Princess Sumaya University for Technology

Department of Data Science

Fall Semester 2023/2024

MindControl

BCI System Decoding Imagined Speech EEG Signal

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Project Submitted in partial fulfillment for the degree of Bachelor of Science in Data Science

Fall Semester – 2023/2024

Declaration of Originality

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Acknowledgments

We would like to express our heartfelt gratitude for our university, Princess Sumaya University as they provided and supported our project with a fund. The success of our project relies on the guidance and support provided by experienced individuals. Therefore, we want to extend our sincere thanks to those who passed on their knowledge and assisted us in completing our project journey so far. Our deepest gratitude goes to Dr. Serin Atiani, for being our monitor and supervisor in this project. We also would like to thank Dr. Adiy Tweissi and Dr. Remah Bani Younisse for their invaluable support and dedication. Their encouragement fueled our motivation, and every interaction with them, seeking assistance or presenting our work, left us inspired. The collaborative efforts and support from all project contributors played a crucial role in our achievements. We also appreciate the encouragement and support provided by our family individuals throughout our experience.

Summary

Advanced technologies in biomedical signal processing and in neuroscience have made it possible for humans to directly communicate with machines through brain signals. Brain-computer interface studies have been emerging with interest in the field of artificial intelligence. AI has led to noticeable improvement in automatic detection of patterns in brain signals allowing BCI systems to be more reliable and accessible. The best non-invasive analysis that helps in monitoring brain activities, studying changes in a person's mind, and controlling movement to either body parts or devices is the electroencephalography (EEG) technology. EEG has been used mostly in medical applications to assist people with disabilities perform normal tasks independently. And it is the most commonly accepted method due to its high temporal resolution, low cost, safety, and portability [1].

In this project, our main focus is concentrated around people with severe paralysis such as, quadriplegia and dysarthria paralysis. Loss of communication or speech can also be a cause to implement EEG-BCI based systems to help them avoid difficulties when communicating with others leading to an increased quality-of-life.

This project aims in processing and decoding imagined speech from EEG brain signals to be able to move a wheelchair to the four directions (forward, backward, left, right). Because our project is just a proof of concept, the physical design is implemented using a demo car which can be implemented with little modification to any electrical wheelchair. Imagined speech recognition is a difficult task to achieve within an acceptable range of classification accuracy when comparing it to other modalities like motor imaginary.

List of Abbreviations

BCI: Brain-Computer Interface.

EEG: Electroencephalogram.

fMRI: Functional magnetic resonance imaging.

fNIRS: Functional infrared spectroscopy.

MEG: Magnetoencephalography.

MRI: Magnetic resonance imaging.

PET: Positron emission tomography

ECoG: Electrocorticography.

SNR: Signal-to-Noise Ratio

Table of Contents

Table of Figures

Table of Tables

Chapter 1

Introduction

1.1 Overview

Strokes, spinal cord injuries, mistakes during childbirth and nerve disorders can cause paralysis. Paralysis is the inability to move a part of the body. Degree of paralysis severity can determine the case of paralysis, whether permanent or temporary. Permanent paralysis means the person cannot recover the injured nerves and is irreversible, which makes them dependent on mobility devices to assist them in their everyday life.

Brain-computer interface (BCI) is a technology that has been made increasingly available to the medical field to help support people with quadriplegia paralysis (spinal cord injury), dysarthria paralysis (speech disorder) or with communication disabilities with their speech or movement through brain signals. BCI systems have been mostly used to read brain signals from the motor cortex in the brain that take place when a paralyzed person imagines making a movement with a limb, he/she can no longer control. The BCI system then decodes that brain signal to use it to direct a motor of a wheel chair or an artificial limb. This project aims to build a BCI system based on imagined speech rather than imagined movement.

1.1.1 Project Motivation

Our project aims to build a system to help assist people who suffer from quadriplegia paralysis and who have lost their ability to speak; dysarthria paralysis. Our system will read the brain electric signal from a subject using an electroencephalogram system (EEG). The goal of our system is to decode the imagined speech by subject and based on their choice of imagined word (forward, backward, right, and left) the system will output a control signal that will control an electric motor of a device. As the system we are building is a proof of concept and since buying an electric wheelchair is far too expensive for the budget of this project, we will implement the control signal on the electric motor of a small demo car, however the same system with very little adjustment can be implemented with an electric wheelchair affecting its four directional movements.

1.2 Problem Statement

There are numerous technologies that have been developed, to accommodate the needs of people with paralysis, however they are unable to accommodate all degrees of paralysis, in particular the patients who lost utter movement and communication abilities. The focus of the previously developed devices was mainly on decoding imagined motor cortex signals, a part of the brain which provides a high level of interpretation of brain signals.

For more severe forms of paralysis and for people who have been paralyzed for a long time, imagined motion of an arm or a leg can no longer be a viable option, and for that the principle of BCI systems has to develop to use signals from other sources in the brain. In this project we will work on developing a BCI system that uses imagined speech signal that emits from the auditory cortex when the subject imagines saying one of four words (forward, backward, right, and left).

Our project will use an imagined speech signal that is captured using a simple EEG system with 5 acquisition probes. Using the imagined speech signals rather than the imagined motor signal poses added theoretical and practical difficulties due to the noisier nature of the imagined speech signal. Yet this transition to imagined speech as an example of using BCI systems with a wider range of brain signals is important to widen the scope of BCI systems in general to allow them to serve a more diverse set of functions.

1.3 Related Work

Approximately 5.4 million people have some form of paralysis [2]; they are usually dependent on mobility devices for assistance in everyday life. For this reason, recent research has shown that the use of biomedical signals can help in communication between humans and machines or devices.

1.3.1 BCI System

In more than 50 years of research, Brain-Computer Interface (BCI) has been used to exchange information between the brain and computers [3]. The first attempt to record electrical activities from the brain using an EEG based BCI system was in 1973 by Vidal, J. J. [4]. BCI systems have been used in various application fields such as in the medical field, as it is used to restore mobility in patients with motor impairment and restore completely locked-in individuals, it also enhances user experience in computer games and it is widely used in research tools to give real-time feedback when decoding brain signals [3].

1.3.2 EEG Signals

Signal acquisition can be categorized into an invasive and non-invasive BCIs. One of the most important non-invasive methods is the EEG which is a technique measuring the electric activity patterns of the brain from the surface of the scalp. A 128 channel EEG system is represented in *Figure 1* below from reference [5], consisting of wearing a cap placing each electrode in its position to read EEG signals that can be translated to operate devices including assistive devices to help patients with movement and communication, or for rehabilitation including helping patients recover from motor and cognitive disability [6].

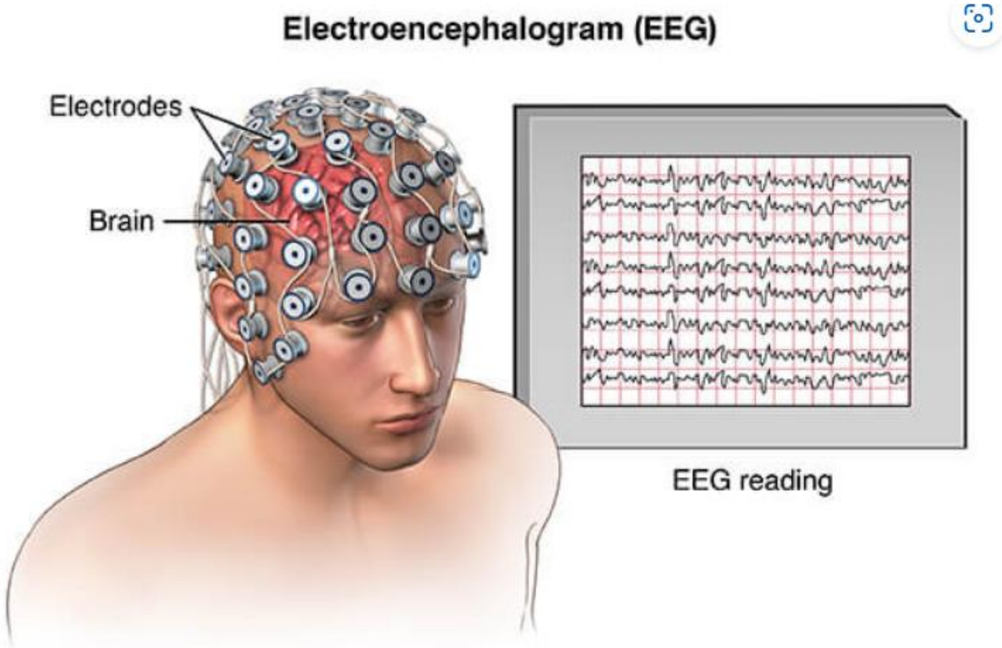

Figure 1: EEG system with 128 channels

EEG is mainly used in diagnosing medical conditions, as its main purpose is to diagnose and detect seizure activity; seizures often associated with the abnormality of the electrical activity which may cause the patient to experience confusion, hallucinations and even to collapse completely if it continues [7]. EEG could also be used to detect and diagnose other conditions that revolve around neuroscience and brain activity in general.

It's been widely known to use EEG test to perform neuroscientific researches, as the EEG provides a real-time data that can give insights about the activity of the specific electrode location that is seeked after, these insights could be used for clinical researches or BCI application implementations.

One of the main challenges of captured EEG signals is that it suffers from poor spatial resolution meaning that researchers would face the inability to exactly determine the source of the electric signal acquired making it difficult to pinpoint the section of the brain that is active [8]. A second challenge EEG signals suffers from is overlapped noise that is sourced from muscle and eye movement, power line and interference with other devices. These noises could be extracted or eliminated using high pass filters but we need to keep in mind that these noises can only be eliminated and not removed.

However, the low cost and mobility of EEG compared to other non-invasive methods such as MEG, MRI, fMRI, and PET makes it more appealing to the researchers and is a reason why it is still important in the field of neuroscience.

1.3.3 Literature Review

From previous work, each of the Brain activity measurements using EEG recorded during: imagined speech, speech production, listening to speech, and motor imagery has strengths and limitations found.

Speech production encoding, where participants are asked to read out individual words, usually performed to test speech decoding and synthesis approaches from neural data to develop speech Brain-Computer Interfaces [5]. As well as psychophysiological studies compare brain activity during the covert and overt production of names and nominal phrases of the same picture [9].

Another study explores the connection between speaking and singing in people who have had a stroke and developed language difficulties. Results show that both speaking and singing are controlled by the left side of the brain, which is responsible for language processing [10]. Speech production encoding is usually used with comparing its results to imagined speech or inner speech, in order to know if they are processed differently and which neural mechanisms are involved [11].

Another developing method is recording EEG during imagined speech. Imagined speech refers to the mental simulation or recreation of external speech within one's mind. It involves mentally hearing or imagining someone's speech without them actually speaking aloud.

Past studies that use EEG signals during imagined speech have a purpose of helping patients with spinal cord trauma, locked-in individuals, people suffering from dysfunctioning neuro or muscular diseases to restore their speech [12]. Other studies used imagined speech decoding with motor imaginary signals in order to compare their accuracy.

Imagined speech is often confused with inner speech. Inner speech, also known as "internal speech" or "self-talk," is the cognitive process of silently talking to oneself in one's mind. It involves thinking in words and sentences without actually vocalizing them. Inner speech involves thinking in words and sentences within one's own mind, whereas imagined speech involves mentally simulating external speech or voices. Both of these processes are important components of human cognition and play distinct roles in our mental and social activities. Inner speech has a distinct definition in psychology [13] [14], however in the discipline of brain computer interface literature the definitions of imagined and inner speech share a conceptual framework so for clarification and consistency we will refer to all cited references as imagined speech throughout our project.

Recording EEG signals during imagined speech, grabbed attention from researchers to explore the impact that this technology has. Surprising results have found that EEG signals during imagined speech have 97% accuracy when decoding simple phonemes [15].

1.3.4 Limitations

Despite the emerging EEG technology used during imagined speech, speech production, listening to speech, and motor imagery, it's yet new and recently being explored. There are some limitations of the past research and have been discussed as follows:

- **Low accuracy:** It is difficult to compare a model's performance to other used and implemented models because of its varied and distinctive implementation and prioritized focus. Another evaluation measure that can affect the accuracy is, for example in the case of motor imagery, it is a challenging technique that often requires high concentration and extended training from users and a significant percentage of participants do not achieve good accuracy even after training [16].
- **Limited Data:** The size of data gathered in previous studies has been limited to a scope of experimenting. Few studies have gathered individuals with no disorders [17], while some gathered signals from patients suffering disabilities such as with epilepsy [4].
- **Experimental Design Choices:** In this project our aim is to use EEG signals to implement an application. The attention of past studies has been limited to them being research based [18]. Applications of past studies were mostly used when collecting data from the motor cortex (motor imaginary) method rather than imagined speech.
- **Research Limitation:** This project has been limited to an application of moving a demo car recording from EEG signals during imagined speech that can be implemented on a wheelchair; therefore, we may have missed studies discussing other ways. Moreover, EEG signals modality was our focus on the data. We excluded other modalities, such as ECoG, FNIR, fMRI, etc., so we may have missed some studies that used other modalities.
- **Low signal-to-noise ratio.** This low SNR causes the component of interest of the signal to be difficult to recognize from the background brain activity given by muscle or organ activity, eye movements, or blinks. Furthermore, even EEG

equipment is sensitive enough to capture electrical line noise from the surroundings.

- **Variation to the interpretation and understanding of an individual**: Although all participants were asked to perform the same way, not all participants have the same understanding, imagination, or concentration.
- **People with long hair or have a head gear on:** Data collection with Emotiv or similar EEG devices can be challenging when dealing with people who have long hair or wear headgear. The presence of hair or headgear can interfere with the proper contact between the EEG electrodes and the scalp, potentially leading to data inaccuracies.

1.3.5 Strengths

Introducing BCI to use in new technologies had a huge interest to try and implement the uses and benefits from it to humans. Past research studies have used some preprocessing methods that we may implement in our work. Since recent interest in the research of the emerging technology using EEG based BCI systems is increasing, they show widely used techniques when implementing signal decoding and classification that might be useful when applying them in our project.

1.4 Contribution

Novelty in the idea:

This project's novelty lies in creating a brain-computer interface (BCI) using imagined speech decoded signals rather than using motor imaginary BCI. The complexity here lies in the complexity in decoding the imagined speech signal, which is a noisier cortical signal that emanates from different parts in the brain including the auditory cortex, and linguistic areas in the brain. Deciphering that signal, feature engineering, and the classifier will be all novel. And using that classified output of an imagined speech signal in an application to control an electric device is novel as well.

The Audience that it serves:

This project will mainly focus on helping people suffering from quadriplegia paralysis which affect their mobility from neck down, dysarthria paralysis which affect they mobility and speech, and those who seek some independency in their mobility. Giving these people in need a tool that can be directed using signals emanating in different parts of the brain opens the BCI technology to people with different types of paralysis. It becomes that in principle if no matter what area of the brain is functioning then a BCI system can be deployed to assist the person with their specific and personalized need.

Novelty in the choice of the model:

We will build a neural network model that takes the decoded signal and additional features engineered to classify it into one of the four imaged spoken words, while we have not decided on the model to use yet as the critical part in our system the decoding component, the model we will build will be novel in how it is deployed

Novelty in the structure of the pipeline:

Our system will have a pipeline that requires low computational resources, to ensure that our system can be deployed in small devices, this introduces novelty in the structure and the modules that we will build as it needs to have low memory and low processing. This allows the system to be accessible and deployable for different uses/applications that considers low cost of computation as a priority for their system.

1.5 Document Outline

The documentation outline for the project is shown in Table 1.

Table 1: Document Outline

No.	Chapter	Description
1	Introduction	Considering the general overview of the project, problem description, project outcome, the project proposes a system that uses EEG signals to decode imagined speech and enable direct communication for quadriplegic patients.
2	Project Plan	Considers project deliverables, project tasks, roles and responsibilities, risk assessment, cost estimation, and project management tools.
3	Requirement Specification	Considers stakeholders and the project requirements that include platform, functional, and non-functional requirements.

4	System Design	Consider the logical and physical model design.
5	Date Preprocessing	Considers preprocessing techniques
6	Implementation	Includes implementation of the system
7	Testing	Considers the testing approach and tools
8	Conclusion and future work	Explains the results and future plans

Chapter 2

Project Plan

2.1 Project Deliverables

The purpose of this project is controlling an assistive device to move by acquiring from brain signals, decode them and finally classify the directional command accurately in real-time. Achieving this goal will be by extracting unique features for each signal, feeding them to the machine learning model that will regulate the classification process and display the classified direction on a moving device. The plan is to build a pipeline of the system, starting off at the data acquisition stage and ending in a moving device based on a classified direction.

The table below briefly explains the project deliverables and their descriptions.

Table 2: Project Deliverables

Deliverable ID	Deliverables	Description
D1	Source code	Code is written in Python to construct a classification model for labeling the directions (forward, backward, right, left)
D2	Documentation files	Detailed documentation of the project as well as the documentation file of the code.
D3	Dataset	A dataset consisting of signal features from the user, which captures brain activity and physical movement during a session.
D4	Acquisition Protocol	1) Enhance the volunteer's concentration in a quiet environment while trying to reduce the impact of external disturbances. 2) Explaining the requirements of the experiment to the volunteer, he/she must imagine that he/she is saying one of the four directions in his mind, and this process will be recorded for each

		direction several times. After completing this process, the second experiment will begin, and the volunteer must say one of the four directions out loud, and this process will be recorded for each direction several times. 3) When starting the trial, the volunteer should imagine saying one of the four directions (left, right, up, down) and record the imagination process; each direction should be recorded multiple times by the volunteer by pressing on the record button when he starts and pressing again on it when he finishes imagining. 4) Next, capture another trial by having the volunteer say each direction out loud and recording the statement the same way, with multiple repetitions of recording each direction to ensure solid results. 5) Export the results to a csv file to start working on it.
D5	Device	Device controlled by the output of the classification system to move to four directions.

2.2 Project Tasks

This project is divided into four main tasks: analysis, design, implementation, and deployment, and each major task is divided into smaller tasks. The requirements will be determined and modeled during the analysis phase, and a project plan will be created. We will investigate relevant past work and examine the modeling and preprocessing methods employed. During the design phase, collecting data, developing the system's pipeline and system design definitions will be created. During the implementation phase, a machine learning model and feature extraction procedure will be constructed. To ensure that the system will offer an acceptable experience, several unique assessment techniques will be used to test the system. In the last stage, known as the deployment phase, a device control will be created and tested to ensure that it satisfies all requirements. The code that has been implemented will also be documented.

Table 3: Analysis Phase tasks

Task ID	Task Name	Description	Predecessors	Duration (days)
A1	Project Definition	Project idea, domain specification, and use case specification.	-	7
A2	Feasibility Analysis	Review all aspects of the project and assess their Feasibility.	-	5
A3	Literature Review (technical, non-technical, methodology)	Study the preprocessing and modeling techniques of the related work available online and explore all available BCIs.	A2	12
A4	System Review	Study previous related systems and their specifications.	A3	5

Table 4: Design Phase tasks

Task ID	Task Name	Description	Predecessors	Duration (days)
D1	Pilot data collection	Investigate all possible approaches to collect the data for the emotive device.	A3	15
D2	Research System Components	Investigate all possible feature extraction, feature engineering, modeling techniques, and modules to implement the system.	A4	3
D3	Design a System Pipeline	Define the system's components.	D1	15
D4	System modules Design	Deciding/Specifying which modules and techniques are going to be used in the system.	D2	7

Table 5: Implementation Phase Tasks

Task ID	Task Name	Description	Predecessors	Duration (days)
I1	Pilot Data Processing	Investigate all the approaches and methods that need to be used for Dealing with the data (raw signals) and to process the signal.	D3	15
I2	Pilot Implementation	Investigate the possible approaches to solve the problem and implement a trial code of the elementary parts of the system (preprocessing, decoding the signals and model deployment) on the collected data.	D3	20
I3	Build a model	Build a Model that will classify the decoded signals into the four commands (Right, Left, Forwards, backwards).	D2	7
I4	Code Implementation	Build a pipeline that involves all stages of the project, starting off at the input, data preprocessing, signal decoding and ending with the classification process.	I1	30
I5	Testing	Evaluate the preprocessing technique and machine learning model constructed in the previous task using various evaluation metrics, such as accuracy, f1-score, precision, and recall.	I2	10
I6	Code Documentation	Prepare a document that explains the code implemented in detail.	I4	7

Table 6: Deployment Phase Tasks

Task ID	Task Name	Description	Predecessors	Duration (days)
DP1	Device control	Investigate the appropriate configurations for the board and the appropriate connection to the system.	_	5
DP2	Board code implementation	Implement the code that will connect the whole system together (decoded signals -> board -> assistive device).	DP1	15
DP3	Model Optimization	Adjust the model in order to yield more valid results.	I2	10
DP4	Test all connected component of the system and devices	Test the overall system with the assistive device connected to it and check if it moves according to the directional command that stems from the model.	D2	10

The Gantt charts illustrated below show the timeline of the project tasks.

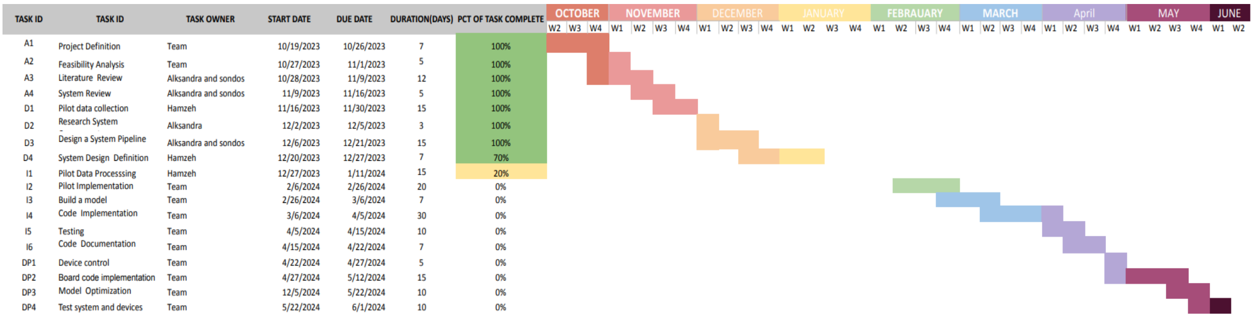

Figure 2:Gantt Chart

2.3 Roles and Responsibilities

Table 7 summarizes the tasks allocated and conducted by each team member, referring back to the designated task ID quoted in the tables above.

Table 7: Roles and Responsibilities

Task Owner	**Task ID**
Hamzeh Hatamleh	A1, A2, D1, D4, I1, I2, I3, I4, I5, I6, DP1, DP2, DP3, DP4
Alksandra Aljabery	A1, A2, A3, A4, D2, D3, I2, I3, I4, I5, I6, DP1, DP2, DP3, DP4
Sondos Ali	A1, A2, A3, A4, D3, I2, I3, I4, I5, I6, DP1, DP2, DP3, DP4

2.4 Risk Assessment

The potential risks that may occur and the prevention of sufficient performance when following through with the application is described in Table 8.

Table 8: Risk Assessment

Risk ID	Risk	Description	Probability	Solution
R1	Connectivity with Emotiv	When placing the device on the head, we may encounter risks related to the connectivity and EEG signals. Signals may not be taken accurately, due to	Moderate	During data collection, volunteers are usually advised to reduce head movements and relax to obtain

		excessive movement of the user, This can introduce artifacts and interference in the EEG signals leading to wrong classification		more accurate readings.
R2	Connectivity between Arduino board and the computer/robot	The Arduino board's connection to the computer/robot is essential for accurate transfer of decoded EEG signals. but poses risks such as communication issues and signal interference. Potential failures in the connection may lead to loss of control or unintended movements by the robot.	Moderate	Implement a reliable communication protocol, such as Bluetooth or Wi-Fi, or a cable connection with suitable shielding to prevent interference. To discover and repair data transmission errors, use error-checking methods included into the communication protocol. Creating a fail-safe system can allow the robot to halt or return to a safe state in the event of a communication failure.
R3	Accuracy and Reliability	Variability in data quality, such as noise, or inconsistent signals, can have an influence on signal interpretation. This increases the possibility of misinterpreting the user's intent and sending incorrect directional commands to the Arduino board. Excellent data	Moderate to High.	Filter away distortions and noise from EEG data using signal processing methods. Use signal quality assessment techniques to detect and delete unreliable data

		quality is required for accurate and reliable robot control.		segments. To improve the accuracy of decoding the signals, Give the user feedback to ensure they are in an ideal state for.
R4	Interference and Environmental Factors	Interference and environmental factors can impact EEG signals during data collection. These effects can introduce noise, distortions, or inaccuracies in the EEG readings, External sounds may create artifacts, making it challenging to distinguish between brain-generated signals and noise.	Moderate	Before collecting data: ensure that the volunteer is in a quiet place without any influential sound to ensure high concentration and correct collection of data.
R5	Ethical Considerations	BCI systems that have access to brain signals may be intrusive to an individuals' mental privacy and may lead to manipulation of sensitive information.	Moderate	Informed Consent is one way to ensure that individuals allow the acquisition of information from their brain. Transparency of the processes conducted by the system and their outcomes is critical to ensuring the trustworthiness of the application.
R6	Data inconsistency	Data inconsistency occurs due to several factors: 1) Inconsistent contact between the EEG electrodes and the	High	1) Check the electrodes continuously and ensure that the hair is free of

		volunteer’s scalp, Factors such as dry skin, hair, or oils can affect the electrical impedance 2) The volunteer’s instability and excessive movement 3) The presence of noise in the surrounding environment 4) Incorrect calibration of the device: calibration includes how to adjust the device to the correct places to ensure connectivity. 5) Hardware Issues: Defects in the sensors may cause inconsistency in data final 6) EEG noise resulting from a subject's mental processes that are not related to the task at hand.		drying oils and not dry. 2) Emphasize to the volunteer the importance of remaining still and calm throughout the period of data collection. 3) Ensure that the volunteer is in a quiet place without any influential sound to ensure high concentration and correct collection of data. 4) Adjust the device to the correct locations on the head and always ensure that the EEG signals and the connectivity are more than 90%. 5) Perform regular maintenance on the device to ensure that there are no defects in the sensors and connectors. 6)Correct training for the

				subject to allow them to focus on the task at hand.
R7	Hardware Reliability	Hardware such as the device, sensors, and power supply are necessary to complete the process correctly.	High	Make sure the connection is stable, the device has long battery life and the device is comfortable to use to ensure efficiency.

2.5 Cost Estimation

The cost estimate that follows a prediction for a year of application use is shown in Table 9:

Table 9: Cost Estimation

Description	Price	Amount	Total
Emotiv Insight device 5-CHANNEL WIRELESS EEG HEADSET	$499	-	$499
Emotiv pro subscription	$99 per month	2 months	$198
Arduino or Raspberry pi	$175	-	$175
2WD SMART ROBOT CAR CHASSIS (V2)	$15	-	$15

2.6 Project Management Tools

The tools used in this project to serve the purpose of project management and enhance team performance are listed and described in Table 10.

Table 10:Project Management Tools

Tool	Description
Google Workspace	Storing and managing shared files and tasks
Google Docs	Editing and viewing shared documents as a team.
Google Sheets	Assigning tasks to team members and following up on them.
Google Colab	Running sample data preprocessing and machine learning deployment model and sharing it with the whole team.
Board Programming (Arduino /raspberry pi)	Running the code that will allow the robot to move based on the label directional command
Diagrams.net	Creating diagrams to demonstrate the processes of the system.
Emotive Application	Collecting EEG signals data from volunteers
Emotive Analysis Tool	–

Chapter 3

Requirements Specification

3.1 Stakeholders

The system's stakeholders are listed and described in Table 11.

Table 11: Stakeholders

StakeHolder ID	Stakeholder	Description	Importance
S1	End Users/ Quadriplegia/ Dysarthria	Individuals who will use or benefit from the system. This may include people with disabilities who rely on BCI for mobility.	High
S2	Wheelchair Manufacturers	Companies specializing in wheelchair manufacturing can benefit from this system in their products. As It has the ability to increase their market competitiveness while meeting the needs of people with mobility disability.	High
S3	Healthcare Professionals	Medical practitioners or therapists who could use the technology for rehabilitation purposes. They may be interested in applications that support patients with motor disabilities or other health conditions.	Medium
S4	Nonprofit Organizations	Non-Profit organizations that are committed to assisting people with disabilities may partner with or fund projects aimed at improving the	Medium

		quality of life for their target population.	
S5	Insurance Providers	Insurance companies may find value in supporting or endorsing technologies that improve the quality of life for individuals with disabilities. As a result, long-term care and rehabilitation expenses are lowered.	Medium

3.2 System Requirements

3.2.1 Hardware Requirements

Table 12: Hardware Requirements

ID	Requirement	Justification	Priority
HR1	Computer	Processing power should be enough to handle real time signal processing, The RAM and storage need to be reasonable.	Essential
HR2	Emotiv EEG device	Emotiv Insight 5 channels	Essential
HR3	Arduino Board	Communicate with the Arduino-controlled robot-car.	Essential
HR4	Robot-car	The robot base with motors and wheels for movement (left, right, forward, backward).	Essential

3.2.2 Software Requirements

Table 13: Software Requirements

ID	Requirement	Justification	Priority
SR1	Emotiv Software	Application that collects data (Emotiv pro)	Essential
SR2	Signal processing Software	converting EEG signals to CSV files. Use python to prepare the data and preprocess it to make it ready for classification	Essential
SR3	Machine learning/Classification Software	Software for training and deploying a classification model (e.g., Python with scikit-learn or TensorFlow).	Essential
SR4	Arduino/ Raspberry IDE	Used for programming the Arduino/Raspberry pi board. Write the computer code and upload this code to the physical board	Essential
SR5	Motor Control Libraries	Controlling the movement of the robot	Essential

3.2.3 Recommended Requirements (Not Mandatory, but Enhances Performance)

Table 14: Recommended Requirements

ID	Requirement	Justification	Priority
RR1	Advanced Signal Processing Tools	Use more advanced algorithms or processing tools to enhance the accuracy of EEG signal processing	Recommended
RR2	Machine Learning optimization	Optimize machine learning model training and execution. Use more specialized hardware	Recommended
RR3	More advanced EEG device	It is used because it contains 14 sensors instead of 5 sensors, so the data will be more accurate even though it is more complex.	Recommended

3.3 Functional Requirements

Table 15 shows the function requirements of the system, the information on each requirement, and its priority.

Table 15: Functional Requirements

Requirement ID	Requirement	Description	Priority
FR1	Input imagined speech signal	To receive real-time input from EEG headset	Essential
FR2	EEG Signal Processing	The new signal recordings should be cleaned and processed.	Essential
FR3	EEG Signal Decoding	The system should be able to isolate the imagined speech signal and decode using different techniques.	Essential
FR4	EEG Signal classification	Decoded signals should be classified into a word out of four.	Essential
FR5	Device Motion System Control	The system outputs the classified outcome as to control and move the device.	Essential

Table 16:Detailed Description of the Functional Requirements

ID	**Input**	**Output**	**Constraints**	**Process**
FR1	Signal acquired from EEG signal	Saved EEG file on computer	Hard disk space and meta data of EEG file	The user must think of one of four words (up, down, right or left) that must be clear to process and classify.
FR2	EEG file on computer	Cleaned EEG signal	Different types of noise, ambient, muscular signal degradation	Multiple EEG cleaning techniques from filtering to ICA
FR3	Cleaned EEG signal	EEG rhythm data, filtered and ready for classification	Irrelevant yet valid EEG signal from different brain sources	Filtering, Feature engineering, Similarity indicators
FR4	Decoded EEG signal	Word class label	Inefficient decoding, noisy decoding	Build classifier using a technique to be determined.
FR5	Word class label	Motion of vehicle	Connection stability	Device receives the class label and directs motion of device accordingly.

3.4 Non-Functional Requirements

The table below describes the non-functional requirements of the system, along with their descriptions and their priority.

Table 17: Non-Functional Requirements

ID	Requirement	Description	Priority
NFR1	Reliability	The system is built to help assist people in need and should be reliable.	Essential
NFR2	Usability	The system is built with the user in mind and should be easy and enjoyable to use.	Essential
NFR3	Speed	The system should give immediate results.	Essential
NFR4	Accuracy	The system should give output with high accuracy.	Essential

Chapter 4

System Design

4.1 Architectural Design

4.1.1 System Description

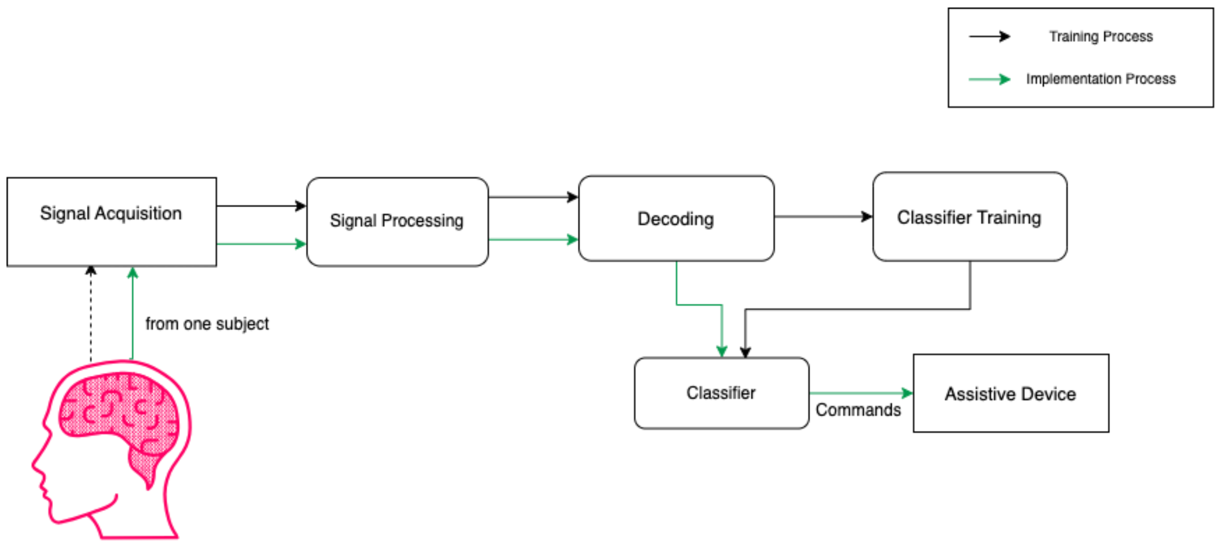

Figure 3:Architectural Diagram

The system design starting from data collection ending in the movement of the assistive device is represented in *Figure 3*. *Figure 3* shows a parallel track of the entire system and can be divided into 5 stages; signal acquisition, signal processing, signal decoding, signal classification, and the assistive device control.

Both tracks, the training process and the implementation process, starts from signal acquisition; collecting data using the Emotiv 5-channel wireless EEG headset [19]. In the acquisition process stage, signals are being recorded and collected with the use of 5 EEG channels. *Figure 4* below shows each channel's location and name placed on the skull. Signal is analog and it is converted using the Emotiv system into a digital signal. In the training process, data is collected from more than one subject to train our classification model to get accurate and trustworthy test results. On the other hand, signal acquisition in the implementation process, only collects brain signals from one subject to send to the assistive device the command to move in real-time, that means the collection of the brain signal and moving the device must be of simultaneous action.

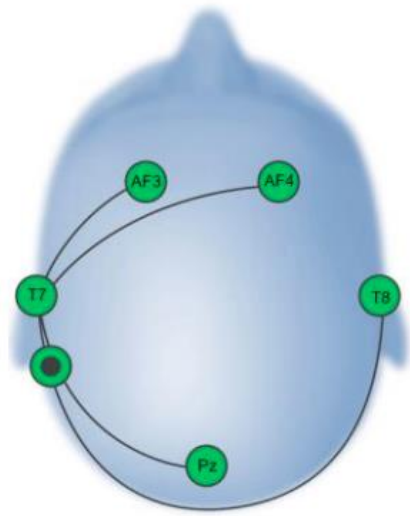

Figure 4: Electrodes labels and placements

During data acquisition, EEG signals is a complex signal that is the aggregate of many components that arise from different sources in the brain. To isolate the important signal and increase the signal-to-noise ratio (SNR) of the EEG signal, a few signal processing techniques must be implemented to help reduce the computational complexity of the problem and improve the efficiency of the classifier. In order to send the processed signal into the classifier, signals should be decoded and extract the most significant features and information from the signals.

During training, important features are being trained on a training classifier to forward into the classification model and get one of four labels (forward, backward, left, right). During implementation, the extracted features are directly fed to the classifier to perform classification and voting is done on the output to get the final classification result and send it to the assistive device to trigger and move the motors.

4.1.2 Component Diagram

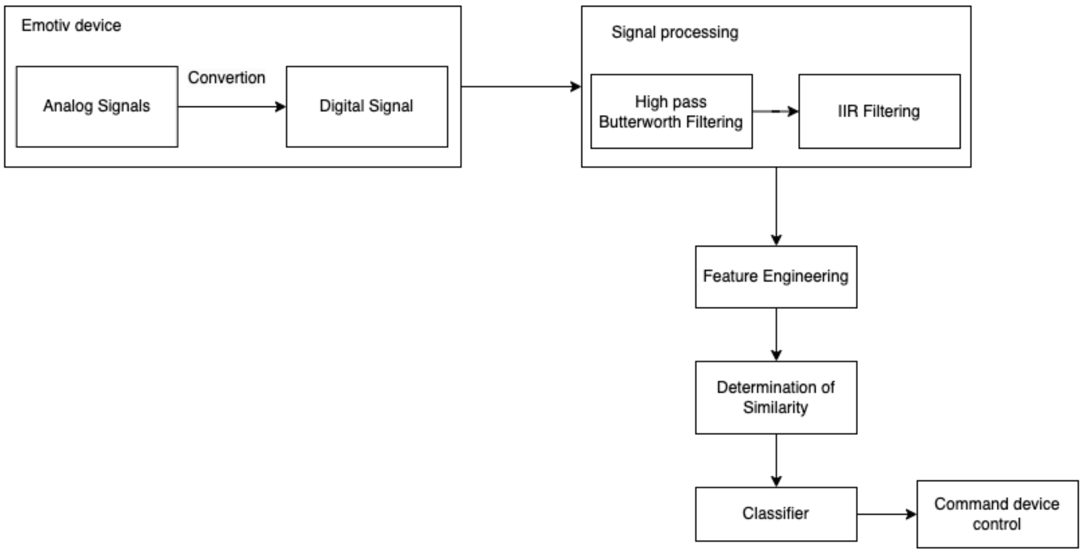

Figure 5: Component Diagram

The architectural diagram in *figure 5* shows a narrower representation of the system. During data acquisition, EEG signals are converted from analog to digital signals. In order to get the highest approximation of the analog EEG signal, the signals are sampled at 128 samples per second. After collecting the data, signals are processed through a high pass butterworth filter where the cutoff frequency is 0.2 Hz to remove muscle contraction and eye blinking activities. High pass butterworth filter is applied to all of the 5 channels available. Signals are also processed through an infinite impulse response filtering to modify the frequency characteristics of the signal using feedback. IIR filter is used because the linear phase is not important. Important features are then extracted during signal decoding, applying feature engineering to all channels. Then, similarity determination measures the similarity of the engineered features with the features of every output of interest, in order to classify the signal to one of the four outputs (forward, backward, left, right). The classifier then sends the command to the device control to move.

4.2 Logical Model Design

4.2.1 Use Case Diagram

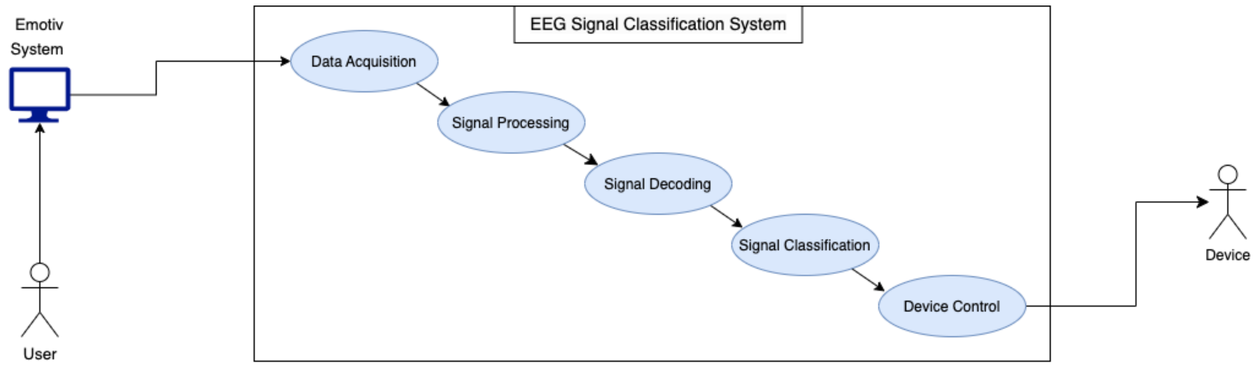

Figure 6: Use Case Diagram

The diagram in *Figure 6* represents a user, wearing the Emotiv device, using the EEG Signal classification system to control the device's movement. The Emotiv System records and displays the user's EEG signals and saves them as a csv file. Signals are then processed to remove unwanted information and keep components of interest. Then important features are extracted during signal decoding. The classification model then classifies the decoded signal and sends it to the device to control its movement.

4.2.2 Sequence Diagram

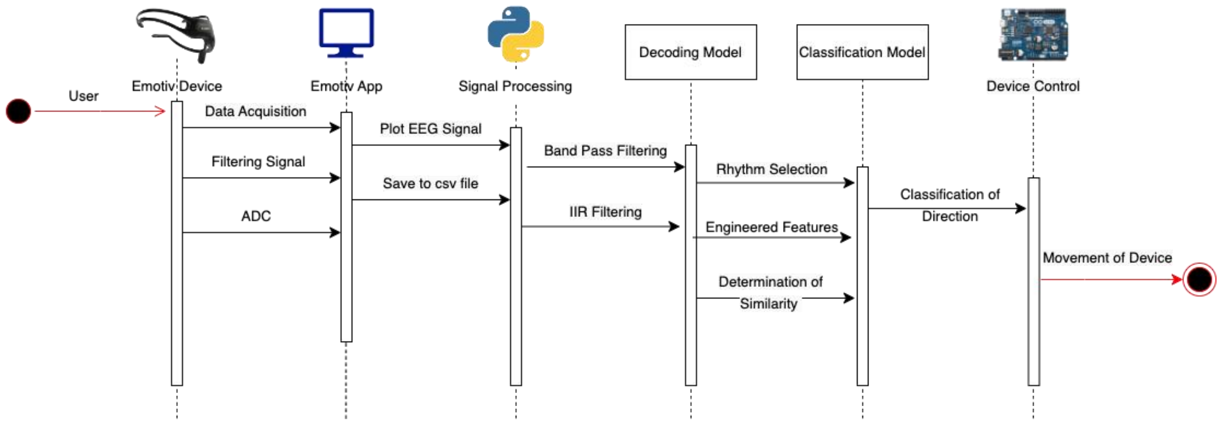

Figure 7: System Sequence Diagram

Figure 7 above shows a sequence diagram that represents the steps taken from recording signals from a user to controlling the device's movement. In preparation of the Emotiv device, a conductive gel is placed on every sensor or electrode, so the device can read the EEG signals from the brain. The user places the Emotiv device on their scalp and starts to imagine one of the four words (forward, backward, left, right). The Emotiv device filters the signals and performs digitization which means that it converts them from analog to digital signals. A more detailed description of filtering the signals is discussed in *Figure 6* below. The Emotiv system saves the information of each channel into a csv file. As explained previously, butterworth high-pass filtering and IIR filtering is applied to each channel in the signal processing stage. Rhythm selection helps to extract important features from the signal during the decoding process. The four types of rhythms are the delta rhythm (0.5-4 Hz), theta rhythm (4-8 Hz), alpha rhythm (8-13 Hz), beta rhythm (13-30 Hz) and gamma rhythm (>30Hz). Measuring the similarity between the rhythm types of each channel can help in extracting significant features from each channel. After determining the important features for each output of interest, the engineered features are forwarded to the classification model to send the output to the device.

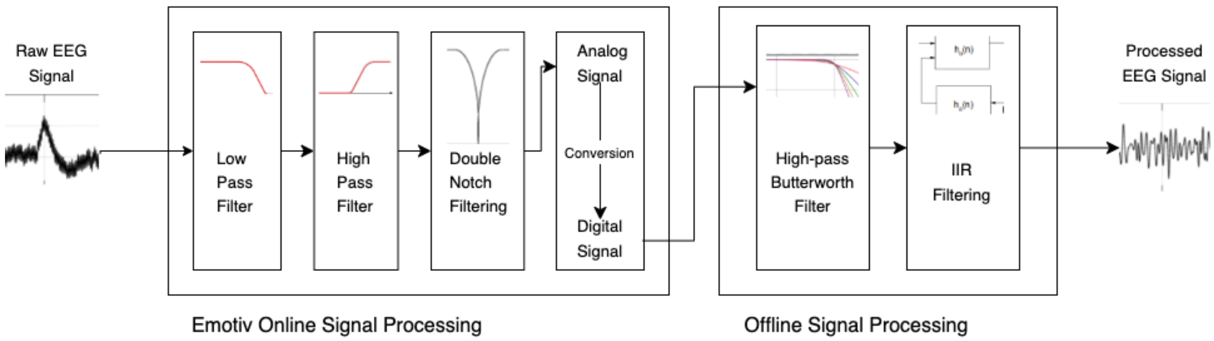

Figure 8: Signal Processing Diagram

Figure 8 illustrates a detailed representation of signal processing during data acquisition and after data acquisition. Signal processing done at the time brain signals are recorded is called online signal processing. Most EEG hardwares including Emotiv headset low-pass filters the data at the time the signals are recorded. The threshold is usually determined depending on the sampling rate of the device. According to the Emotiv system, it low-pass filters signals with a threshold of 85Hz to prevent the harmonic of electrical mains. Signals are also high-passed with a threshold of 0.2Hz to eliminate the muscle contraction activities. Then the Emotiv device applies a double notch filtering on signals at 50Hz and 60Hz to remove the interference from the electrical power supply. And because the sampling rate to convert the analog to digital signal is at 128 Hz, it is enough to represent the highest frequency of the original signal. As mentioned in the Emotiv website the frequency response is from 0.5-43Hz which is enough for our interest due to the range of the types of rhythms varies from 0.3-40Hz. Signals are displayed and saved as raw data. Second step of processing, offline processing, is applied after data is collected. As mentioned above, butterworth high-pass filter is manually applied to each channel at 0.2 Hz to eliminate muscle contraction and eye blinking activities, as well as IIR filter is applied to all 5 channels. This will provide us with processed brain signals to help in the efficiency of the classification model.

4.2.3 Activity Diagram

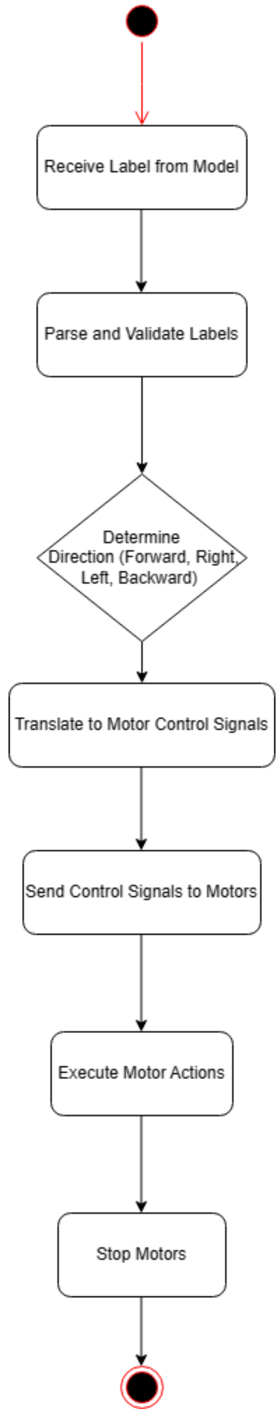

Figure 9: Assistive device Control

The diagram in *Figure 9* represents the flow of activities in a system that receives a label from a model that classifies a decoded signal into four directional commands, then the received label is processed to extract relevant information, a validation checkup is done to ensure correctness and integrity of the data, based on those data the system make a decision of the direction in which the motors need to operate (forward, right, left, backward), the determined direction is then translated into a specific control signals that is sent to the motors as they define the direction that the motors needs to take, after that the motors execute these actions resulting in physical movement aligned with the specific direction. After the motor actions have been executed, the system issues commands to stop the motors, and this is considered the system's final state.

4.3 Physical Model Design

For the physical model, the system will be implemented on an Arduino board that will be connected to a robot acting as an assistive device or a demonstrative wheelchair prototype.

The model of the robot that will be used is 2WD SMART ROBOT CAR CHASSIS (V2), it will have a platform featuring three wheels, with two rear wheels each connected to a gear motor for a precise control over the forward and backward motion, and a front center single wheel without any gear motor strategically positioned to ease the motion when turning or mimicking the movement of a traditional wheelchair.

To power the system, a 4 AA battery box is integrated into the robot's design and will be placed on top of the platform alongside the Arduino board that is securely positioned on top of the platform.

For the board and its model, either Arduino or Raspberry pi will be used; it will be specified based on the complexity of the decoded signals, and a wired connection between the board and the computer will be established to ensure that the connection will be strong and to eliminate any risks that could happen. The classified signals, extracted from the collected EEG signals are transmitted from the computer to the Arduino board allowing it to interpret these signals into specific directional commands, this is achieved by linking the Arduino board to the gear motors of the robot sending them the directional command. *Figure 8* shows the physical model design of the assistive device control.

Figure 10: Physical Model Design

Chapter 5

Data Preprocessing

5.1 Data Collection description

The data for this project was collected using the EmotivPro Insight device, a neuroheadset designed for capturing brain activity. The device was placed above the participants' heads during the data collection process, and it has a built-in library that can convert the signals into a csv file with multiple features suitable for our project.

The data collection process consists of two distinct data acquisition protocols aimed at assessing the brain activity of participants and understanding neural responses during specific tasks:

1) Loudly Speaking acquisition protocol: The recording session is divided into many takes, at the beginning of each take or recording the participant presses the record button on the Emotiv system. Then the participant says one of the four directions (left, right, up, down) loudly while wearing the Emotiv pro Insight device, and then the participant presses the button to stop recording this specific take. We have to record many takes of the participant speaking each direction loudly to ensure consistency and to have enough data to understand and remove the different forms of noise.
2) Imaginary Speaking acquisition protocol: the participant imagines saying one of the four directions (left, right, up, down) mentally while wearing the Emotiv pro Insight device, this process is recorded, we have to record each direction many times to ensure consistency

The data is saved as csv files generated using the Emotiv system from the previous process. A sample of our csv files is given below as a picture, this csv file converted using our Emotiv device with a pro subscription. The data presented corresponds to a participant who actually speaks the direction "down," recorded as indicated above. As mentioned, before we also collect data from the same subject in the same session and while keeping the EEG channel in place while the participant imagines speaking the direction ‘down’ and that process is repeated many times.

In the below image, we see the signals resulting from the Emotiv device after recording a “down” loud form the participant for 2 seconds, he/she pressed on the record button, then say “down” loudly and then stop recording, this signal is not preprocessed, so it contains noise that we have to deal with and filter it.

	Timestamp	OriginalTimestamp	EEG.Counter	EEG.Interpolated	EEG.AF3	EEG.T7	EEG.Pz	EEG.T8	EEG.AF4	EEG.RawCq
0	1.700938e+09	1.700938e+09	111.0	0.0	4218.846191	4270.769043	4093.076904	4189.871582	4225.128418	0.0
1	1.700938e+09	1.700938e+09	112.0	0.0	4230.000000	4267.948730	4100.256348	4207.563965	4236.922852	0.0
2	1.700938e+09	1.700938e+09	113.0	0.0	4232.436035	4268.077148	4095.897461	4192.948730	4234.230957	0.0
3	1.700938e+09	1.700938e+09	114.0	0.0	4233.333496	4269.615234	4095.384521	4179.487305	4236.153809	0.0
4	1.700938e+09	1.700938e+09	115.0	0.0	4232.692383	4261.410156	4103.461426	4190.512695	4245.256348	0.0
...	...	...	...	...	...	...	...	...	...	...
332	1.700938e+09	1.700938e+09	59.0	0.0	4254.615234	4261.410156	4103.077148	4156.282227	4259.230957	0.0
333	1.700938e+09	1.700938e+09	60.0	0.0	4252.820313	4271.922852	4103.077148	4176.666504	4256.153809	0.0
334	1.700938e+09	1.700938e+09	61.0	0.0	4249.102539	4270.000000	4095.897461	4191.794922	4248.205078	0.0
335	1.700938e+09	1.700938e+09	62.0	0.0	4248.077148	4260.128418	4098.717773	4174.615234	4244.871582	0.0
336	1.700938e+09	1.700938e+09	63.0	0.0	4250.769043	4272.179688	4107.692383	4151.025879	4248.461426	0.0

Figure 12: DataFame Representation

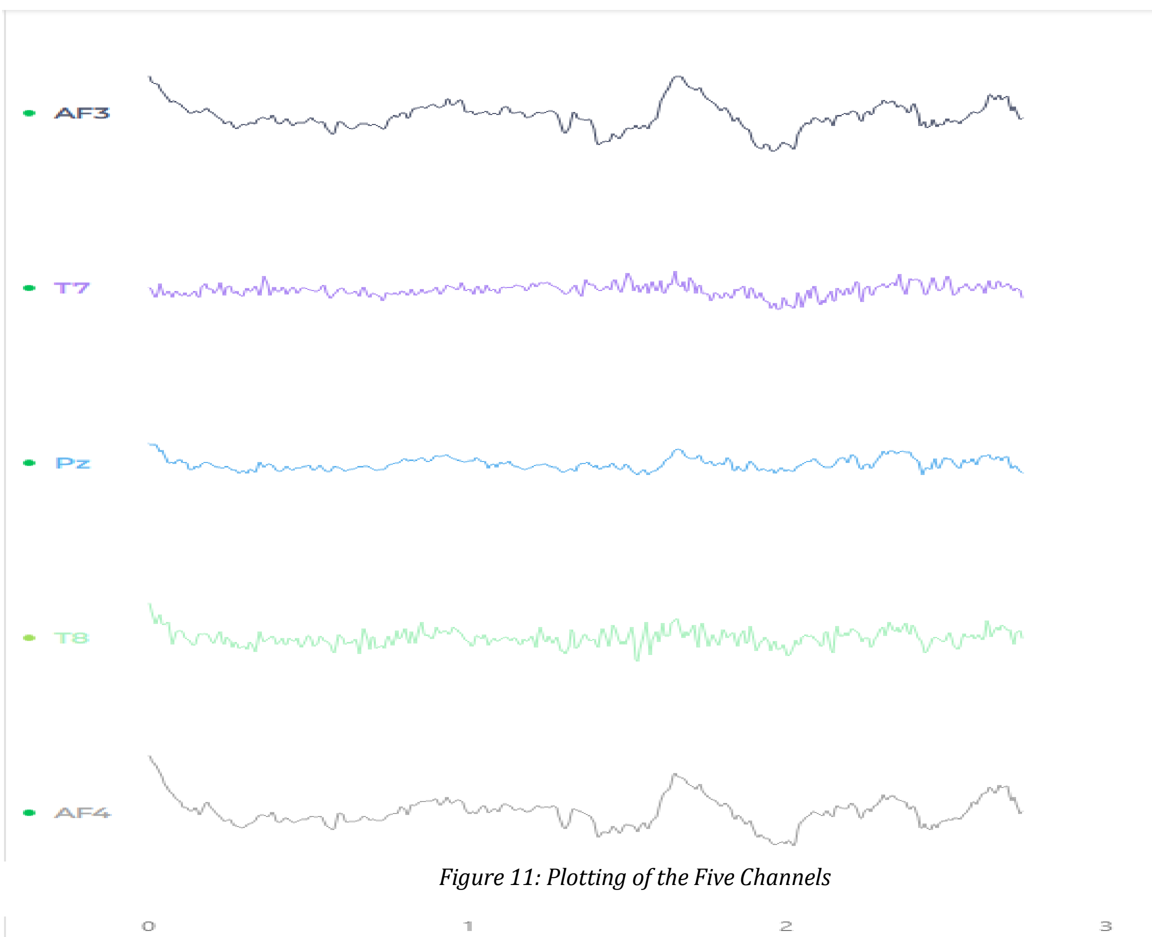

Figure 11: Plotting of the Five Channels

5.2 Data Profiling and Engineering

- **Remove the DC offset from the data:**

In the context of EEG signals, DC offset is the regular voltage degree that might be in the recorded signal. Removing the DC offset is a critical preprocessing step because it enables in focusing on the real variations inside the EEG sign without the interference of this steady thing, this can be done using 2 ways:

A) apply a high-pass filter with 0.2Hz cutoff and with 128 hz frequency which matches the characteristics of the electronics:

By the use of a high-pass filter. An excessive high pass filter lets in better-frequency components of the signal to high pass filter while removing the decrease-frequency additives, including the DC offset.

We have followed a frequency threshold of 0.2 Hz based on the advice from the Emotiv tool group. This desire aligns with the unique traits of the alerts we are detecting, consisting of muscle movement and blinking, which generally arise at frequencies lower than 0.2 Hz. Setting this threshold allows mitigate noise interference, ensuring more correct and reliable signal detection.

SSSB) Another method is to use an IIR filter: The infinite impulse response (IIR) filter is a recursive filter in that the output from the filter is computed by using the current and previous inputs and previous outputs. Because the filter uses previous values of the output,

there is feedback of the output in the filter structure. It tracks the background level and subtracts it.

“The benefit of the usage of an IIR filter in this situation is that it may adapt to variations in the baseline over the years. This is in particular useful at the same time as the baseline waft is not ordinary or even as it is modified in a slow manner. By continuously updating the estimate of the history level, the IIR filter out can correctly do away with the slow modifications inside the signal, deliberating better isolation of the desired sign components.” [20]

Using an IIR in this context provides a dynamic and adaptive manner to estimate and subtract the history degree from the sign, supporting moderate baseline drift and slow adjustments within the facts.

The images in figure 13 and 14 below show us the high pass filtering with 0.2 cutoff and the IIR filtering with 128 Hz frequency.

```python
# High-pass filter parameters
cutoff_frequency = 0.2
order = 1

# high-pass Butterworth filter
b, a = signal.butter(order, cutoff_frequency / (sampling_rate / 2), btype='high', analog=False)


# Apply the high-pass filter to each EEG channel
filtered_eeg_data = np.zeros_like(eeg_data)
for i in range(eeg_data.shape[1]):
    filtered_eeg_data[:, i] = signal.filtfilt(b, a, eeg_data.iloc[:, i])
```

Figure 13: Applying High-pass Filter to Signals

```python
import numpy as np

frequency = 128  # Desired

# Calculate the time const
IIR_TC = 1 / (2 * np.pi * frequency)


EEG_data = data.iloc[:, 4:9]

# Get the number of rows and columns in EEG_data
rows, columns = EEG_data.shape

# Initialize AC_EEG_data with zeros
AC_EEG_data = np.zeros((rows, columns))

# Copy the first row of data into the background
back = EEG_data.iloc[0, :].copy()

# IIR filter
for r in range(1, rows):
    back = (back * (IIR_TC - 1) + EEG_data.iloc[r, :]) / IIR_TC
    AC_EEG_data[r, :] = EEG_data.iloc[r, :] - back
```

Figure 14: Applying IIR Filtering to Signals

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