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BRAIN MEMORY CAPTURING

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ABSTRACT

Brain memory capture is a futuristic technology that records brain waves and signals, aiming to convert human memories into hardware memory for use in AI robots. These robots can then mirror human behavior in multiple scenarios. Advanced signal sensing and enhancement technology are used to collect precise EEG signals, offering insights into cognitive states during various tasks. EEG-based Brain-Computer Interface (BCI) enables control of multiple AI robots simultaneously and holds potential for capturing human thoughts and even dreams. Recent advancements in neuroscience and technology, such as wearable sensors and machine learning, have driven interest in EEG-based BCIs for healthcare and translational applications. EEG, which records brain activity non-invasively, is a valuable tool for characterizing brain function in various contexts.

Keywords: Brain Computer Interaction, Electroencephalogram And Brain Memory Capture.

I. INTRODUCTION

Brain-Computer Interfaces (BCIs) are computer-based systems that acquire and interpret brain signals, translating them into commands for controlling external devices without using traditional pathways like peripheral nerves or muscles. BCIs strictly deal with signals from the central nervous system (CNS). For instance, voice or muscle-activated systems are not considered BCIs. Additionally, an Electroencephalogram (EEG) alone is not a BCI, as it merely records brain signals without generating output for interaction with the environment. BCIs should not be confused with mind-reading devices; they enable users, after training, to generate brain signals encoding intentions, which are then decoded by the BCI to control external devices. BCIs respect user intention and cooperation. EEG is a common non-invasive technique for mapping brain signals, which has evolved from subjective visual inspection to quantitative analysis methods. Research in BCI has grown significantly, with Information Transfer Rates (ITR) improving from 5-25 bits/min to 84.7 bits/min, mainly benefiting individuals with conditions like "locked-in" syndrome. Advances in technology and interdisciplinary research have fueled BCI progress.

The initial concept of brain memory capture introduces an innovative transmission channel that doesn't rely on the traditional output paths of peripheral nerves and muscles within the brain. In its early stages, this concept involved the measurement and interpretation of brainwave signals to control a prosthetic arm and execute specific actions. Brain-Computer Interface (BCI) systems are designed to understand and capture human cognitive patterns through brain activities. They utilize recorded brain activity to establish communication with computers, enabling the control of external devices or environments in alignment with human intentions. This capability extends to tasks like controlling wheelchairs or robots, making BCIs a valuable technology for enhancing the quality of life for individuals with physical disabilities By bridging the gap between human cognition and artificial intelligence, brain memory capture opens doors to a new era of human-machine collaboration and understanding. As research continues and technology evolves, the boundaries of what we can achieve with brain memory capture are bound to expand, paving the way for exciting discoveries and innovations in the realm of brain-computer interfaces and cognitive science.

II. METHODOLOGY

Hardware

1. EEG Machine
2. SSD Device
3. Wifi Device
4. Battery (Li-Ion)

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5. Motion Sensors
6. AI Robots
7. Signal Synthesizer

Software

1. Arduino IDE
2. 3Ds Max Design (Animation Software)
3. Unity (Animation Software)

Brain Signals

Neurons facilitate communication by transmitting both chemical and electrical signals. They are interconnected through minuscule junctions known as "synapses." Impulses, akin to electrical currents, propagate along slender fibers, functioning like wiring, and pass from one neuron to another. Electrical signals course through neurons, but in addition to these electrical transmissions within the nervous system, the brain employs chemical signals to regulate various bodily processes. The human brain, with its vast assembly of billions of neurons working in concert, continuously dispatches signals to influence how you feel and function, shaping your state of being from one instant to the next.

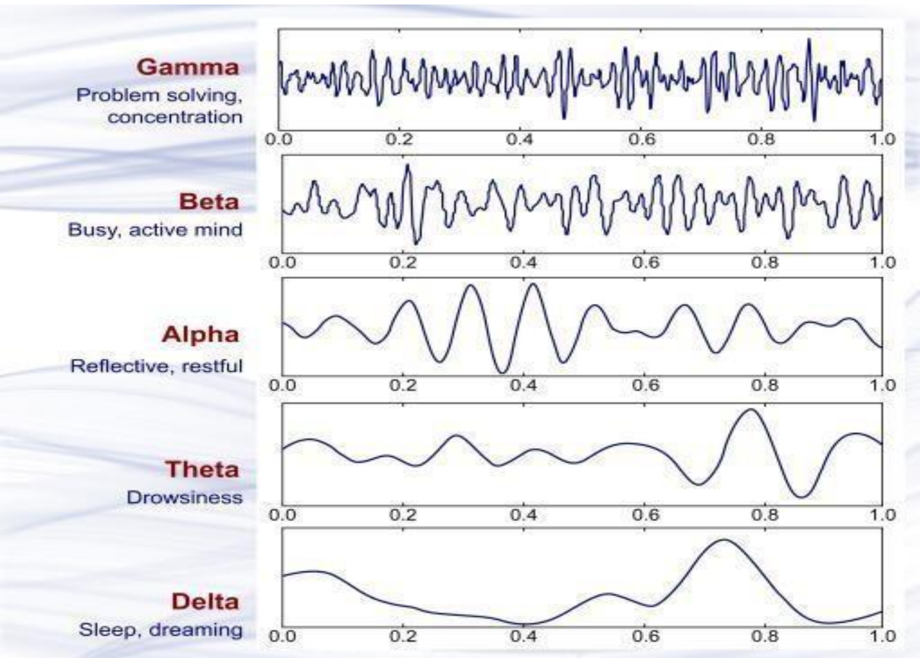

Figure 2.1: Brain different wave forms

Signal Processing

We use filters like notch filters (50 Hz) to remove noise and high-pass filters (below 0.5 Hz) for low-frequency components, while low-pass filters (40–70 Hz) eliminate high-frequency noise. Techniques like Hamming and Hanning are applied for signal windowing, improving hand motion detection. The next step involves preprocessing, including signal filtering, segmenting, scaling, expert mark verification, artifact detection, averaging, and segmentation. EEG signal acquisition is primarily in the time domain, so we use signal processing to extract relevant features over time and frequency, which may be obscured by noise.

Frame Work of Brain Memory Capturing

BCI systems come in different types. The active BCI system interprets patterns from user-controlled brain activity, enabling direct control over a device independently of external events. In contrast, the reactive BCI system extracts outputs from brain activity in response to external stimuli, allowing indirect control over applications modulated by the user. Passive BCI systems represent a third type, focusing on understanding user perception, awareness, and cognition without the goal of voluntary control. Instead, passive BCIs aim to enhance information enrichment

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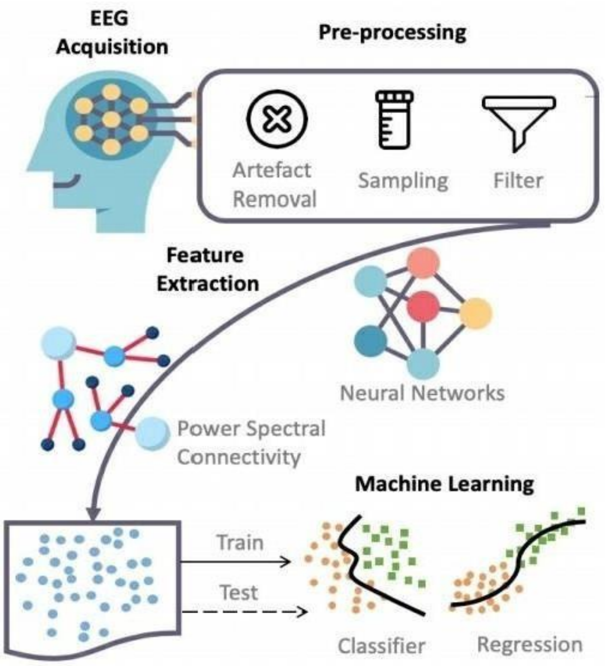

Figure 2.2: EEG Acquisitions

Proposed System

Brain memory capturing involves the acquisition of brain waves and signals, and it employs advanced signal sensing and enhancement technology to ensure the collection of clean and precise EEG signals from the brain. Electroencephalogram (EEG) based signal capture serves various functions, particularly in assessing cognitive states during repetitive tasks. This technology holds the potential to control multiple artificial intelligent robots concurrently, enabling the capture and manipulation of human thoughts. Moreover, the aspiration to capture human dreams represents a promising future application of this technology. Advances in neuroscience and computer science have fueled exciting developments in Brain-Computer Interface (BCI) technology, positioning BCI as a prominent interdisciplinary research field in computational neuroscience and intelligence. Recent technological strides, including wearable sensors, real-time data processing, machine learning, and deep learning, have intensified interest in EEG-based BCI for healthcare and translational purposes

Features

The ability to establish a connection between brain activity and peripheral devices has become feasible through advancements in cognitive neuroscience and brain imaging technologies. This progress has enabled the monitoring and real-time control of activities through the brain's thought processes. Such technology is particularly valuable for individuals with disabilities, as it offers an effective means of communication. A brain memory capturing system, for example, can be a tremendous aid to individuals with severe motor disabilities and can support biofeedback training for patients recovering from conditions such as stroke, epilepsy, or attention deficit hyperactivity disorder (ADHD). This system employs electrodes or sensors to record changes in electrical potential, magnetic fields, and ion supply alterations resulting from the excitation and inhibition of neural networks driven by brain activity

Feature Extraction

The Heisenberg uncertainty principle implies a trade-off between accuracy in time and frequency domains: increasing accuracy in one domain may reduce accuracy in the other. Combining features from both domains often yields better results. Time-frequency domain analysis, which integrates time and frequency domain analyses, represents signal energy distribution in the time-frequency plane (t-f plane) and is useful for revealing rhythmic information in EEG signals. Coherence techniques measure phase regularity between signal pairs in each frequency band but cannot separate amplitude and phase information, while synchrony quantifies phase locking between narrowband signals. Space-Time-Frequency (stf) analysis is popular for multichannel EEGs, where the spatial dimension considers electrode positions. Space-time-frequency methods have shown better results than time-frequency domain approaches in discriminating between tasks, as demonstrated in studies such as Suleiman et al.'s work that used a wide scalp region for data collection.

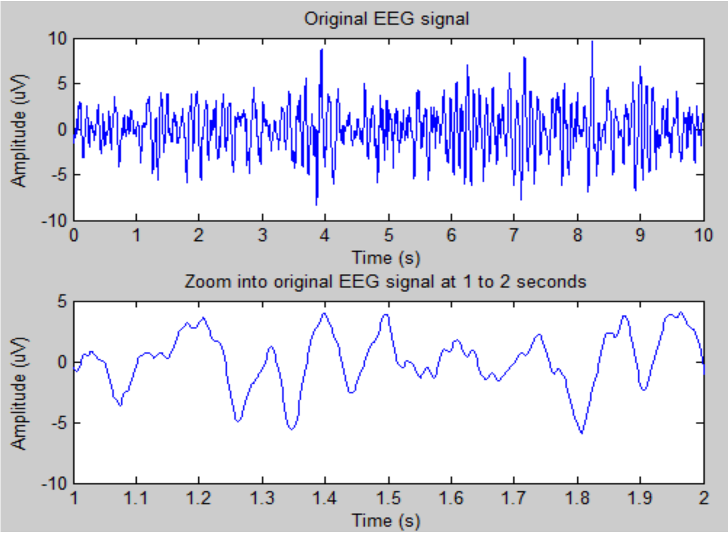

Figure 2.3: Signal Synthesizer

III. MODELING AND ANALYSIS

Sensing Technologies

Recent advancements in sensor technology have facilitated the creation of compact and intelligent wearable EEG devices designed for lifestyle and medical applications. These innovations have paved the way for wireless EEG monitoring devices that utilize dry sensors. In this section, we outline the progress made in EEG devices, whether they use wet or dry sensors. Additionally, we provide a comparison of commercially available EEG devices, considering factors such as the number of channels, sampling rate, portability, and the capability to cater to the diverse requirements of EEG users.

Wet Sensor Technology

Wet electrode caps typically require the use of gels to create a conductive interface between the sensors and the user's scalp. These wet sensors rely on electrolytic gels to establish a clean conductive pathway. The purpose of using this gel interface is to reduce the impedance at the skin-electrode contact interface. Without it, the impedance can be uncomfortable and inconvenient for users, making it impractical for daily use due to the time and effort required. However, it's essential to use the conductive gel because it enables the measurement of electrode-skin impedance, ensuring the quality of the recorded EEG signals is not compromised.

Dry Sensor Technology

Dry EEG sensors have evolved significantly, offering advantages such as ease of use and quick setup, making them suitable for real-world applications. These sensors eliminate the need for gel application or skin preparation, making them more user-friendly. For example, bio-sensors designed by Siddharth et al. provide high-quality signals without skin abrasion or gel use. Novel dry EEG sensors with active noise filtering have been developed and compared to traditional wet sensors, showing comparable accuracy in tasks like SSVEP BCI. Additionally, wireless wearable devices with dry, non-contact EEG electrodes are emerging, showing promise for EEG applications and mobile BCIs. Augmented BCIs (ABCIs) are proposed for everyday environments, emphasizing non-intrusive, easy-to-use EEG solutions, making long-term data collection comfortable and robust. The future of mobile brain imaging lies in developing portable EEG devices with dry electrodes, driven by biosensing technology and devices.

EEG Preprocessing

BCI research is focusing on real-time monitoring of cortico-cortical interactions, wearable device development, and artefact removal methods. A model processes EEG data from a high-density dry EEG device, enabling real-time analysis. Another study enhances this with artefact removal, source localization, and cognitive-state classification for real-time cognitive state identification. An algorithm utilizing recursive least squares whitening and optimized recursive ICA effectively removes artefacts and extracts brain sources from high-density EEG data. Open-source tools like the Real-time EEG Source Mapping Toolbox (REST) facilitate real-time BCI research in various domains. The open-source tools and collaborative efforts in this field are fostering innovation and accelerating progress, making the future of brain-computer interfaces exceptionally promising. These developments are propelling BCI research into exciting new territories with significant implications for human-computer interaction and neuroscience. It's worth noting that the field of Brain-Computer Interfaces (BCIs) continues to evolve rapidly. Researchers are exploring innovative approaches such as the use of augmented reality (AR) in combination with EEG-based BCIs, which can enhance the user experience and expand the range of applications. Additionally, the development of hybrid BCIs, which integrate EEG signals with other physiological or technical signals, holds promise for improving classification accuracy and expanding the capabilities of BCIs. Moreover, the emerging field of adversarial attacks on machine learning models used in EEG-based BCIs highlights the need for robust security measures in BCI technology. Overall, ongoing research and technological advancements in BCIs are opening up exciting possibilities for both healthcare and human-computer interaction.

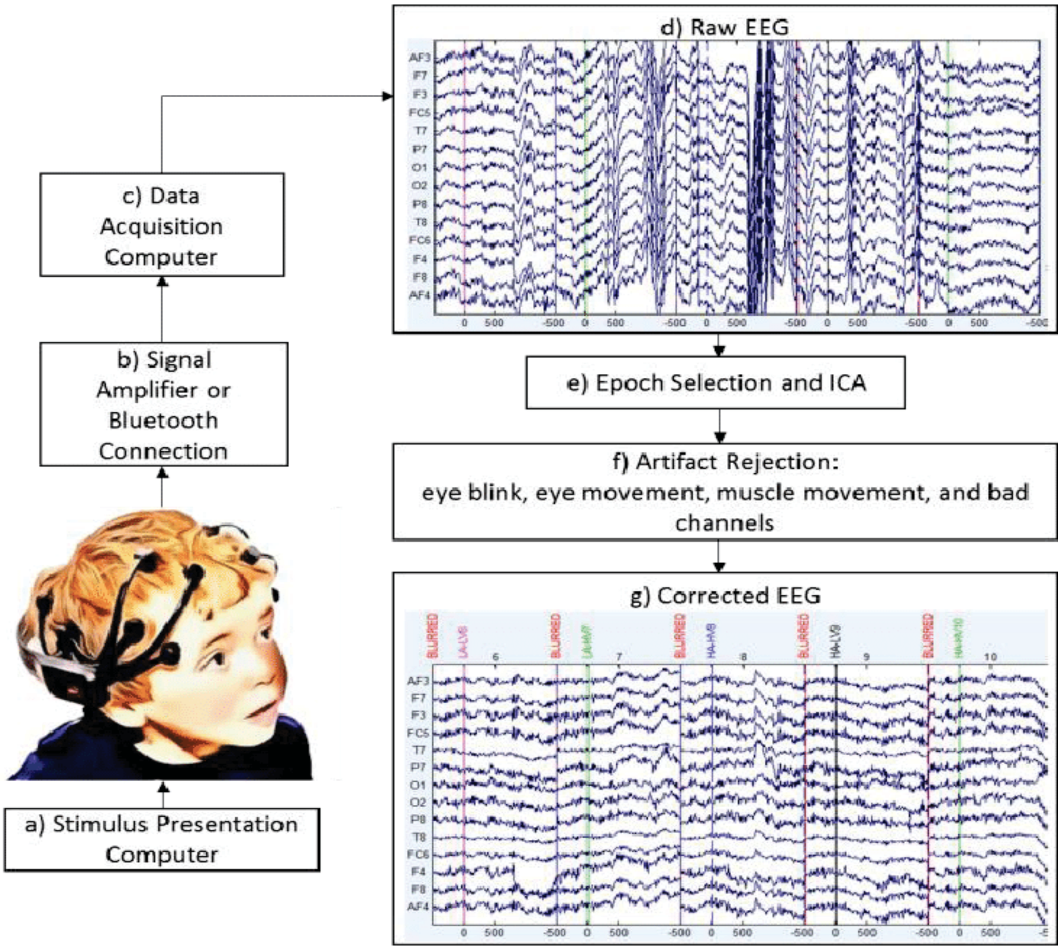

Figure 3.1: Signal Decoding Process

UML Diagram

The Unified Modeling Language (UML) is a standardized language for representing system designs in software engineering. It includes various diagram types, and a use case diagram is one that depicts user interactions with a system, showing the relationships between users and system functions. Use case diagrams help identify user roles and their interactions with the system, often accompanied by other diagram types for comprehensive system modeling.

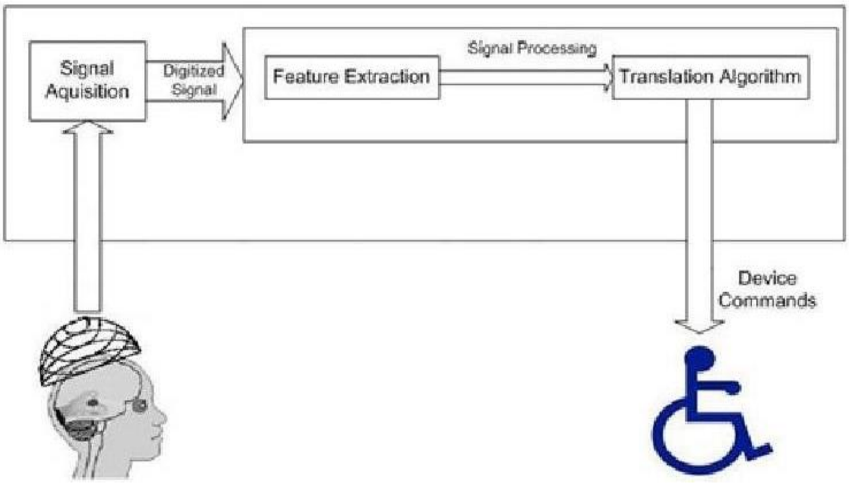

Figure 3.2: Wheelchair operating EEG brian Signal

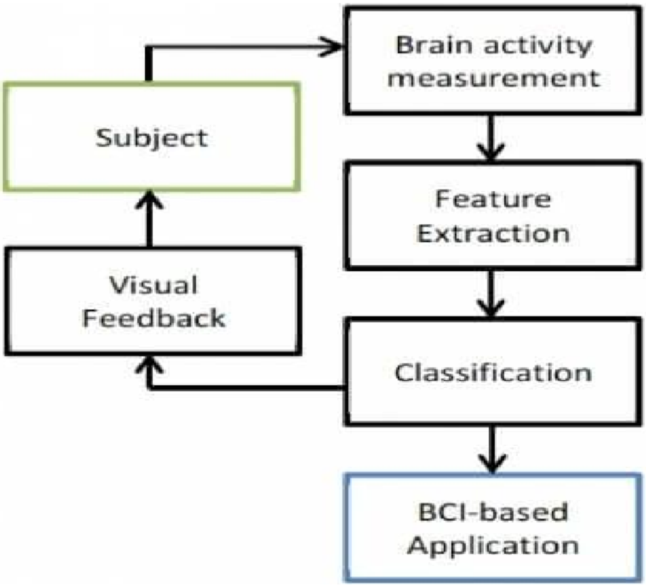

Figure 3.3: class diagram of brain memory capturing

Unified Modeling Language (UML) serves as a crucial tool in the realm of software engineering, offering a standardized and versatile means of visualizing system designs. UML diagrams provide a clear and concise way to represent the architectural blueprints of a system. At its core, a use case diagram within the UML framework serves as a graphical depiction of how users interact with a given system. It delves into the relationships between users and the various use cases or functionalities they engage with. Moreover, use case diagrams offer valuable insights by distinguishing different user types and elucidating their distinct roles and interactions within the system. To provide a holistic understanding of the system's design and functionality, use case diagrams are often complemented with other types of diagrams, facilitating effective communication and documentation in software development projects.

In practical terms, a use case diagram captures the essence of user-system interactions. It paints a visual narrative of how users, whether they are end-users or other systems, engage with the functionalities and features offered by the software. This clarity is vital for software developers, analysts, and stakeholders, as it aids in requirement analysis, system design, and validation of user expectations. Essentially, use case diagrams in UML serve as a powerful communication tool, enabling cross-functional teams to align their understanding of the system's behavior and purpose. This shared understanding lays the foundation for successful software development projects, where efficient collaboration and problem-solving are paramount to delivering systems that meet user needs and expectations

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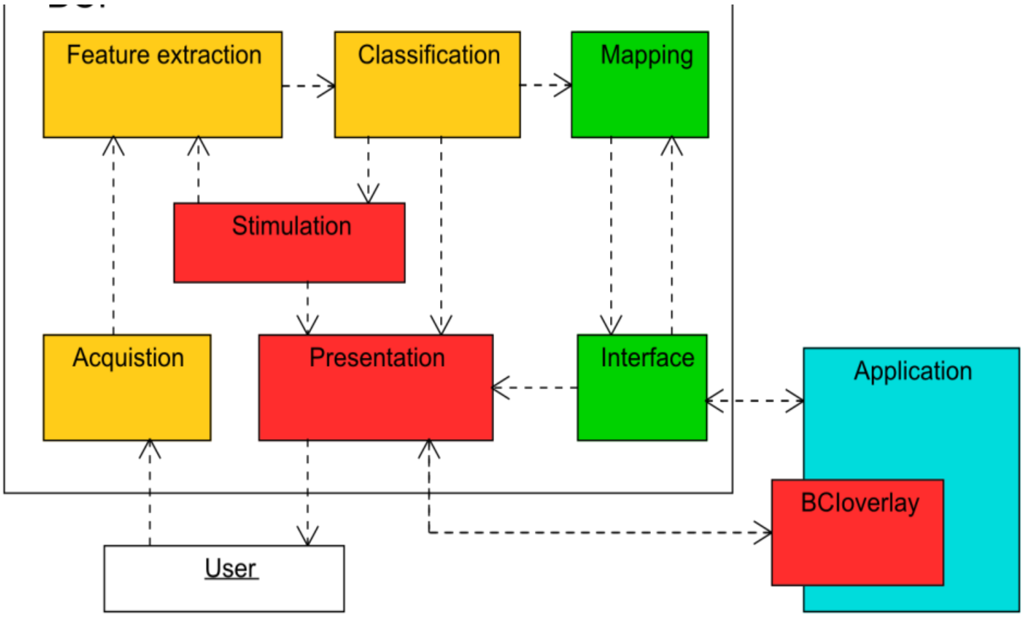

Figure 3.4: UML diagram of brain memory capturing

A Collaboration Diagram, also known as a Communication Diagram, is a UML diagram used to illustrate how objects or components in a system interact by showing the flow of messages between them. It combines elements from various UML diagrams, such as Class, Sequence, and Use Case Diagrams, to provide a comprehensive view of both the static structure and dynamic behavior of a software system. This diagram helps in understanding how different parts of a system collaborate and communicate to accomplish specific tasks or functions, making it a valuable tool for designing, documenting, and comprehending complex systems. In sensor-based lighting systems, the placement and accuracy of sensors may not be perfect, leading to the incorporation of a delay time before triggering any lighting changes. Users often have the option to customize this delay time, but a common default value is around 15 minutes. This means that the sensor must detect no motion for the entire delay period before the lights are either switched off or dimmed. In more advanced systems with dimming capabilities, the lights gradually decrease in intensity over several minutes, minimizing disruption in nearby areas. If the lights are off and someone enters the space, most current systems will automatically switch the lights back on when motion is detected. However, systems designed to turn lights off completely in unoccupied areas, requiring occupants to manually switch them back on when needed, are gaining popularity due to their potential for increased energy savings.

System Design

- Memory chip built in the shape of headphones that recognises voice and movement
- It will be immediately connected to the system through the network (Internet).
- The voice synthesiser will synthesise the speech and save it to the hardware memory (SSD).
- Motion sensors will be linked directly to Artificial Intelligence Robots.
- Face and fingerprint recognition to protect data security

IV. RESULTS AND DISCUSSION

The result of brain memory capturing technology and Brain-Computer Interfaces (BCI) is a significant advancement in the field of computational neuroscience and intelligence. It allows for the collection of clean and accurate EEG signals from the brain, enabling various applications in understanding cognitive states, controlling artificial intelligent robots, and potentially capturing and manipulating human thoughts and dreams. Recent technological advances, including wearable sensors and machine learning techniques, have further fueled research and development in this interdisciplinary area, offering promising prospects for translational and healthcare applications. Brain memory capturing and BCI are at the forefront of cutting-edge research, offering exciting possibilities for the future of brain-computer communication and understanding human cognition.

V. CONCLUSION

Recent advancements in Brain-Computer Interfaces (BCIs) and EEG-based brain memory capturing techniques offer promising opportunities for reshaping human-computer interaction and healthcare. These developments, driven by improvements in signal sensing, computational intelligence, and wearable sensor design, have the potential to enhance the accuracy and usability of BCIs. However, challenges such as privacy concerns, the need for real-world usability, and defense against adversarial attacks must be addressed. Looking ahead, the integration of EEG-based BCIs with emerging technologies like Augmented Reality (AR) and the exploration of hybrid BCI systems hold exciting prospects. Despite these challenges, continued research and innovation in this field are poised to unlock new frontiers in neuroscience and human-computer interaction, bridging the gap between science fiction and reality. the advancements in EEG-based BCIs, the focus on improving sensor materials and user experience through comfortable sensor attachments is enhancing the feasibility of BCI applications. Research in adaptive EEG-based BCI training, artefact removal, and hybrid BCI systems combining EEG with other physiological signals further enrich the potential of these technologies. The vulnerability of deep learning models in EEG-based BCIs to adversarial attacks underscores the need for robust security strategies. Overall, the convergence of neuroscience, machine learning, and wearable technology is propelling EEG-based BCIs towards a future where they play a pivotal role in healthcare, human-computer interaction, and beyond, promising a profound impact on our lives.

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