Final Year Project Report

Brain-Controlled Prosthetic Arm for Paralyzed Persons

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Session 2025-26

Submitted by

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Dedication

This work aims to assist individuals with physical disabilities in completing basic everyday activities. The project will utilize tools based on the latest technologies available in order to help users increase their independence, build confidence and live more fulfilling lives.

Final Approval

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Acknowledgment

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Thank you also to the faculty. We are very appreciative of the Department and faculty for all the resources & academic environment they created to enable us to complete this project successfully. The knowledge we gained from working on this project has enhanced our understanding of Embedded Systems, Assistive Technology, and Brain-Computer Interface.

Finally, we would like to express our gratitude to all individuals who were directly or indirectly involved in the completion of this project. All the candidates agree this was a very rewarding experience on both a professional and academic level.

Shah Bano

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Plagairism Report

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Abstract

The objective of this project is to develop a safe and effective way for people with physical disabilities or paralysis to control a prosthetic arm using their thoughts through brain-computer interface (BCI) technologies. The result will consist of an EEG (electroencephalogram) helmet that records the activity in the brain and translates those impulses into actionable commands for the functionality of a robotic arm. The proposed design includes various ways to achieve this using a microcontroller (ESP32) for signal processing and decision-making; a bipolar approach to Bluetooth connectivity; and an EEG acquisition system that incorporates a TGAM chip for analog to digital conversion. In order to produce movements such as "grip" or "release" from the prosthetic arm, the RAW EEG signals from the EEG acquisition system will need to be filtered, processed and classified based on previously established threshold logic, which will ultimately create output. An EEG-based control system that is low-cost, modular, and non-invasive has been proven experimentally to provide reliable basic movement control and is demonstrated through stable signals from the system and effective conversion of attention-based brain signals into robotic arm movement control with an acceptable response time. The architecture of the system includes subsystems such as motor actuation, wireless communication, embedded processing, power management, and signal acquisition. The design of the system is thus concluded to represent an affordable, functional assistive device with potential for improvement towards enhanced accuracy, speed, and multifunctionality of prosthetic applications in real-world environments.

REVISION CHART

Version	Primary Authors	Description of Version	Date of Completion
1.0	Hiba Nadeem, Shahbano , Saqib Azair	Proposal Defense: The project's fundamental concept and overall plan were familiarized and presented.	Nov 07, 2025
1.1	Hiba Nadeem, Shahbano , Saqib Azair	Components such as ADS1256, HC-05, and ESP32 were identified and purchased during market research.	Nov 14, 2025
1.2	Hiba Nadeem, Shahbano , Saqib Azair	Prepared the first testing setup and made the hardware order.	Nov 21, 2025
1.3	Hiba Nadeem, Shahbano , Saqib Azair	The first failure occurred when an Arduino with an ADS1256 was used, but the complex EEG data was excessive for the Arduino processor to deal with.	Dec 05, 2025

1.4	Hiba Nadeem, Shahbano , Saqib Azair	Second Failure: To get additional power, I switched to an ESP32, but the signals were too noisy and interfered with to be helpful.	Dec 19, 2025
1.5	Hiba Nadeem, Shahbano , Saqib Azair	Pivot: To address the processing and noise problems, the TGAM Module was studied and finalized.	Jan 02, 2026
1.6	Hiba Nadeem, Shahbano , Saqib Azair	Headset Validation: Clear brain signals were successfully recorded, and the stability of the headset was examined.	Jan 16, 2026
1.7	Hiba Nadeem, Shahbano , Saqib Azair	3D Modeling: CAD software was used to design the prosthetic arm.	Feb 02, 2026
1.8	Hiba Nadeem, Shahbano , Saqib Azair	Final Documentation: The technical diagrams, result analysis, and project report were finished.	Feb 07, 2026

Project Title	Brain-Controlled Prosthetic Arm for Paralyzed Persons
Objective	To design a non-invasive Brain Computer interface(BCI) system that captures EEG Brain signals and convert them into movement commands for a prosthetic arm to assist individuals with physical disabilities.
Undertaken By	Saqib Azair 22017020004 ShahBano 22017020017 Hiba Zari Nadeem 22017020013
Supervised By	Mr. Syed Waleed Husain
Starting Date	07 November 2025
End Date	23 Feb 2026
Tools Used	**Hardware:** TGAM module Esp32 Dry forehead electrode Ear clips electrode Battery Bluetooth module **Software:** Arduino IDE CAD Software Draw.io
Operating System	Windows 11
Documentation	Microsoft Word

List Of Acronyms

BCI	Brain-computer interface
EEG	Electroencephalogram (brain Signals)
TGAM	ThinkGear AM (EEG Sensor chip)
MCU	Microcontroller Unit
CAD	Computer Aided Design
ADC	Analogue to Digital Converter
IDE	Integrated Development Environment (Arduino software)
UART	Universal Asynchronous Receiver-Transmitter
UML	Unified Modeling Language (for diagrams)
BT	Bluetooth

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1. INTRODUCTION

The domains of robotics and the Internet of Things (IoT) are connected to this project. Its main goal is to create an assistive robotic arm that can be operated by brain impulses. The technology creates a gadget that can be watched over and managed in real time by combining smart sensors, signal processing methods, and Internet of Things-based connectivity [10].

The research makes use of technology known as Brain-Computer Interface (BCI), which enables direct connection between a machine and the human brain. This technique detects electrical activity from the brain using electroencephalography (EEG) rather than muscle signals. The user wears a specialized EEG headset with sensors that record brainwaves while the user imagines moving their hand or arm [7].

These brain impulses are received by a computer, which interprets, processes, and evaluates them. Since raw EEG, signals are weak and noisy, signal-processing techniques are used to clean and prepare the data. Artificial intelligence algorithms then ascertain the purpose of the user. For example, the system can decide whether the user wants to open or close the robotic hand.

The system translates the identified intention into control commands that move the robotic arm. This creates a direct link between the brain and the robotic device. The system is non-invasive, so surgery is not required. The externally worn EEG headset is a more economical and safe alternative to implant-based systems [5].

However, EEG signals are often noisy and unpredictable. They can be affected by eye movements, blinking, and other body movements. The project requires an intelligent real-time signal processing and categorization system to ensure accurate and smooth control of the robotic arm [8].

1.1 Motivation

Worldwide, a large number of people suffer from neurological diseases, spinal cord injuries, strokes, or accidents that result in limb loss or movement impairments. For these individuals, everyday tasks like eating, lifting, and grasping objects can be very difficult. The operation of conventional prosthetic arms frequently depends on muscle signals (EMG signals). However, people whose muscle activation is weak or nonexistent should not use these prostheses. Because of this limitation, there is an urgent need for alternative assistive devices that do not require muscular movement. Brain-Computer Interface (BCI) technology, which uses brain impulses to directly control devices, presents a promising solution. By directly interpreting brain input rather than using muscles, people with severe movement disabilities can regain some degree of independence.

This project aims to create a simple-to-use, realistic system which enables people with disabilities to do everyday things with greater ease and confidence. Our technologies will provide low-cost, safe and effective non-invasive solutions that are accessible to a wider audience, particularly in the developing world.

The advancements in signal processing and artificial intelligence will enable us to overcome some difficulties, for example, dealing with the noise produced by EEG machines to creating a means for real-time processing. Our projects will pursue enhancing the independence and improving the quality of life of and providing hope to those people with limited ability to move.

1.2 Project Overview

The primary objective of the current phase of this project is to develop an EEG acquisition module for a robotic arm control system using brain-computer interface (BCI) technology. A non-invasive EEG helmet has made it possible to record brain impulses in a secure and comfortable manner. To detect the electrical activity generated by the brain, sensors are placed on the helmet's scalp. These signals are recorded in real time and then transmitted to a monitoring system for observation and analysis. At this point, the main objective is to ensure consistent, clear, and reliable signal collection.

Now, it is possible for the device to capture EEG signals clearly, and any problems with the hardware level noise have been addressed by secure connections and proper electrode placement, which has increased the stability of the signals being produced. The data being recorded exhibits consistent brainwave patterns and thus would allow for analysis that is more detailed. At present moment, a light bulb will continue to be turned on and off as a method of testing whether the signals are able to function properly. Currently, Motor Imagery (MI) and other advanced methods of interpreting the EEG signals captured have not yet been used.

To locate out important trends in collected EEG signal data at this replication step, structured processing will occur. The EEG signal data will be methodically processed to enhance important EEG signal features, and then focused more finely. The characteristic patterns discovered during this signal enhancement stage will be associated with specific control intentions. Ultimately, the goal is to slowly convert brain activity patterns to commensurate command signals. This should result in the system's transition from simple signal monitoring to interactive control.

A robotic limb will ultimately be directed by the EEG helmet's generated command signals. The helmet will provide the brain with the ability to directly start movements such as lifting, holding and moving through the interface between the robotic limb and the helmet at the time of an impulse coming from the brain. A real-time feedback system will allow the user to track how the robotic limb is responding to their brain commands and adjust their concentration as necessary. This method will maintain the safety and reliability of the system, while allowing for coordinated movement between the brain and robot.

1.3 Problem Statement

Why are EEG-controlled robotic arms impractical for regular use? While many scientists have developed systems that respond to brain signals, most of them are in an experimental phase.

They tend to work effectively when tested under controlled conditions, but they have been unsuccessful when tested outside of these controlled environments. There are limitations due to human nature, technical limitations and inherent weaknesses and inconsistencies associated with EEG signals that prevent the successful operation of robotic arms as smoothly and naturally as they would be controlled without any of these issues. Thus, the ultimate goal to develop a fully functional, brain controlled prosthetic zed limb for those who are paralyzed or have functional disabilities has yet to be achieved.

1.3.1 Weak and Noisy EEG signals

When recording EEG signals on the scalp, they are very weak signals and are susceptible to interference from blinking and other types of electric noise in the environment as well as muscular tension. As a result, there are many times that robotic arms do not move correctly or consistently due to interference preventing the system from determining what the actual activity of the brain is.

1.3.2 Systems Have Problems Functioning in Real-Time

Many systems that performed well in a simulated or offline environment do not perform well when functioning in real-time. Sometimes brain commands will be misclassified and the response of the system will be slow. Both of these situations cause reduced user confidence in the system and make it difficult for the user to continue using the system.

1.3.3 Delays in Response and Slow Processing Times

Due to all the different steps required when filtering the signals and extracting features of the signal, users may experience a noticeable delay between when they want to move the robotic arm and when the robotic arm actually moves. This delay can disrupt a person's ability to feel they have control of the robotic arm and make everyday tasks more complex and difficult to perform.

1.3.4 Amount of Training needed and Limited range of movement control

At present, the majority of existing EEG based control systems can only provide a small number of basic actions for users to perform; for example: "open hand," "move forward," etc. Therefore, they are unable to move in multiple directions at once, nor do they have a high degree of dexterity. Additionally, many of these systems require a user to undergo extensive training and or frequently recalibrate their EEG devices so they can use the system on a regular basis.

1.4 Research Question

a) How can a custom-built EEG helmet capture and transmit brain signals for the operation of prosthetic arms on a consistent basis?

Hardware and data collection will be the main areas of investigation. The goal of this project is to develop a custom-designed EEG helmet that provides stable data transmission; is comfortable to wear; and gathers high-quality signals. Ultimately, there must be a steady stream of brain impulses used as input to control the prosthetic arm.

b) How do we extract precise control commands for fluid movement of an artificial limb from EEG data?

The purpose of this computations is to develop the tools and methods to enhance and DE-noise raw EEG signals to discover and identify the meaningful patterns and convert them into usable control commands for the prosthetic arm to allow for accurate and successful control of the device.

c) What steps can be taken to enhance overall system accuracy and speed so that a prosthetic hand controlled by thought is functional enough for daily tasks?

This question deals with performance scaling and system integration. The purpose of improving overall accuracy and reducing delays is to create a more efficient system from both the arm's movement and the acquisition of signals. The end goal is to create a usable technology interface for persons with functional mobility impairments and to provide dependable operations in an everyday environment.

1.5 Research Objectives

a) Create a custom EEG helmet to capture better brain signals for controlling a prosthetic.

This part of the project is the hardware piece of it. The goal is to develop a custom EEG acquisition device that will be comfortable to wear and provide reliable, clear data to the user. The construction of a working brain-computer interface (BCI) will use a high-quality ergonomic helmet as its base.

b) The aim is the development of an effective technique for converting EEG signals to accurate control commands for the fluid movement of the prosthetic arm.

This component of the aim will focus on the software or data processing elements of the overall project. These elements will be used to eliminate noise from the source of the EEG signals and identify statistically significant patterns in those signals; this will then allow for the accurate translation of these signals into control signals for the prosthetic arm, so that the prosthetic arm will steadily and consistently move according to the neuro-activity of the user.

c) **The objective of the research is to enhance both the effectiveness and reliability of the brain-controlled prosthetic arm in relation to speed and accuracy for practical use in real life.**

The aim of this project is to develop an integrated system that integrates both the functional and practical aspects of prosthetic hands into one cohesive unit, while at the same time optimize overall system performance in terms of command accuracy, command execution time and consistency of functionality within normal use. The goal of the project is to create a user-friendly prosthetic hand for individuals experiencing movement difficulties.

1.6 Scope And Significance

Developing a non-invasive EEG-based control system for communication between assistive devices and brain signals is the major goal of this project. The overall aim of the project is to develop an assistive device that operates using "Brain Controlled Technology" (BCT). A specially designed EEG (electroencephalogram) headset provides improved signal quality by reducing noise, optimizing data acquisition and ensuring realistic signals. All of the prior design work is being tested with a series of manufacturing tests to verify whether the data collected during this phase is representative of actual brain activity.

In the next phase of the project, we will validate the conversion of signals into control signals for assistive devices, while the current phase will only verify that the signal acquisition process is functional. The project provides new opportunities for the continued development of assistive technology for the paralyzed and those with physical disabilities, creating technologies that empower users to live more independently and enhance their quality of life through functional, low-cost brain-controlled products. The project will also contribute to regional research and innovation in the emerging field of brain-computer interfacing and will provide a foundation for future design and development of next generation smart prosthetics.

2. LITERATURE REVIEW

2.1. Related Work

Stroke survivors find using brain signals for rehabilitation machines challenging (2025). By fusing EEG and EMG input, slight motion detection improvements were achieved, but extensive preprocessing (which required many complex calculations) hampered the overall system's responsiveness. Given the results were not impressive and real-time capability was dismal, the study would be nearly impossible to utilize in a practical setting due to both a complicated setup and high computation requirements. Chen & Wang (2025) concentrated on decoding brain-wave/robot communication to enhance that process. Although mostly conceptual in nature and little real world testing to validate this method, it showed some promise toward improving motor coordination between thought and robot. The results in practical usage were not convincing, and lack of physical testing limits that method's reliability. Bait et al. (2025) fused brain waves with voice commands to reduce control errors; however, improving responsiveness required only modest improvements due to the necessary robust hardware requirements and complex setup. Performance was not yet stable enough for everyday application. Its limitation lies in the heavy hardware requirements and complex installation process.

Zare et al. (2025) demonstrated a soft robotic glove to facilitate hand rehabilitation. The results, which were based on a small testing group, were not very encouraging, despite the fact that the device helped with movement during therapy. The hand motion only slightly and erratically improved. One significant flaw that undermines the findings is the small sample size**. Torad et al. (2024)** constructed a low-cost robotic arm using simple components. The mechanical strength was weak and calibration took a long time, even though it was reasonably priced. The final performance was not reliable or long-lasting. Its shortcomings include weak mechanical joints and reduced long-term stability. **Lee et al. (2024)** investigated instability caused by user-specific variations in EEG signals. Users' weariness and distraction considerably decreased system performance, even though their adaptive calibration showed faster correction. The results were inconsistent and not totally trustworthy. One major disadvantage is decreased reliability in normal daily situations.

No	Author (year)	Problem Statement	Key Findings	Methodology	Tools & Devices	Results	Limitations	Scope & Features
[1]	Zaim et al. (2025)	Stroke patients face difficulty in controlling rehabilitation devices using brain signals	Combining EEG and EMG signals improves movement intent recognition	Iterative learning network for signal calibration	EEG sensors, robotic system	Faster adaptation to new users	Requires heavy preprocessing and high computation	Personalized brain-controlled systems
[2]	Chen & Wang (2025)	Brain-machine interaction is difficult due to signal complexity	Deep learning helps synchronize human thoughts with robotic systems	EEG signal processing using ICA analysis	32-channel EEG system	Accurate hand motion classification	Mostly conceptual and not fully tested in real environment	Brain-controlled hand devices
[3]	Basit et al. (2025)	Signal noise causes errors in prosthetic control	Hybrid system using brain signals and voice commands increases accuracy	Wavelet transform with machine learning	Sensors and ML algorithms	Better detection of walking and movement patterns	Requires strong hardware and complex setup	Lower limb prosthetic systems
[4]	Zare et al. (2025)	Limited effective tools for hand rehabilitation	Soft robotic glove provides safe and smooth assisted movement	Review of new electrode materials	Flexible sensors (PEDOT:PSS)	Clearer and more stable signals	Small testing sample size	BCI hardware development

[5]	Torad et al. (2024)	High cost of robotic prosthetic arms	Low-cost design using simple components makes system affordable	Mechanical design and embedded control	Raspberry Pi, TGAM module	Improved natural finger gestures	Mechanical strength is limited	Bionic hand for daily activities
[6]	Lee et al. (2024)	EEG signals vary between users causing instability	Adaptive calibration improves system reliability	Systematic literature review	EEG-based systems	Shows progress and trends in research	Performance decreases when user is tired or distracted	Artificial arm development
[7]	Maibam et al. (2024)	Muscle signals not always available for control	Brain synergy patterns can detect hand movement without muscle input	Review of motor BCI techniques	Motor brain-computer interface	Suggests future direction for natural control	High computational processing required	Advanced prosthetic systems
[8]	Zafar et al. (2024)	Movement detection affected by signal noise	Advanced signal analysis improves activity recognition	Data fusion machine learning approach	EEG + EMG sensors	Stable control for multiple hand movements	Noise artifacts reduce accuracy	Multi-function prosthetic control
[9]	Li et al. (2024)	Traditional electrodes give poor signal quality	Flexible electrode materials improve signal clarity and comfort	3D printed prosthetic design with haptic feedback	Emotiv EEG, prosthetic arm	Added sense of touch during object handling	Manufacturing cost is high	Low-cost prosthetic development
[10]	Cheng & Liu (2024)	Robotic fingers lack natural movement	Dual-linkage mechanical design mimics natural finger motion	ROS-based EEG teleoperation with VR environment	Emotiv EEG, PC simulation	Flexible testing platform for research	Mechanical wear and maintenance issues	Assistive robotic arm research

[11]	Satam (2023)	Prosthetic control technology still developing	Overview of latest EEG-based control methods	Iterative learning network for signal calibration	EEG sensors, robotic system	Faster adaptation to new users	Lack of real-world testing	Personalized brain-controlled systems
[12]	Wang et al. (2023)	Current systems use limited binary control	Continuous control methods needed for natural movement	EEG signal processing using ICA analysis	32-channel EEG system	Accurate hand motion classification	Mostly lab-based experiments	Brain-controlled hand devices
[13]	Radha et al. (2023)	Single signal control is unstable	Combining EEG and EMG signals improves stability	Wavelet transform with machine learning	Sensors and ML algorithms	Better detection of walking and movement patterns	High power consumption	Lower limb prosthetic systems
[14]	Cutipa-Puma (2023)	Prosthetic arms are expensive	Low-cost prosthetic with touch feedback improves user experience	Review of new electrode materials	Flexible sensors (PEDOT:PSS)	Clearer and more stable signals	Materials are less durable	BCI hardware development
[15]	Nandikolla (2022)	Limited real-world testing of robotic arms	Virtual simulation helps test control systems	Mechanical design and embedded control	Raspberry Pi, TGAM module	Improved natural finger gestures	Not fully validated in real physical environment	Bionic hand for daily activities

Table 2.1 Related Work

Maibam et al. (2024) looked into brain signals to detect hand movement without the use of muscles. Although the classification accuracy was satisfactory, the system's high processing overhead rendered it useless. The end product turned out to be unusable in real time. Its disadvantage is that it requires a lot of processing power. **Zafar et al.'s (2024)** study focused on improving movement detection affected by signal noise. Even with advanced signal analysis, noise artifacts continued to reduce accuracy. The results remained inconsistent and disappointing. The main disadvantage is sensitivity to signal disturbances**. Li et al. (2024)** investigated flexible electrode materials to improve signal quality and comfort. Even though the signals were more distinct, it was not economically feasible due to the high cost of production. The cost was not justified by the improvements. The limitation is the high cost of manufacturing the materials.

To mimic natural motion, **Cheng and Liu (2024)** constructed a robotic finger. Gestures were more organic looking, but mechanical wear and tear required them to be maintained regularly. The performance degraded and it wasn't very robust. Mechanical maintenance issues are its downfall. A review on the developments in EEG-controlled prosthetic was presented by **Satam (2023)**. Even though this analysis showed there were scientific progress, almost all of devices had little viable strength and very few have ever been tested in reality. The results were minor and descriptive. The caveat is experimental validation is limited. The importance of graded control over a ternary rather than purely binary form of movement was pointed out by **Wang et al. (2023)**. However, most systems described were only tested in a laboratory and performed low practical results. In the practical field, results were inconclusive. The limitation is the reliance on laboratory experiments.

To improve stability, **Radha et al. (2023)** combined EMG and EEG data. The system's power use and computational strain increased even in spite of a little increase in control stability. The performance improvements were insignificant and inadequate. One negative of it is its high energy usage. **Cutipa-Puma** developed in **2023** a cheap prosthetic arm with touch feedback. The extra feedback slightly improved the user experience, but the supplies used were not sturdy. The performance was generally unimpressive and transient. The barrier is weak material strength. **Nandikolla (2022)** examined a robotic arm mechanism in a virtual simulation setting. While being useful for research testing, it was not validated in actual physical settings. The results were not strong enough to be used in practical application. The drawback is the lack of practical application.

2.2. Comparative Study of Existing Study

New technology such as myoelectric controls, visual systems, and electronic muscle (EMG) systems continue to advance due to the new types of sensors and dynamic algorithms that are now available. Each method is designed to restore the hand to movement that looks as close to a biological hand as possible by looking at biological and environmental models, data, and mobility.Prosthetic limb designs use these new sensors and algorithms to create an improved level of functionality; the user has greater levels of accuracy in controlling their movement and overall adaption with their limb.

While progress has been made, many issues still exist with the systems including the power consumption of the device leading to inadequate battery life and/or limited usage durability, noise and interference that cause the systems to operate inaccurately, and device durability issues, which create problems for long-term functionality. Clearly, there remain many advancements needed to create a completely natural and functional limb for restoration, however, the current advancements in prosthetic devices and technologies have greatly improved these opportunities

No.	System Name	Year	Control Type	Technologies / Components	Core Features	Limitations	Mechanical Features	Publicly Available / Usage
[1]	EMG-Based Prosthetic Arm	2024	EMG control	EMG sensors, 3D-printed frame, servo motors, microcontroller	Converts muscle signals into hand movement, customizable grip	Affected by signal noise, needs recalibration, limited fine control	3D-printed fingers with servo motors, basic grip design	Laboratory prototype, not commercially available
[2]	High-Response Myoelectric System	2025	Myoelectric	EMG electrodes, amplifier, embedded controller, fast actuators	Fast response, reduced movement delay	High power use, Costly, complex design	Compact hand with fast motor system	Experimental stage, limited clinical testing
[3]	Multimodal Adaptive Hand	2024	Vision + tactile	Camera, tactile sensors, IMU, ML algorithms	Adaptive and precise grasp using sensor fusion	Calibration complexity, processing delay	Multi-finger design with touch sensors	Research-based system, not for public medical use
[4]	3D-Printed Grasp Arm	2023	Force + position	FSR sensors, servo motors, 3D-printed body	Lightweight; basic grasp detection	Low strength, servo heating; limited motion range	Lightweight plastic frame with small motors	Educational/ prototype use, not commercial-grade

Table 2.2 Comparative Study of Existing Study

2.2.1. EMG-based Prosthetic Arm (2024)

A prosthetic hand using EMG for motion relies on the control of muscular signals for hand movement. In addition to EMG sensors, servomotors and microcontrollers (which can easily be modified) are also involved in this technology, which uses 3D printing as its means of construction. Thus, this technology allows Stoner's prosthetic arm to work more naturally.

However, the performance of this device is largely dependent on the quality and intensity of EMG signals. However, the motion of the hand becomes erroneous or delayed if the muscle signals are weak or irregular. The device is highly susceptible to signal noise and recalibration. Additionally, it offers low fine motor control and moderate absorbing power. Consequently, the device may inadequately function in precise tasks or dragged use, making it less dependable for diurnal conditioning

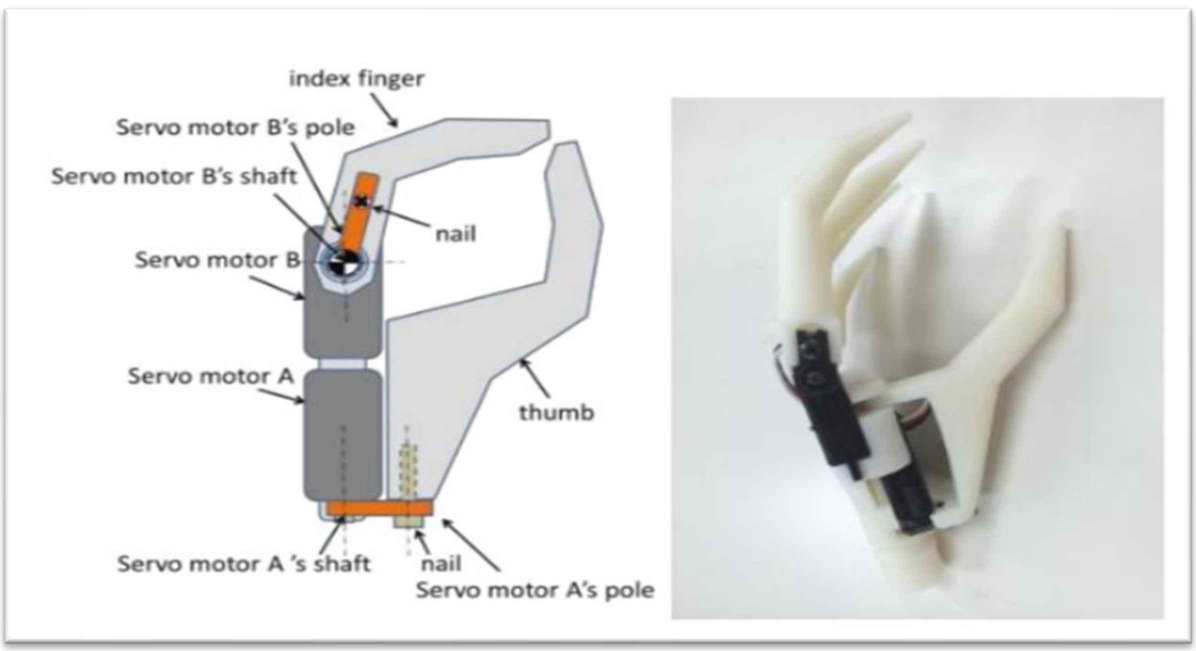

Figure 2.2.1 EMG-Based Prosthetic Arm (2024)

2.2.2. High-Response Myoelectric System (2025)

The High-Response Myoelectric System incorporates the use of EMG detectors, signal amplifiers, and a bedded regulator to ensure faster and smoother movement of the prosthetic arm. The primary goal of the High-Response Myoelectric System is to minimize the detention of stoner intention and mechanical response, perfecting real- time response and stir smoothness.

Despite the high response speed, the system is complex and requires a high quantum of power. The system demands constant estimation to ensure delicacy of the signal. The system is also prone to electrical noise, which may interfere with signal processing and cause instability. Due to the high cost of the system and the complexity of the tackle, conservation becomes delicate.

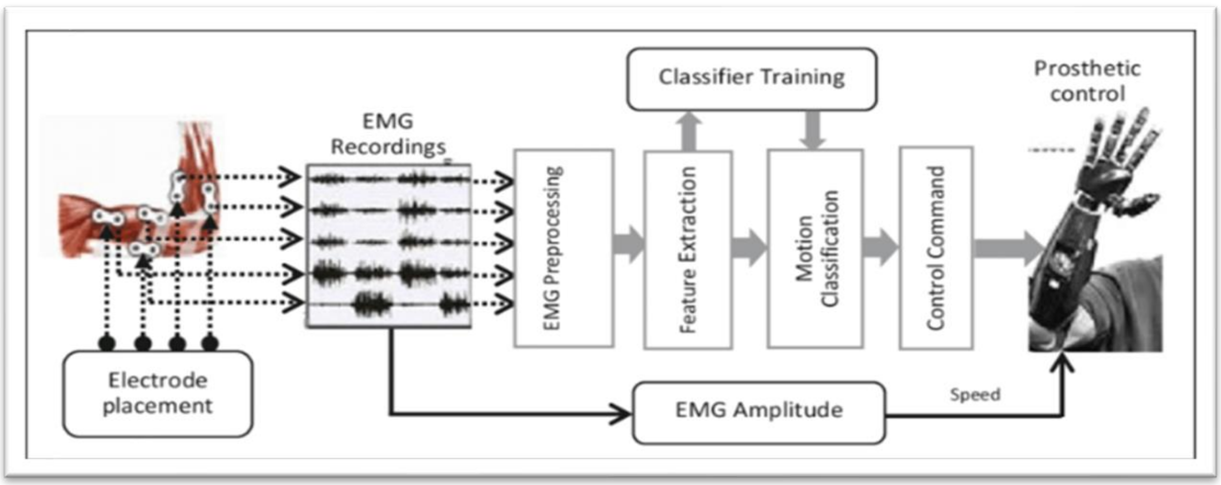

Figure 2.2.2 High-Response Myoelectric System (2025)

2.2.3. Multimodal Adoptive Hand (2024)

The multimodal adaptable arms combine video, touch and motion sensors to provide both adaptive and accurate control of movements in a prosthetic limb system. A combination of camera modules, inertial measurement units (IMUs), and algorithms utilizing machine literacy, remap the various types of input for achieving accurate tracking of movement. This improves both grip perfection and situational awareness (i.e., within one's surroundings).

Given the level of complexity involved in designing this type of system, it requires both substantial amounts of computing power and additional overhead (i.e., such as detectors). Because of this, proper evaluation (including smoking cessation training) will be required to ensure that it works effectively. Additionally, any delays due to the time associated with detection and/or the time taken to process information may slow the overall functioning of the system during actual usage. Preservation of the system under real-life conditions may be very difficult, if not impossible, because of the number and severity of the variables affecting total system performance. Therefore, in general, this type of system (i.e., multimodal adaptable arms) cannot be considered practical for any type of long-term application.

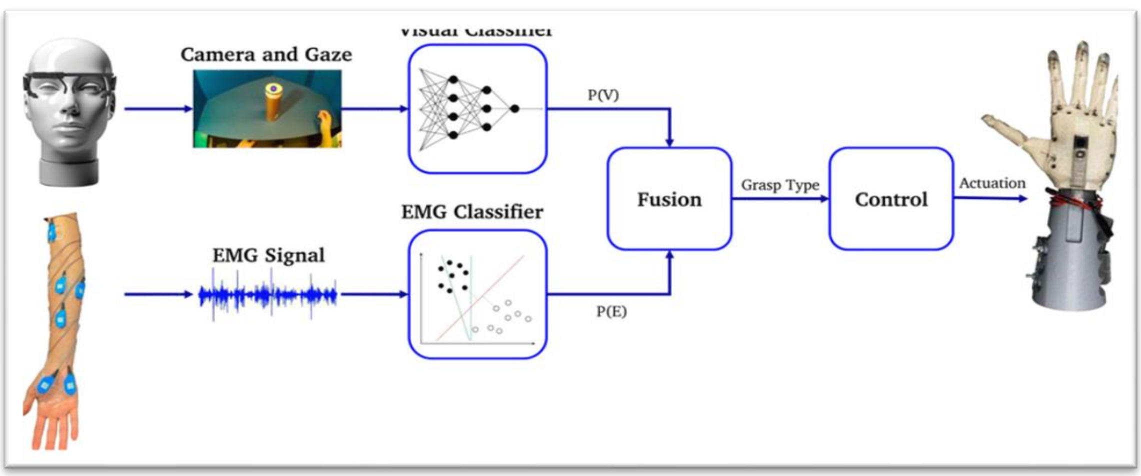

Figure 2.2.3 Multimodal Adaptive Hand (2024)

2.2.4. 3D-Printed Grasp Arm (2023)

The Grasp Arm published in 3D is based on the use of force and position control by FSR detectors and servomotors. The feather light design is achieved by 3D printing, making it cheap and ideal for introductory operations. The system is able to measure the grasping force and movement to guarantee safe operation.

Still, the mechanical robustness of the design is compromised by the presence of feather light accessories. The system has a low cargo-carrying capacity and a specified range of stir. The servomotors are prone to heating when in continuous operation, which is a factor in continuity and stability. The system also lacks fine perfection control, making it infelicitous for heavy or intricate operations.

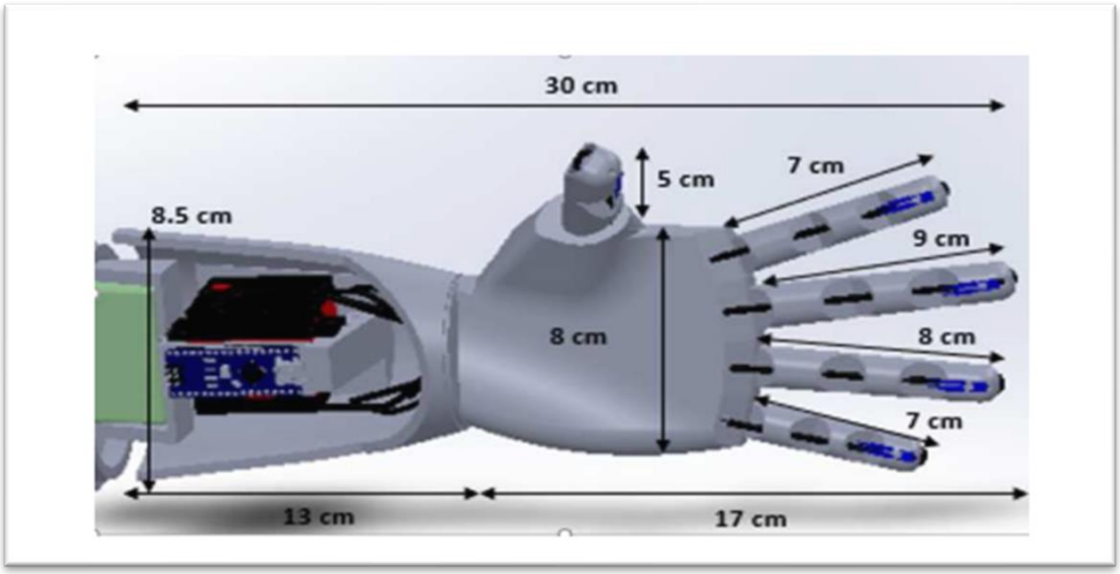

Figure 2.2.4 3D-Printed Grasp Arm (2023)

3. REQUIREMENT ANALYSIS

The system conditions were interlinked via a comprehensive literature review; assessment of what it means to be EEG- grounded prosthetic systems, and discussions with potential users and experts in the biomedical and robotics communities. The foremost ideal was to ascertain the vital attributes required to create a dependable, responsive, and stoner-friendly brain-controlled prosthetic arm. The system conditions focus on improving signal perfection, response detention, perfecting stoner comfort, and affordability through utilization of a custom- designed EEG helmet and open- source technologies.

3.1. System Requirements

3.1.1. Functional Requirements

Functional Conditions outline the particular tasks and operations that the system must undertake to accomplish its desired objects.

a) EEG Signal Acquisition:

The system must acquire EEG signals through a non-invasive headset or a specially designed helmet to precise record the user’s brain exertion.

b) Signal Pre-processing and Filtering:

The system should eliminate noise, unnecessary, and faulty frequency factors from the acquired EEG signals to improve overall signal quality.

c) Command Discovery and restatement:

The system must dissect the filtered EEG signals and restate them into precise control commands that correspond to the user’s willed arm movements.

d) Robotic Arm Control:

The system should transmit accurate and timely control instructions to the robotic arm’s microcontroller, allowing conduct similar as gripping, lifting, or releasing objects.

e) **Data Logging:**

The system should store raw EEG data, reused signals, and produced control commands for testing, analysis, and performance evaluation.

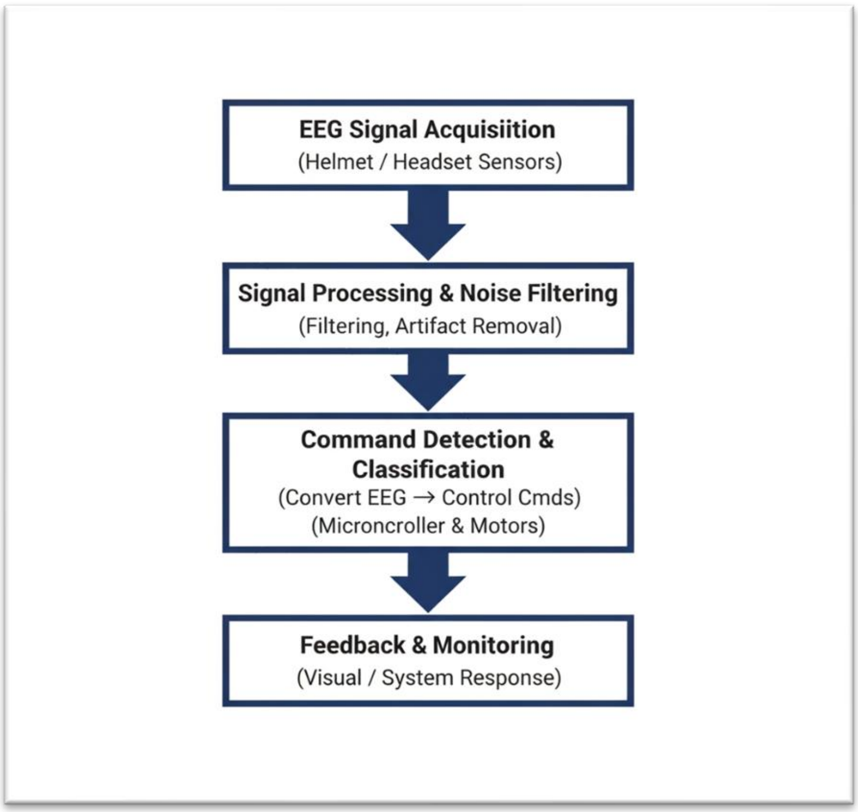

Figure 3.1.1 Functional Requirements

3.1.2. Non-Functional Requirements

Non-functional conditions specify the quality characteristics, performance standards, and usability potential of the system.

a) Trust-ability:

The system should run constantly and have stable performance over a long period without frequent recalibration or signal interruptions.

b) Delicacy:

The EEG signal interpretation and corresponding arm motion should reach a high level of perfection to avoid unintended behavior.

c) Response Time:

The time detention between the stoner’s study and the robotic arm’s motion should be minimum to enable real-time commerce.

d) Scalability:

The system armature should enable unborn expansion, such as the inclusion of fresh detectors or sophisticated AI-grounded modules.

e) Affordability:

The system should remain cost-effective by using readily available tackle factors and open-source software tools.

3.2. Use Cases:

The entire process of working of the proposed EEG-grounded prosthetic arm is a systematic sequence, right from the inception of the system to the movement of the physical arm. Every step is taken to ensure the correct transmission of signals, secure processing, and reliable actuation. The resulting process flow describes the entire functional inflow of the system.

3.2.1. System Power on And Initialization:

Upon turning on the system by the user, the ESP32 microcontroller initializes its peripherals, such as GPIO limbs, periodic ports, and the Bluetooth module. The Arduino-grounded firmware conducts a tone-individual check to insure that all tackle factors are functional. After the successful initialization process, the system positions the prosthetic arm in its dereliction" Home" position, indicating that it is ready to receive commands.

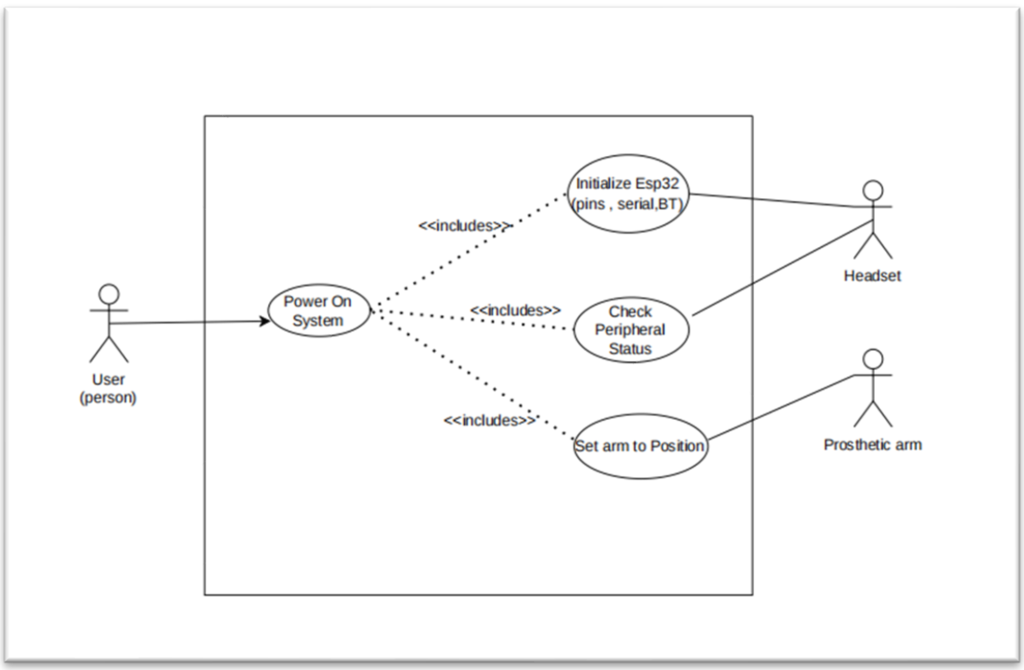

Figure 3.2.1 System Power on And Initialization

3.2.2. Establishing Bluetooth Connectivity:

After initialization, the ESP32 goes into scanning mode to detect the headset through its distinct Bluetooth address. After the device is configured, a secure wireless periodic link is created. This link becomes the central ground for data, enabling the seamless transfer of brainwave data from the headset to the regulator without the use of physical cables.

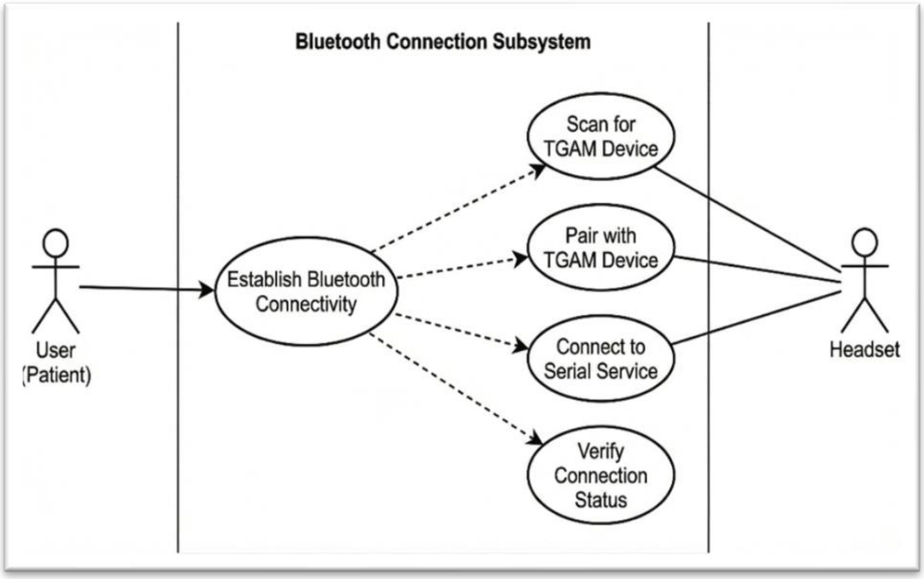

Figure 3.2.2 Establishing Bluetooth Connectivity

3.2.3. Real-Time EEG signal Acquisition:

Once the connection is established, the forepart and observance electrodes of the headset record the EEG activity of the user. The TGAM chip in the headset converts the analog signals into digital packets of data. These packets, which contain the frequentness of the brainwaves, are then sent to the ESP32 for processing.

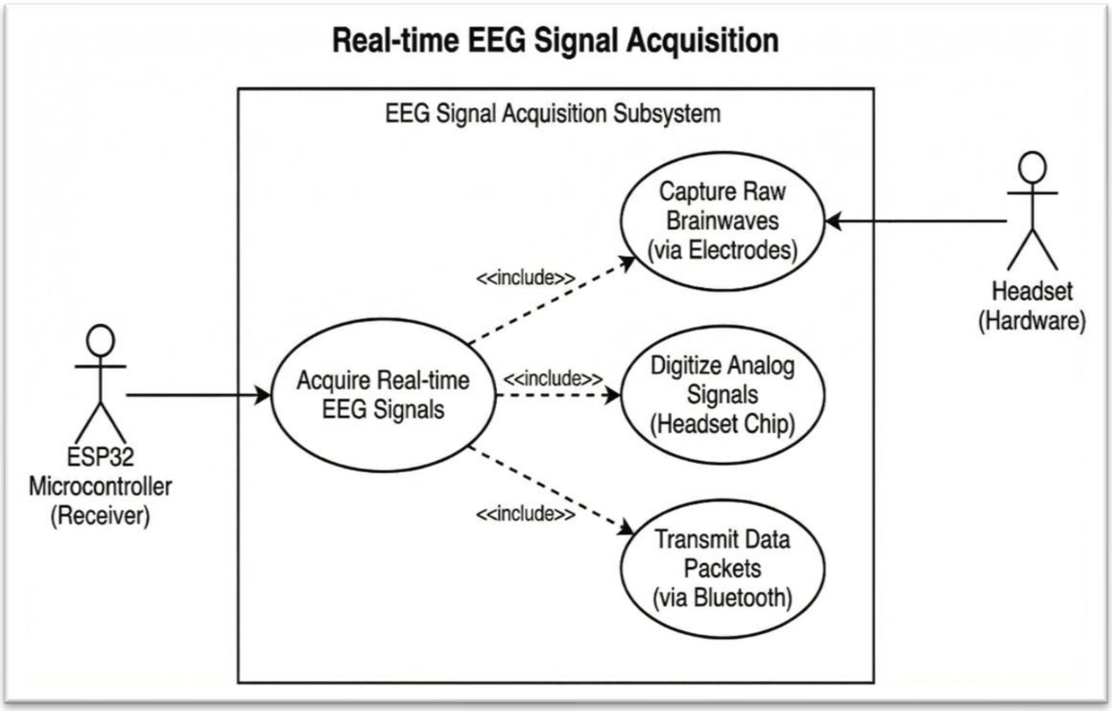

Figure 3.2.3 Real-Time EEG signal Acquisition

3.2.4. Limited range of movement control:

The ESP32 obtains raw bytes of data from the headset and "parses" them to prize usable integer values for Attention and Contemplation. During this process, the system also checks the "PoorSignal" status byte. However, the system cautions the user and halts farther processing to help the arm from making erratic or unintended movements, If the electrodes lose contact or the battery situations are low.

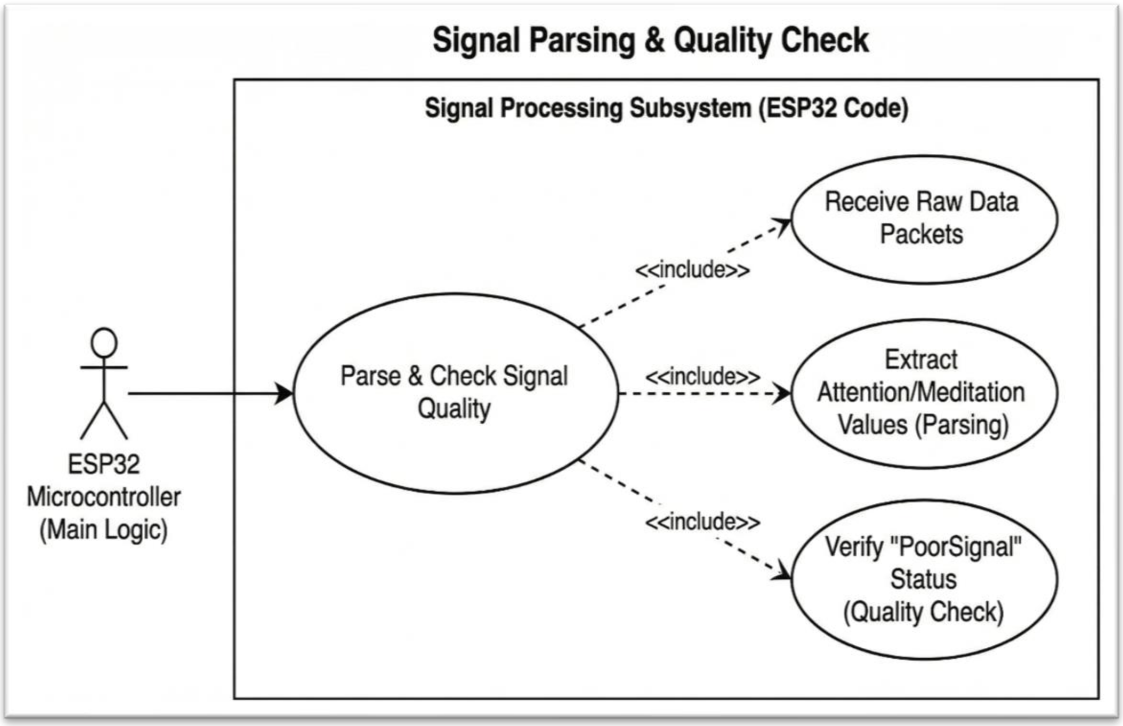

Figure 3.2.4 Signal Parsing And Quality Check

3.2.5. Mental Intent Decoding (Attention/Meditation):

During this stage, the system is able to interpret the internal state of the user based on the values parsed. The ESP32 sense compares the current Attention or Contemplation states. If the user's focus surpasses this threshold, the system is able to interpret this internal intensity as a particular intent, similar to "near Grip" or "Lift Arm," rephrasing abstract studies into practicable commands.

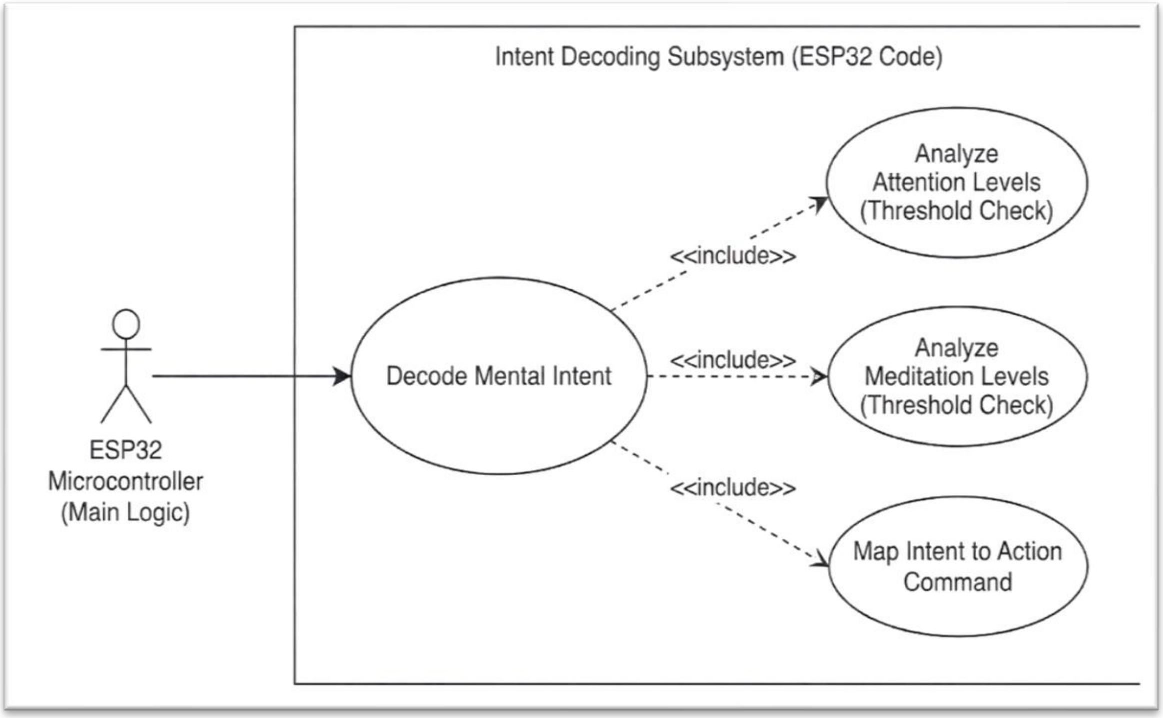

Figure 3.2.5 Mental Intent Decoding (Attention/Meditation)

3.2.6. Servo Motor Actuation (Arm Movement):

After the intent is decrypted, the ESP32 produces control signals that are sent to the servomotors in the prosthetic arm. The motors turn to specific angles as required by the law, acting like opening or closing the hand in physical motion. This final process completes the cycle from the user''s internal attention to physical interaction with the terrain.

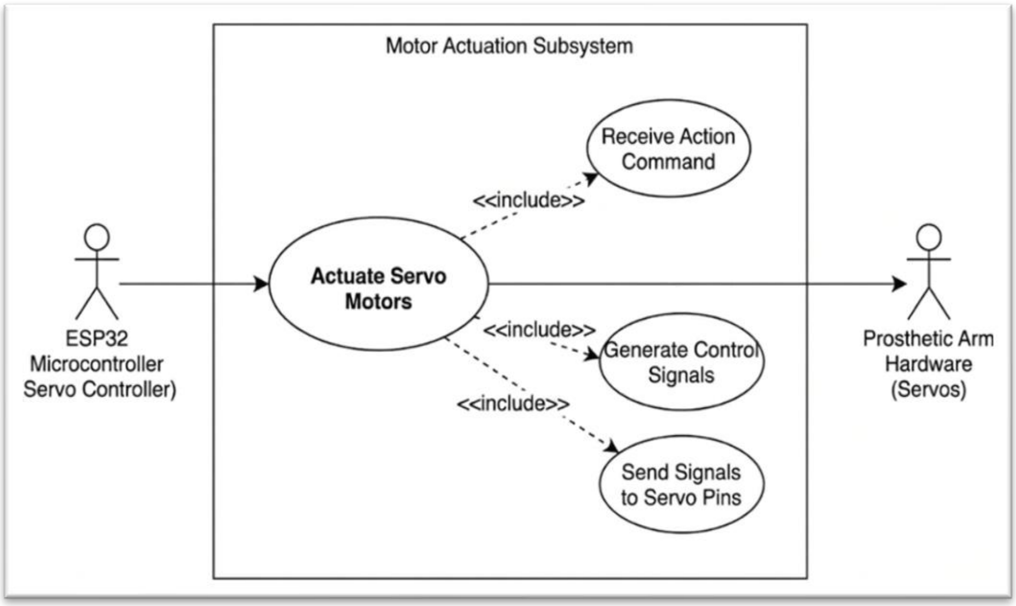

Figure 3.2.6 Servo Motor Actuation (Arm Movement)

4. DATA FLOW DIAGRAM (DFD)

Data Flow plates (DFD) are employed to visualize the inflow of information within the brain-controlled prosthetic system. They illustrate how data is reused by the system in terms of inputs and labors, without fastening on the underpinning control sense of timing.

4.1 Context Level DFD (Level 0)

The Context Level DFD, or position 0, is a representation of the overall Brain-Controlled Prosthetic Arm System as a single high-position process (labeled 0.0). The main goal of this Context Level DFD is to establish the boundaries of the system and determine its relationships with external realities.

From the illustration

a) **System Boundary:**

The completely ESP32-grounded processing unit is depicted in the central circle.

b) **External realities**:

The system has four external sources sinks.

- USER provides the internal intent through brain signals and receives visual/haptic feedback.
- BRAIN SIGNAL Detector (EEG HEADSET) The tackle that captures EEG signals and sends raw digital signals to the system.
- PROSTHETIC ARM (tackle) the physical selector that receives motor control commands to perform actions.
- POWER force provides the required electrical power for the system's operation.

c) **Major Data Flows:**

The main input inflow is the Raw Signal Data from the detector, and the main affair inflow is the Motor Control Commands sent to the prosthetic arm tackle.

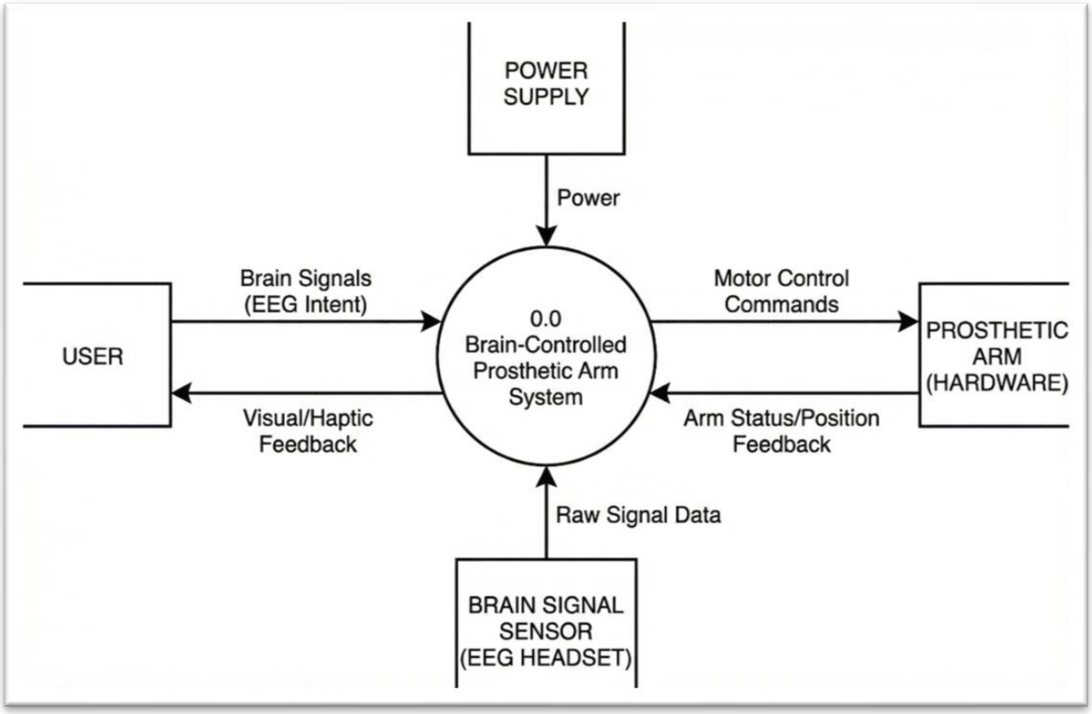

Figure 4.1 Context Level DFD (Level 0)

4.2 DFD Level 1(System Decomposition)

The position 1 DFD system decomposition reveals the major functional modules of the single process from the Context Level, showing the internal data processing method of the ESP32 microcontroller.

This illustration shows four major processes

- 1.0 Bluetooth Communication Manager: This is responsible for managing the wireless communication, where it receives the continuous flow of Raw Signal Data from the headset.
- 2.0 EEG Signal Parser: This module parses the raw data to obtain specific and meaningful integer values for Attention and Meditation levels, filtering out unnecessary noise.

- 3.0 Command Generation Logic: This is the decision-making module. It receives the parsed data and compares it with the predefined settings stored in the D1 System Configuration & Thresholds data store to decide the course of action.
- 4.0 Motor Actuation Controller: This process is responsible for generating the physical signals for the servomotors in the prosthetic arm based on the Action Command received from the logic unit.

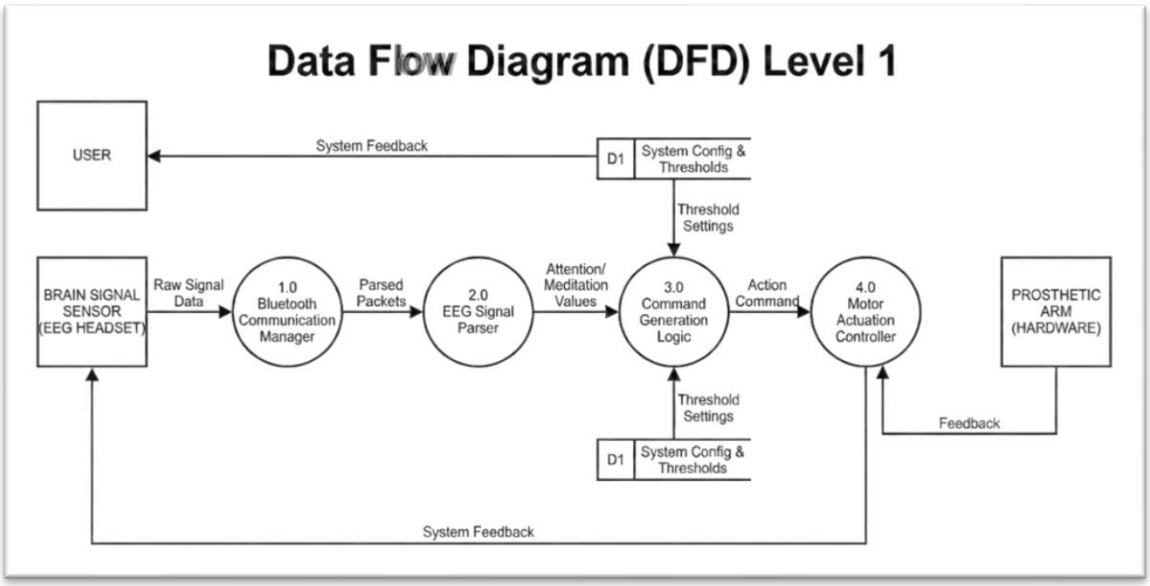

Figure 4.2 DFD Level 1(System Decomposition)

4.3 Detailed DFD Level 2 (Exploding Process 3.0)

The Level 2 DFD breaks down the process "Process 3.0: Command Generation Logic" into minute details about how the system processes brainwave information to arrive at a decision.

Breaking down the process as shown in the diagram:

- Inputs & Data Store: The process takes in real-time Attention and Meditation Values. At the same time, it accesses the Threshold Set points (Attention Threshold = 60, for example) stored in the D1 Data Store.
- Evaluation Sub-Processes (3.1 & 3.2): The values are compared to their respective set points in sub-processes 3.1 and 3.2. This yields an "intermediate State" (such as designating the current Attention level as "High" or "Low").
- 3.3 Apply Decision Rules (Logic Resolution): This final sub-process takes in the states from both evaluation units. It uses pre-defined rules of priority (as shown in the diagram: for example, "If Attention is High -> Grip") to resolve any conflicts and produce a single "Final Action Command" (Grip, Release, or Hold), which is then transmitted to the motor controller.

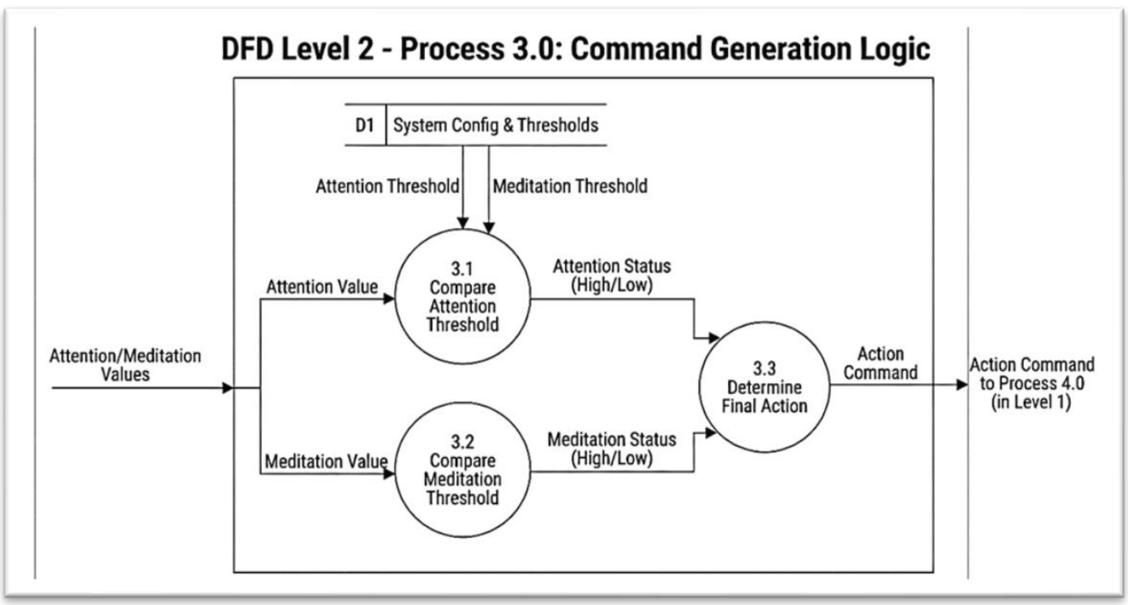

Figure 4.3 Detailed DFD Level 2 (Exploding Process 3.0)

5. SYSTEM DESIGN:

5.1. System Architecture Overview:

High- position functional armature of the suggested Brain- Controlled Prosthetic Arm system is shown in Figure 5.1. Modular, the design is split into five separate subsystems managing incoming stoner information from the neural activity to the ultimate physical action of the prosthetic branch.

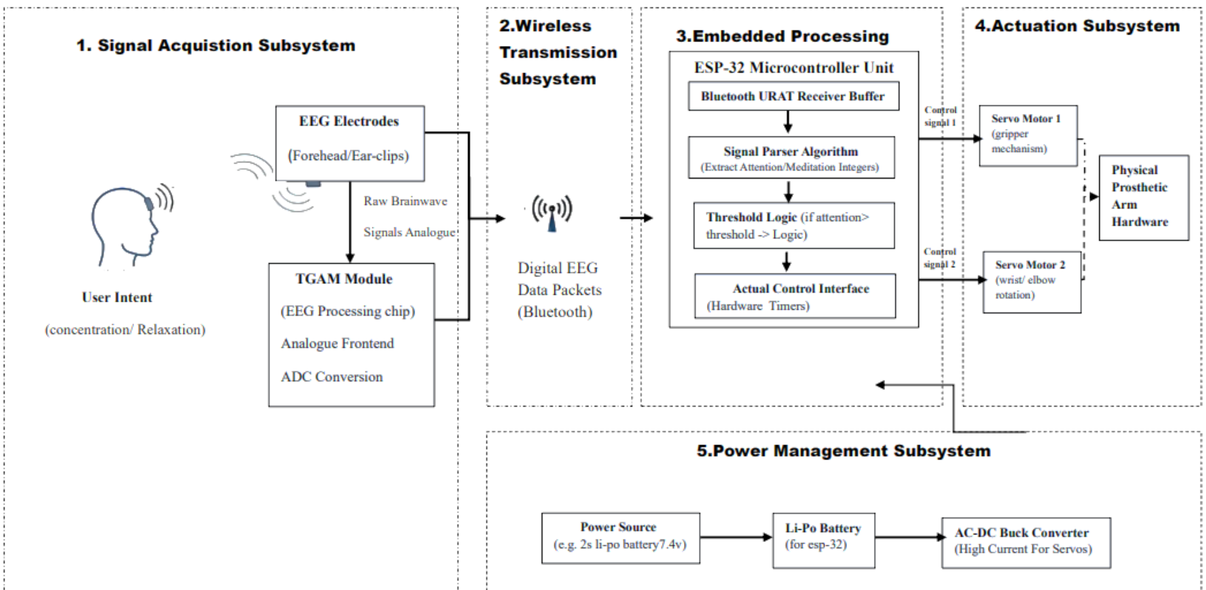

Figure 5.1 System Architecture Diagram of Brain- Controlled Prosthetic Arm

5.1.1 Signal Acquisition Subsystem (Input Layer):

The portal between the mortal stoner and the machine is this. Using dry EEG electrodes positioned on the forehead, or FP1 position, and an observance clip reference, it captures the stoner's intention (like to unwind or relax). The low- voltage raw analog brainwave signals enter the TGAM (Think Gear ASIC Module). To pack the signals into digital data, this module does onboard modification, noise filtering, and Analog- to - Digital Conversion (ADC).

5.1.2 Wireless Communication System:

Bluetooth technology is used to ensure the stoner's mobility and get rid of wired connections between the hat and the arm. The TGAM module produces digital EEG packets that are sent wirelessly as a periodic data sluice to the central regulator unit.

5.1.3. Subsystem for Bedded Processing (Core Logic):

The ESP32 Microcontroller Unit (MCU) lies at the core of the system. Through several internal levels, it manages decision- making and data processing.

- The high-speed incoming periodic data stream is received and temporarily stored in the Bluetooth UART buffer.
- The Signal Parser Algorithm decodes the incoming packets to value useful integer values that is, Attention and Contemplation circumstances reflecting internal countries.
- Decisions Threshold sense Determines if a given action closing gripper, say should be tripped off by comparing the real-time parsed values against preset estimating thresholds.
- Interface for actuators control Based on the decision sense, uses tackle timekeepers to cause exact digital control signals for the motors.

5.1.4. Sub caste Affair, actuation system:

This sub caste converts the digital instructions from the ESP32 into actual mechanical action. Typically composed of several servo motors

- **Servo Motor 1** receives Control Signal 1 to activate the gripper medium— open/ close.
- **Servo Motor 2** gets Control Signal 2 to manage wrist gyration or elbow movement. These engines propel the physical attack of the prosthetic arm unit.

5.1.5. Power Control System:

This subsystem guarantees appropriate and consistent power distribution to all elements. The main power source is utilized, for instance, a 7.4 V 2S Li- Po battery is used. It is will into two ordered roads. The high current needed by the servomotors is supplied by a separate DC-

DC Buck Converter, which prevents MCU resets while the motor is operating. A 5V regulator gives clean power to the sensitive ESP32 MCU.

5.2. UML Class Diagram Description:

The complex object-oriented software architecture created for the ESP32 embedded firmware is shown in Figure 5.2. To provide modularity, encapsulation, and ease of maintenance, the firmware is separated into different classes even though it is developed using the Arduino framework (C++). The diagram illustrates how each module works together to convert brain signals into motions by defining its attributes (data fields) and actions (methods/functions).

The following is a description of the main parts of the firmware structure:

5.2.1. MainSystem_Sketch Class:

This class, which corresponds to the standard Arduino UNO file, serves as the application's primary entry point.

- One of its responsibilities is to oversee the overall operation of the system. While the setup () method initializes all other subsidiary objects, the loop () function offers the continuous execution cycle by carrying out the processing methods of other classes in the correct order.

5.2.2. EEG_Receiver Class:

This class controls the low-level wireless communication layer.

- **Features:** It manages the Bluetooth Serial object (bt_Serial) and includes setup parameters like the baud rate.
- **Operations:** It provides an abstraction layer for hardware serial communication, comprising functions like init () to establish the connection and readRawByte () to retrieve incoming data bytes from the headset's Bluetooth stream.

5.2.3. Signal Parser Class:

This class acts as the data interpreter and implements the specific communication protocol of the TGAM module.

- **Features:** It maintains internal buffers (payload Buffer) to build incoming packets and records the most recent extracted valid measurements for signal Quality, meditation Val, and attention Val.
- **Operations:** The parse_Packet (byte data) core method is used to process the raw stream byte-by-byte in order to identify valid packets. Getter methods like get_Attention () allow other parts of the system to safely access the most recent processed data.

5.2.4. Brain Logic Class:

This module contains the basic decision-making algorithms for the prosthetic system.

- **Features:** it include persistent configuration settings and user-defined thresholds (attention threshold, meditation threshold) that specify when an action should be triggered.
- **Operations:** The evaluate States (int att, int med) method compares the current biometric values to thresholds that have been stored. After determining the appropriate high-level state (such as Grip, Release, or Idle) using predetermined logic rules, it returns a Command State..

5.2.5. The Motor Controller Class:

This class functions as the physical actuation hardware abstraction layer (HAL).

- **Features:**It has the ability to retain the hardware pin assignments of popular Arduino Servo objects, like gripperServo and elbowServo, that match the joints of the prosthetic limb.
- **Operations:** It provides high-level methods like executeCommand (CommandState cmd), which leverage internal helper methods like setGripperAngle() to translate a logical instruction from the BrainLogic module into exact physical actions. As a result, the motors may get the PWM impulses they need.

5.2.6. Inter-class Relationships (Associations):

Figure 5.2's directional arrows show how data and dependencies flow. The MainSystem_Sketch coordinates all classes. EEG_Receiver sends raw bytes to SignalParser, which then sends parsed integer values to BrainLogic. Finally, BrainLogic gives the MotorController instructions on how to execute the actionable directives.

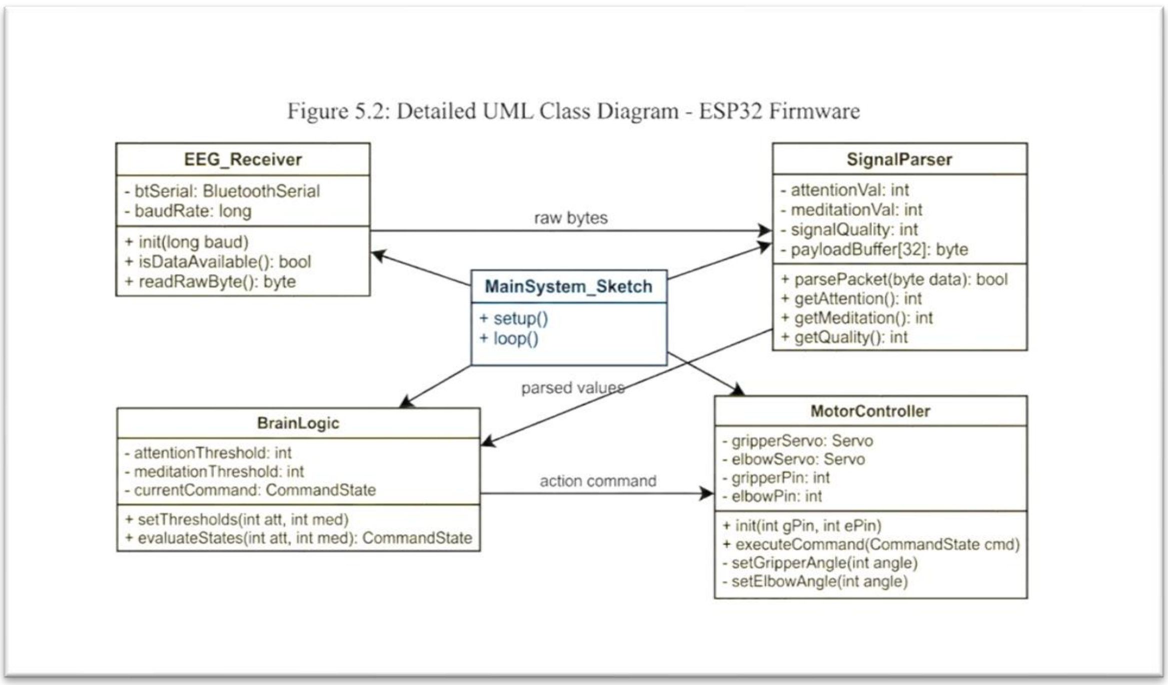

Figure 5.2: Detailed UML Class Diagram - ESP32 Firmware

Figure 5.2. UML Class Diagram

5.3 Description of a UML Sequence Diagram

Figure 5.3 shows the Brain-Controlled Prosthetic Arm system's dynamic behavioral view. It displays the exact temporal sequence of signals transmitted back and forth between different hardware and software components throughout time in order to accomplish the primary use case of translating human neuro-intent into physical actuation.

The sequential flow is described chronologically below:

5.3.1. Initiation and Data Transmission:

When an external user generates brainwaves or neurological signals related to a certain objective, such extreme concentration, the process starts. These signals are recorded, digitized, and packetized by the EEG headset hardware. This stream is then continually transmitted as "Raw Data" via the Bluetooth Serial Port Profile (SPP) to the main processing unit, which is represented by the ESP32 Main System lifeline.

5.3.2. Continuous Processing Loop:

The recurring "loop" frame, which is where fundamental data processing takes place, indicates the ESP32 firmware's primary execution cycle. In every cycle:

- **Parsing:** The received raw data is sent to the :SignalParser object by the ESP32 MainSystem using the parsePacket(rawData) message. The parser returns the obtained integer Attention and Meditation values to the main system after decoding the packet.
- **Logic Evaluation:** After processing these values, the main system provides the Brain Logic object with the evaluateStates(Att, Med) message. After comparing the current data with predetermined criteria to ascertain the required action, the logic module sends a specific Action Command, such as "Grip" or "Release," back to the main system.

5.3.3. Conditional Actuation (Alt Frame):

To ensure effectiveness, an alternative ("alt") frame protects the actual actuation stage. The actuation sequence starts only when [If Command!= Idle].

- The executeCommand(Command) message is sent to the :MotorController object by the ESP32 MainSystem when a valid movement command is received.
- The motor controller changes this high-level command into specific hardware signals. It then sends a write Microseconds (PWM Signal) message to the actual Servo Motor (Hardware).
- Finally, the prosthetic arm moves as the servo motor responds to the PWM signal.

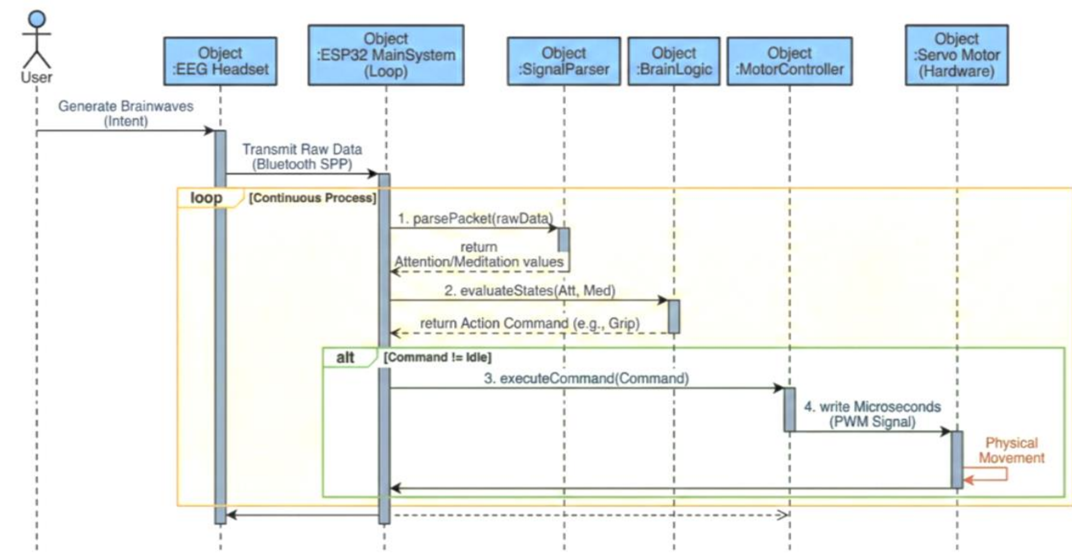

Figure 5.3: System Processing Sequence (Brain-to-Motion Flow)

Figure 5.3 UML Sequence Diagram

5.4 Collaboration Diagram:

A Collaboration Diagram (Communications Diagram) illustrates the structural way the system is organized and the behavioral interactions between each of those structural elements to accomplish a task, such as moving a prosthetic arm to achieve an intended movement based on the user's (brain's) intention. The Collaboration Diagram emphasizes the connection between the objects and their inter-relationships; whereas, a Sequence Diagram focuses on the order in which an object performs an activity.

5.4.1 Interactions Broken Down Technically:

Desire Generation (Message 1): The process starts when the user (amputee) produces cerebral activity, or signals in the brain, that indicate a particular desire, such shutting the hand.

Signal Capture & Transmission (Messages 2-3): These unprocessed brain signals are recorded by the EEG headset and sent to the Bluetooth module. After that, the module sends wireless packets containing the data to the main controller.

Data Analysis & Interpretation (Messages 4-5): After receiving the packets, the Microcontroller_Unit asks the Signal_Processing_Logic to identify the data and filter out noise. The interpreted purpose (such as "Grip") is given back to the controller after classification.

Hardware Actuation (Messages 6–8): The controller issues an actuation instruction to the Motor_Control_Logic based on the intent. The Prosthetic Arm Structure moves physically because of this logic's computation of the required pulse-width modulation (PWM) for the Servomotor.

Importance for the Project:

This diagram demonstrates how the mechanical output layer and the input sensing layer integrate seamlessly. In order to develop a functional Brain-Computer Interface (BCI), it illustrates how the system guarantees real-time communication between hardware components and software algorithms.

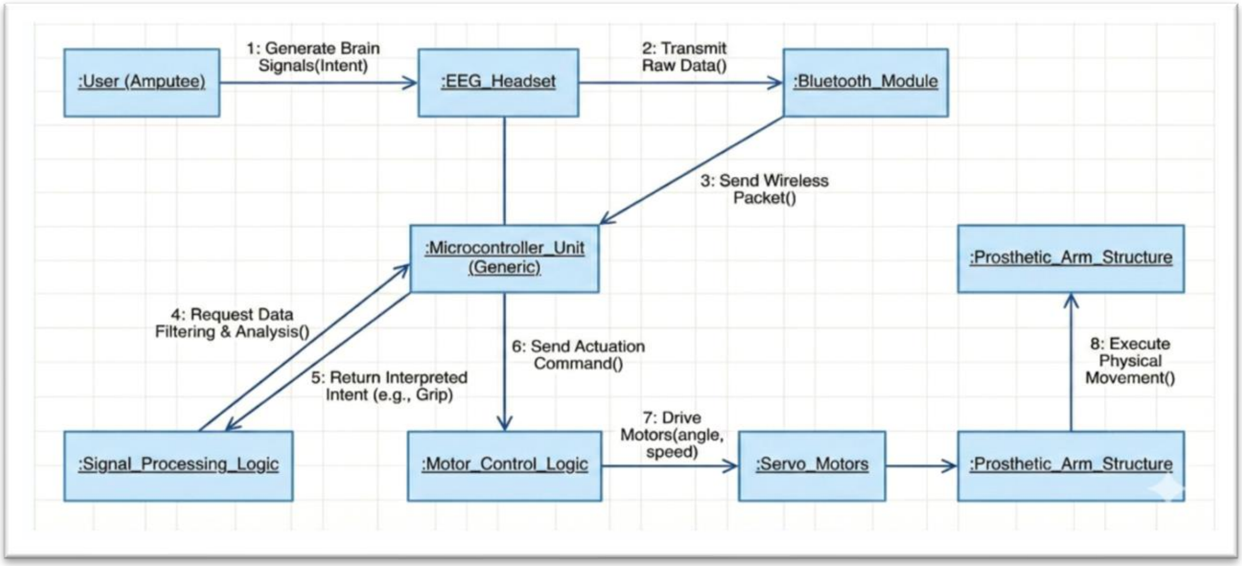

Figure 5.4 Collaboration Diagram

5.4.2 ER Diagram:

An ER (Entity Relationship) diagram depicts the components that make up the Brain Controlled Prosthetic Arm System, where each component entity is represented as an entity; the type of relationship between the entities is shown as a line between the entities;

• **User Entity:** The User Entity is used to represent the user of the system, which has an ability to configure the system and use the brainwave signals from their brain to control the arm, via neuro-signals; a one-to-one relationship exists between User and Headset Unit Entity as they both generate a signal from the user through their brainwaves (neuro-signals).

• **Headset Unit Entity:** The Headset Unit Entity is a composite device containing many other devices (battery pack (2 AA), Bluetooth module, and TGAM Sensor).

• **The TGAM Sensor has the following properties:** Processed Attention Level, Processed Meditation Level and Signal Quality; the TGAM also has electrodes (two types: ear and forehead).

• The **Bluetooth module** stores features related to the transmitted packets of data.

• The **Battery Pack** holds the Voltage Power Status attributes.

• There is a 1-to-1 transmit relationship between the **Headset Unit** and the Esp-32 Controller.

• The **Esp-32**, which is both an Arm Controller and Bluetooth Receiver, receives data from the Arm and controls its movement. It has three major features: the Current Settings, the Threshold Settings, and the Processing Logic Code. It is responsible for controlling 1 or more Servo Motors - thus, each Controller can control many Servo Motors.

• The **Servo Motor,** which acts as the Actuator, is responsible for causing movement. Its two main features are Target Angle Value and Physical Action/Grip.

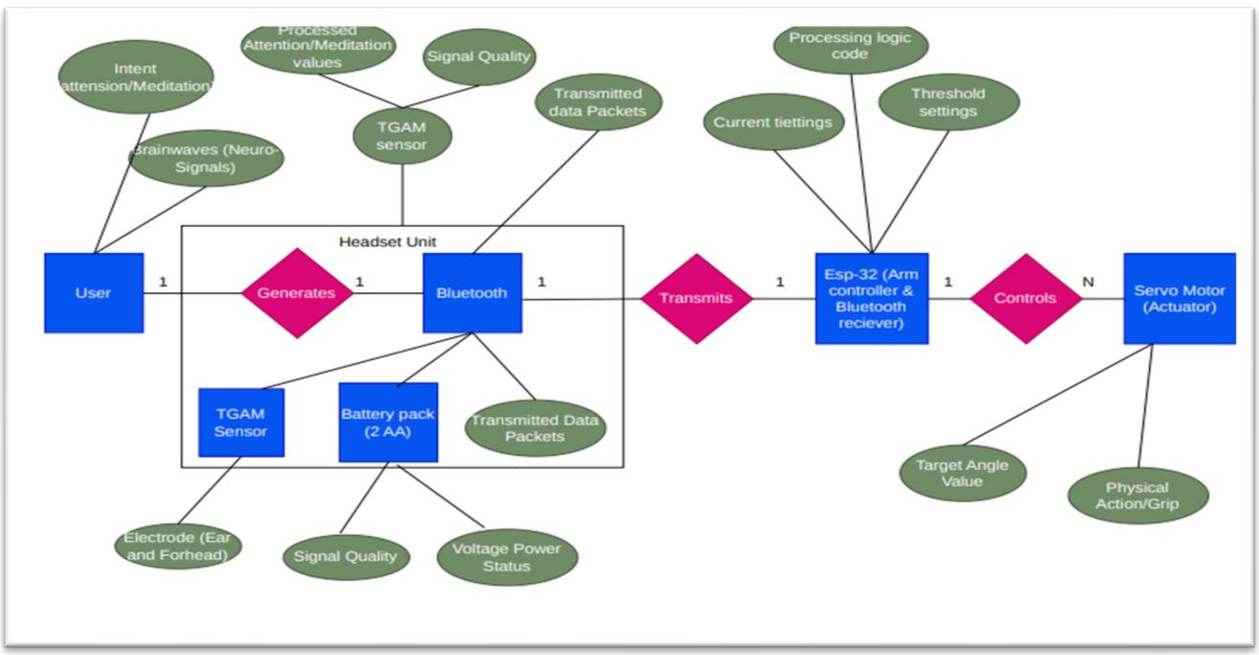

Figure 5.4.2 ER Diagram

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