive scenarios, where abnormal brain activity may indicate discomfort, stress, or potential health issues. The monitoring process runs in parallel with the control system, ensuring uninterrupted operation.

6. Feedback and IoT Integration Layer

The final layer provides real-time feedback and enhances user interaction through both local and remote interfaces. An LCD is used to show parameters such as control mode, EEG values, and appliance status, enabling users to understand system behaviour instantly. In addition, IoT integration is achieved using a web server hosted on the ESP32, where data is transmitted and accessed through the HTTP protocol. This allows users and caregivers to monitor system activity remotely through a web interface. System parameters such as signal values, control status, and device states are updated in real time, improving transparency and usability. The implementation of the IoT web server also enables future expansion, such as remote control, data logging, and system configuration through the web interface.

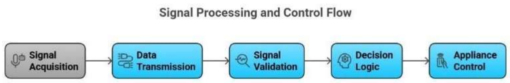

Fig 2: Proposed System Methodology Block Diagram

5. RESULT

System Overview

The developed system integrates EEG-based brainwave sensing with IoT-enabled automation to achieve real-time control of household appliances. The EEG headset captures brain signal parameters such as attention levels and transmits them via Bluetooth to the ESP32 microcontroller, where the signals are processed using threshold-based logic to generate control actions. A gesture-based module is incorporated as a fallback mechanism to ensure continuous operation when brain signals are unstable. The relay module executes switching of electrical appliances based on processed commands, while an LCD and IoT platform provide real-time feedback and remote monitoring. Additionally, the system includes an alert mechanism that detects abnormal signal variations and triggers notifications and buzzer alerts, enabling both automation and safety features within a unified framework.

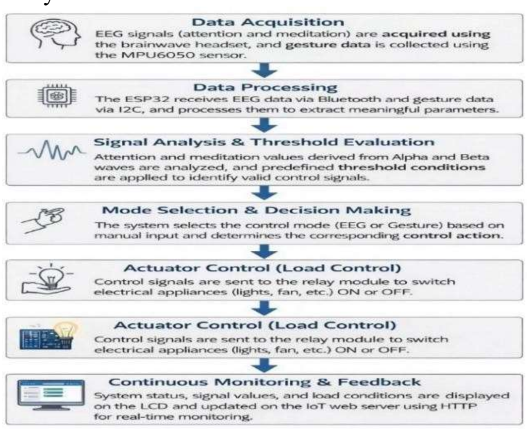

Fig 3: Overall System Workflow of Brainwave-Based Automation

System Architecture

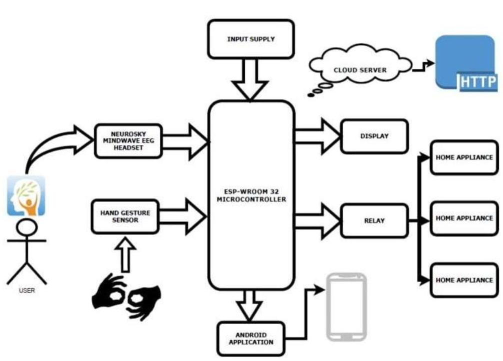

Fig 4: System Architecture of the Proposed BCI-IoT System

a. Signal Acquisition Unit

The unit uses the FT&S Mind Link headband to capture real-time brain signals such as attention levels, which are processed internally and transmitted via Bluetooth communication to the ESP32 controller.

b. Processing Unit

The ESP32 microcontroller receives EEG data through Bluetooth Serial and processes it using Arduino IDE-based embedded code, applying threshold logic and filtering techniques to interpret user intent and avoid false triggering.

c. Gesture Module

This utilizes the MPU6050 sensor to detect hand movements and orientation, where sensor data is processed through programmed logic to map gestures into appliance control commands when brain signals are unstable.

d. Actuation Unit

A relay module connected to the ESP32 GPIO pins is used to control electrical appliances, where the programmed switching logic turns devices ON or OFF based on processed inputs.

e. Feedback Unit

A 16×2 LCD with an I2C interface displays real-time parameters such as attention level, system mode, and appliance status, while the ESP32 hosts an IoT web server and uses the HTTP protocol to enable remote monitoring of system data through a web interface.

Hardware Implementation

The hardware implementation of the proposed system is centered around the ESP32 microcontroller, which acts as the main processing and control unit. An EEG headband is used to acquire brainwave signals such as attention levels, and these signals are transmitted to the ESP32 via Bluetooth communication. A 16×2 LCD module with an I2C interface is connected to the ESP32 to display real-time system parameters including signal values, control mode, and appliance status. For gesture-based fallback control, an MPU6050 sensor is interfaced with the ESP32 through I2C communication, enabling detection of hand movements and orientation. The control of electrical appliances is achieved using a relay module connected to the GPIO pins of the ESP32, allowing safe switching of loads such as lights or fans [17]. The ESP32 also establishes communication with a cloud server using the HTTP protocol through its built-in Wi-Fi capability, enabling transmission of system data for remote monitoring. All components are interconnected to ensure synchronized operation, forming a compact and efficient embedded system suitable for real-time home automation applications.

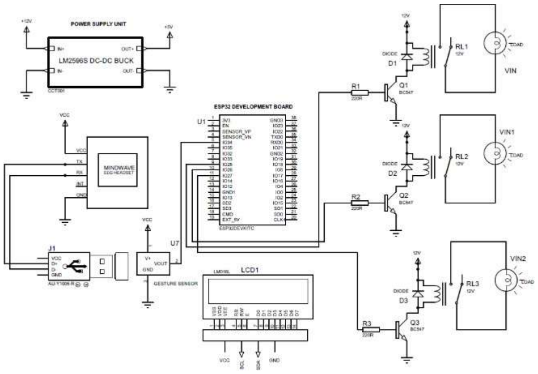

Fig 5: Circuit Diagram of Hardware Implementation

Software Implementation

The software implementation of the system is carried out using embedded C/C++ programming in the Arduino IDE, where the ESP32 microcontroller executes all control logic and communication tasks. The EEG data received via Bluetooth Serial is continuously read and processed to extract parameters such as attention level, which are evaluated using predefined threshold conditions to determine control actions. Sensor data from the MPU6050 is acquired through I2C communication and processed to detect gesture-based inputs, which are used as a fallback when EEG signals are unstable. The control logic incorporates filtering, delay mechanisms, and state-based conditions to ensure stable operation and prevent false triggering of appliances. GPIO pins are programmed to control the relay module for switching devices, while the LCD is updated in real time to display system status, signal values, and operating mode.

Additionally, the ESP32 hosts an IoT web server and uses HTTP communication over Wi-Fi to provide real-time system data through a web interface for remote monitoring. The overall software structure is designed to handle multiple inputs, prioritize control modes dynamically, and ensure synchronized operation between sensing, processing, and actuation components in real time.

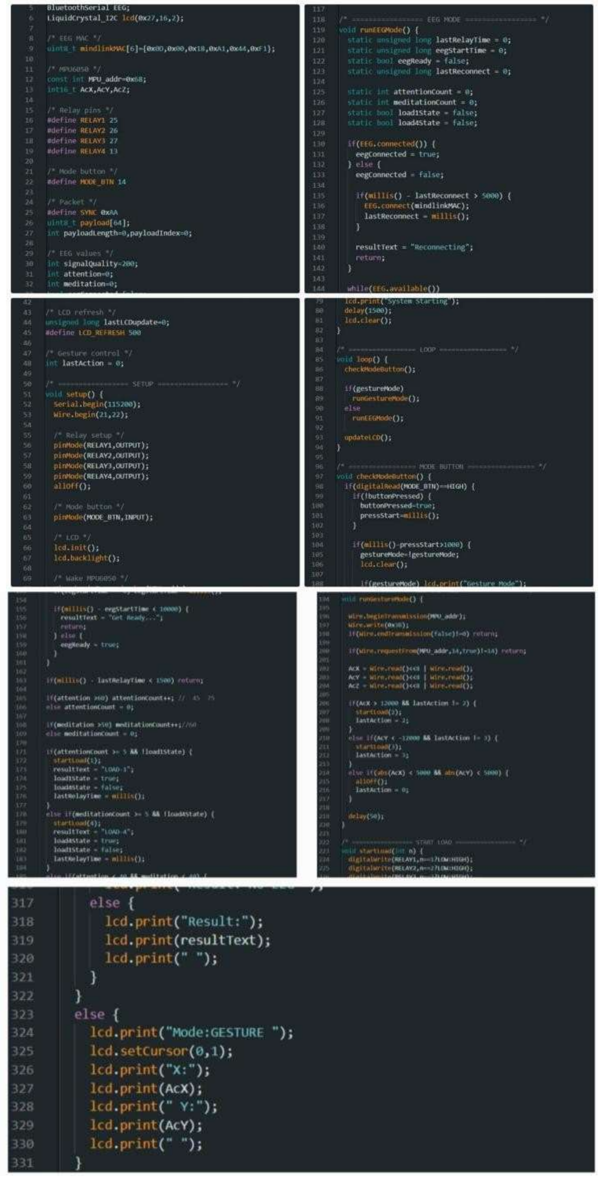

Fig 6: Software of the System Operation

Brainwave-Based Control System

EEG Signal Acquisition

The EEG headset was used to acquire real-time brain signals, including attention and meditation parameters derived from underlying brainwave activity. These parameters are primarily associated with Beta waves (linked to concentration and active thinking) and Alpha waves (associated with relaxation and calm mental states). The acquired data was transmitted to the ESP32 microcontroller via Bluetooth communication for further processing. Continuous monitoring of these parameters revealed that attention and meditation values varied dynamically based on the user's cognitive state and level of focus.

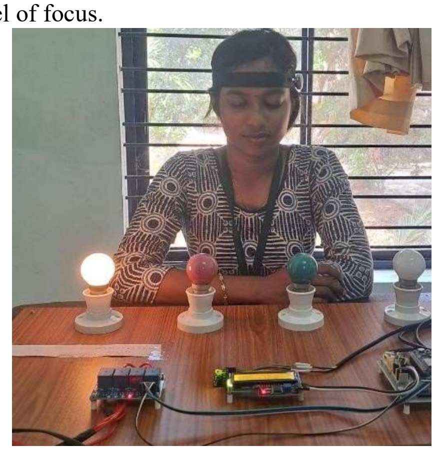

Fig 7: EEG Signal Acquisition and Brainwave Monitoring

EEG Signal Analysis and Threshold

Determination

The acquired EEG signals were analyzed to understand the variation of attention and meditation values corresponding to different brainwave patterns. Attention levels were observed to increase with higher Beta wave activity, while meditation levels showed higher values during dominant Alpha wave states. Based on these observations, threshold values were experimentally determined to distinguish intentional control signals from normal fluctuations. To enhance reliability, the system considered sustained signal levels above the threshold rather than instantaneous peaks, thereby reducing the impact of noise and unintended variations.

Brainwave-Based Load Control

The system utilized the processed EEG parameters to control electrical loads through a relay module. When the attention or meditation values satisfied the predefined threshold conditions for a specific duration, corresponding control actions were triggered. The mapping between brainwave-derived parameters and load control enabled hands-free operation of appliances. The system demonstrated stable performance under controlled conditions, with successful switching actions corresponding to consistent brain activity patterns.

Real-Time Feedback Using LCD

A 16×2 LCD was integrated to provide real-time visualization of EEG parameters, including attention and meditation values, along with system status. This enabled users to observe how variations in their mental state influenced system behaviour. The display served as an important interface for monitoring signal consistency and validating control actions during system operation.

Fig 8: EEG Signal Analysis and Threshold Determination

Hybrid Multi-Model Control System

Gesture Signal Acquisition and Calibration

The MPU6050 sensor was used to acquire motion and orientation data corresponding to hand gestures. The sensor outputs, including acceleration and angular values, were continuously monitored to study variations for different hand movements. Based on experimental observation, distinct patterns were identified for specific gestures, and suitable threshold ranges were determined to differentiate between control actions. This calibration enabled reliable detection of gestures under varying conditions.

Integration of EEG and Gesture Control

The EEG-based control system developed in Phase 1 was integrated with the gesture-based control module to form a unified system. Both input mechanisms were incorporated into a single control framework, allowing the system to process signals from either source. The integration ensured that the system could handle multiple input modalities while maintaining synchronization between sensing, processing, and actuation components .

Fig 9: Gesture-Based Control Using MPU6050 Sensor

Multi-Load Control Implementation

The system was extended to control multiple electrical loads through the relay module. A total of four loads were implemented, where two loads were associated with brainwave-based control and two loads were assigned for gesture-based control. The control logic was designed to map specific input conditions to corresponding loads, enabling independent and flexible operation of appliances within the system.

Manual Mode Switching Mechanism

A manual mode switching mechanism was implemented to select between EEG-based control and gesture-based control. The system operates in EEG mode by default, and switching to gesture mode is performed through a manual input. This approach ensures controlled operation and prevents unintended switching between modes due to signal fluctuations. The selected mode is displayed on the LCD, allowing users to clearly identify the current control mechanism.

Fig 10: Real-Time Feedback Display Using LCD

Real-Time System Operation and Feedback

The integrated system operates in real time, processing input signals and executing control actions with minimal delay. The 16×2 LCD provides continuous feedback, including control mode, signal values, and load status. This enables users to monitor system behaviour and interact effectively with the system during operation. The coordinated functioning of multiple modules ensures smooth and responsive performance.

IoT Web Server Communication Using HTTP Protocol

The ESP32 hosts an IoT-based web server and communicates using the HTTP protocol through its built-in Wi-Fi capability. The system transmits real-time data, including EEG parameters, control mode, and load status, to the web interface, allowing users to monitor system operation remotely through a browser. HTTP requests are used for data exchange between the ESP32 and the web server, enabling efficient and lightweight communication. This implementation enhances system accessibility and provides a simple platform for remote monitoring and future expansion of control features.

Overall Result

The overall system demonstrated successful implementation of a brainwave-based and gesture-assisted IoT home automation framework with reliable real-time performance. The EEG-based control system was able to interpret user intent through attention and meditation parameters derived from Beta and Alpha wave activity, enabling hands-free operation of electrical loads. The use of threshold-based logic with temporal validation ensured stable performance while minimizing false triggering due to signal fluctuations.

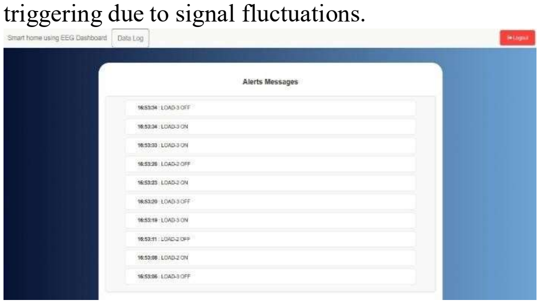

Fig 11: Multi-Load Control Implementation and System Output

The integration of gesture control using the MPU6050 sensor enhanced system flexibility by providing an alternative control mechanism, allowing the system to operate effectively under varying conditions. The implementation of multi-load control, with separate loads assigned for EEG and gesture inputs, enabled independent and efficient appliance management. The manual mode switching mechanism ensured controlled operation and prevented unintended transitions between input modes.

The system operated in real time with consistent response, supported by continuous feedback through the LCD and remote monitoring via the IoT web server using HTTP communication. The combined functionality of signal processing, multi-modal control, and IoT-based monitoring demonstrates the effectiveness of the system in providing a practical, reliable, and scalable solution for smart home automation.

6. FUTURE SCOPE

The capacity to interpret and adapt to brain signals can be improved to upgrade the proposed system. Currently, the system's decision-making is threshold-based. More advanced techniques could involve machine learning and adaptive algorithms to recognize EEG patterns. Such techniques could allow the system to adjust to the brain patterns of the user, distinguishing between voluntary and involuntary actions. Furthermore, the use of advanced signal processing techniques such as filtering, artifact removal, and feature extraction from EEG data may improve the accuracy and precision of the proposed system. Advanced EEG equipment and devices that offer better electrodes' precision and stability can also be used to achieve better performance in real-life settings. In the future, the system could be expanded to control a larger number of devices. The system can be expanded by adding more IoT-enabled devices to manage and monitor a smart home. The web server could also be more interactive, with more options for viewing and interacting with collected data from the system. It would be interesting to also add data storage capabilities so that users could see long-term trends in how the system behaves. Moreover, additional functionalities could be provided to the system which could make it more intuitive and user-friendly. The gesture control module could also benefit from more sophisticated sensors or visual input to read more types of gestures.It could also automatically switch between gesture and brain control based on whether a reliable brain signal is detected, without the need to manually switch control modes. In the future, the system could also provide health monitoring functionalities, such as reading the brain activity to see the stress level or detect abnormalities. This would make the system a dual purpose tool which can manage as well as monitor a person with disabilities. Another idea is to make the system more compact and energy efficient, portable, which would allow it to support more practical applications in the future.

❖ CONCLUSION

The proposed Brainwave-Based IoT Home Automation System is a feasible solution for hands-free control of electrical appliances using EEG signals. The attention and meditation parameters extracted from the brainwave signals were successfully utilized to develop a control system that effectively decodes and translates the intent from brain signals into control commands. The thresholding of signals along with time domain filtering was effective in suppressing erratic signals and ensuring reliable control of the system. The findings make it possible to consider further development of this system and consider EEG signals as a suitable input method for controlling home appliances.

The addition of gesture recognition was effective in adding another control methodology for the given application. The integration of an MPU6050 sensor is a good option for this particular application. The multi-load control function in the project is a suitable demonstration of control of multiple appliances using EEG and gesture inputs. Similarly, the manual switching between different control inputs ensures reliable switching between control methods.

The feedback provided by the LCD and IoT web server demonstrates the functionality of having multiple displays to provide updated information about the status of the application. Both the local and remote monitoring options can offer a more advanced level of interaction with the brain-computer interface. Overall, the proposed system is a great application of current technology that provides a solution for a specific need.

ACKNOWLEDGEMENT

We acknowledge the support given by Adithya Pallavi S P, Anudhyana A S, and Devana A S, students of the Electronics and Computer Engineering Program, LBS Institute of Technology for Women, Thiruvananthapuram.

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