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EEG-based Mouse Cursor Control using Motor Imagery-based Brain-Computer Interface

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An undergraduate senior project submitted by

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in consideration of the partial fulfillment of the requirements for the degree of

BACHELOR OF SCIENCE

in

ELECTRICAL AND ELECTRONIC ENGINEERING

Department of Electrical and Electronic Engineering

Summer 2023

DECLARATION

I do hereby solemnly declare that the research work presented in this undergraduate thesis has been carried out by me and has not been previously submitted to any other University / Institute / Organization for an academic qualification / certificate / diploma or degree.

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The Authors
October, 2023
Dhaka, Bangladesh

ABSTRACT

A brain-computer interface (BCI) framework uses computer algorithms to detect mental activity patterns and manipulate external devices. Most commonly used in imaging technologies is electroencephalography (EEG) because of its non-invasiveness. The evaluation method used in assessing the output of an EEG-based BCI system is classifying EEG signals for particular applications. In this study, we present a system of EEG-based mouse cursor control using a Motor Imagery-based Brain-Computer Interface (MI-BCI). The growth of technology and artificial intelligence inspired us to develop a system for physically impaired individuals as well as to work with electroencephalogram (EEG) signals. This signal is a noninvasive and low-cost method to extract brain signals from a subject. Our work also includes the EEG signal acquisition as well as advanced signal processing methods to utilize the MI-BCI-based brain activity. This work also includes the machine learning algorithm which carried out the system to do the successful cursor movement using binary classification. Furthermore, the successful mouse cursor movement added up the higher accuracy of 93.83% which is the result of the offline dataset.

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CHAPTER 1

INTRODUCTION

1.1 Overview

Over the last few years, Brain-Computer Interface (BCI) technology has emerged as an evolutionary field, revolutionizing human-computer interaction and presenting new opportunities for people with motor disabilities. BCIs create a direct line of communication between the user's brain and other external devices, allowing them to operate different applications solely using their cognitive activity.

Since EEG waves are very non-stationary, effectively extracting features and classifying these signals is quite difficult. BCIs have grown in popularity as a means of aiding people with impairments by opening a new line of contact with the environment through devices such as computer mice, keyboards, wheelchairs, and artificial limbs. The goal of a BCI is to directly record brain impulses and translate them into a language that computers or other devices can understand.

A Brain-Computer Interface (BCI) is a user-friendly interface that enables computer control through cognitive activity [1]. Users can freely control external devices by using peripheral brain activities involving muscles and nerves, acting as a communication channel between the brain and the computer. BCIs largely rely on brain signals to transmit commands to external devices, enabling people with disabilities - developed naturally or accidentally – to use them independently.

Hans Berger's discovery of the electrical activity of the human brain and the subsequent creation of electroencephalography (EEG) in 1924 marks the beginning of the history of BCIs. With his groundbreaking experiment in 1977 that used non-invasive EEG to manipulate graphical objects like cursors on a computer screen based on visually evoked potentials (VEP), UCLA professor Jacques Vidal is known as the creator of BCI. [2][3]

1.2 Background and Motivation

According to the World Health Organization, there are currently more than 1 billion people around the world who have some kind of disability [5]. These include conditions where people have trouble moving their limbs. The most common movement impairment includes Parkinson’s disease, Congenital Limb Deficacy, strokes, and Paralysis or Paresis.

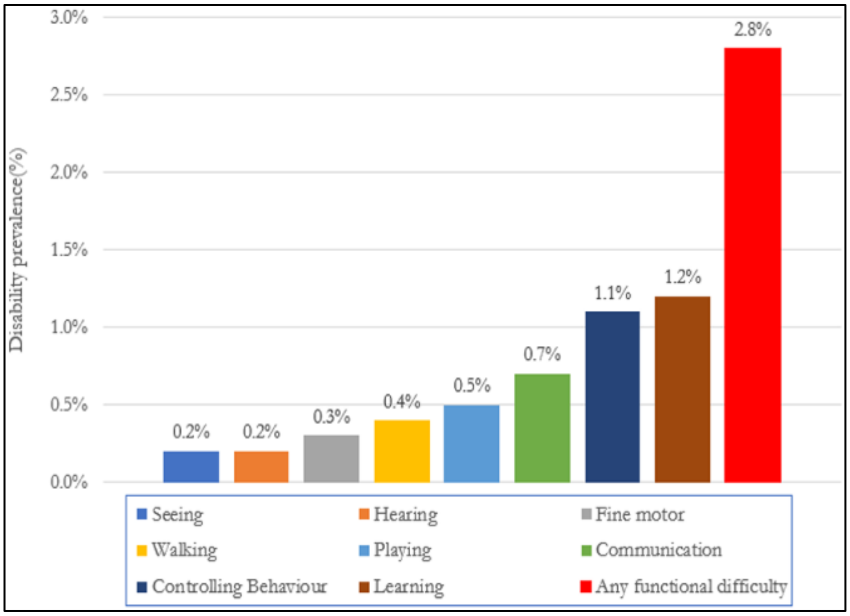


Figure.1.1 Types of Disabilities and their Prevalence

When stroke affects the cerebellum and the primary motor cortex of the brain, mobility is impaired [8]. Mortality after a major stroke can reach 60% in the first year, and survivors are also highly susceptible to immobility-related problems such as falls, contractures, discomfort, and pressure sores. Located at the bottom of the brain, the cerebellum controls motor functions such as balance, posture, and movement. If the cerebellum is impaired, people may move sluggishly or uncoordinatedly, tremble during movement, and have weak muscles. Speech, eye movements, and swallowing skills can all be affected as well [9].

Congenital upper limb deficiency, congenital limb amputation, or congenital limb reduction are terms used to describe a missing or incomplete arm at birth. The prevalence is 7.9 per 10,000 live births [10]. Congenital anomalies of the upper extremities can be classified using a variety of methods, including anatomical or topographic, embryological, teratology sequencing, genetic, and various combinations thereof [11].

A rare condition known as Phocomelia can affect newborns where children have underdeveloped or missing upper or lower limbs. One or multiple limbs may be affected by Phocomelia. Getting around and performing common tasks can be difficult. However, with the development of prosthetic technology and the help of medical teams, their mobility can be improved, preventing muscle atrophy and leading to normal development [12].

Every amputee is unique, so each prosthesis must be made specifically for the patient's body. Manufacturing a custom prosthesis requires meticulous attention to detail and constant dialogue with the patient. Several processes are performed during the design and manufacture of prosthetic limbs to develop a useful and functional prosthesis [13] [14].

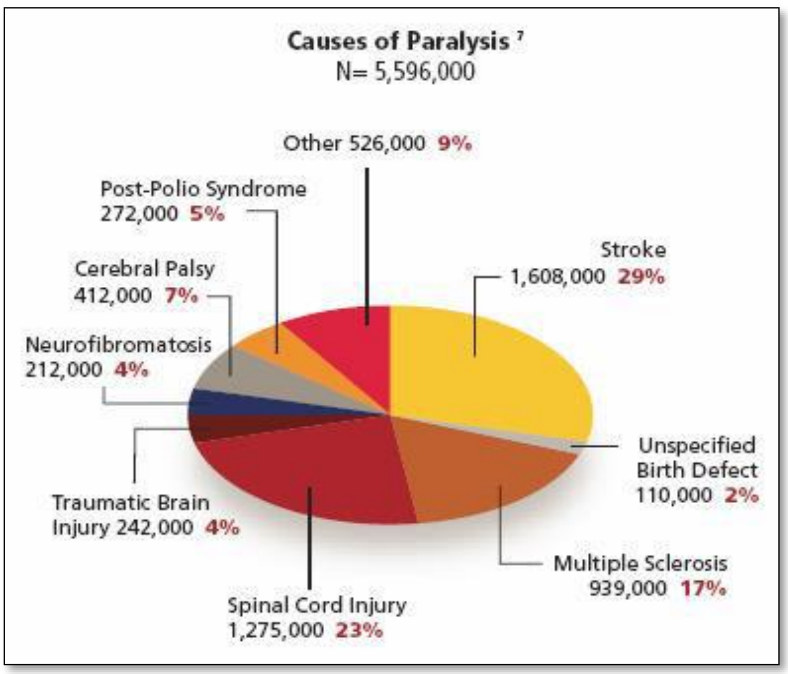


Figure 1.2 Causes of Paralysis and their Contribution.

The one thing all these conditions have in common is the lack of a way to effectively operate communication devices (computers, smartphones, etc.) without the assistance of another individual. We aim to create a device/ algorithm that will not only allow disabled people to independently use devices but also one that will enable people regardless of the particular issue they are facing – whether that is immobility or the lack of a required limb. With the help of BCI technology using brain signals such as EEG and an MI algorithm, that can be achieved.

1.3 Objectives

The goal of this project is to create a system that will let people who have physical limitations use their brain activity to control a computer mouse cursor. The project intends to develop an intuitive and effective control mechanism that enables users to browse and interact with digital interfaces entirely through their thoughts by utilizing the power of Motor Imagery (MI), Brain-Computer Interface (BCI), and EEG signals.

Therefore, our project has two main objectives:

- To record MI-BCI-based EEG data
- To implement the data to control the mouse cursor in real-time.

1.4 Research Methodology

The flowchart given below summarizes the methodology that is intended to be followed for this project:

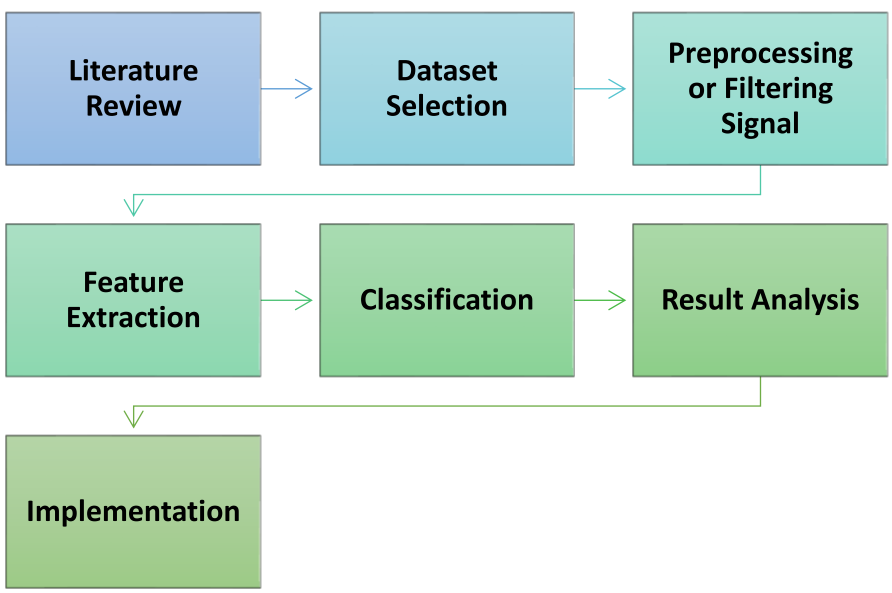


Figure 1.3 Research Methodology Flow Chart

1.5 Project Planning

Early on, a strategy was created to ensure the project's success and a systematic completion of all tasks. The work schedule is made up of three trimesters. An RACI matrix and Gantt chart were created to make sure that the project is carried out in an organized manner. A project budget was created, and steps are done in keeping with it, after defining the tasks of each work and creating a timeframe for finishing it.

1.5.1 Work plan – RACI Matrix

The RACI matrix in table 1.5.1 outlines each group member's responsibilities and role for the task that has been assigned to them.

Table 1.1 RACI Matrix

Period	Assignments	Responsible (R), Accountable (A), Consulted (C) & Informed (I) - RACI Matrix				Start	End	Days	Status
		Dr. Kafiul Islam (Supervisor)	Sayem Bin Rafique	Saima Tasfia Roja	MD. Asikur Rahman				
1st Term	▪ Prepare Plan	C	R	R	R	01.09.2022	30.09.2022	30	✓
	▪ Review Literature	I	R	A	R	15.09.2022	13.01.2023	120	
	▪ Problem Identification	C	A	R	A	24.10.2022	13.01.2023	81	
	▪ Prepare Draft Budget	I	R	R	R	24.10.2022	13.01.2023	81	
	▪ Prepare, Submit & Present (Proposal, Progress Presentation & Progress Report)	I	A	A	A	22.12.2022	13.01.2023	22	
2nd Term	▪ Design MI-BCI	C	R	R	R	01.02.2023	30.03.2023	40	✓
	▪ Data Collection	C	R	R	R	01.03.2023	14.05.2023	74	
	▪ Prepare, Submit & Present (Presentation & Progress Report)	I	A	A	A	01.04.2023	16.05.2023	45	
Final Term	▪ Frequency Band Analysis	C	R	R	R	17.05.2023	17.08.2023	92	✓
	▪ Result & Analysis	C	R	R	R	01.05.2023	30.06.2023	60	
	▪ Prepare, Submit & Present (Final Report & Presentation)	I	A	A	A	01.06.2023	20.09.2023	111	
	▪ Prepare Poster & Present Group Demonstration	I	A	A	A	15.07.2023	21.09.2023	68	

1.5.2 Work plan – Gantt Chart

The tasks that must be completed and their estimated completion times are represented on the Gantt chart in table 1.5.2. To finish the project on schedule, the task's starting dates and anticipated deadlines are followed. The size of the colored blocks indicating a task's timeline corresponds to the task's importance.

Table 1.2 Gnatt Chart

Task Name	1st Term				2nd Term					3rd Term			
	Sept-22	Oct-22	Nov-22	Dec-22	Jan-23	Feb-23	Mar-23	Apr-23	May-23	Jun-23	Jul-23	Aug-23	Sept-23
Prepare Plan													
Research Literature													
Problem Finding													
Prepare Draft Budget													
Prepare & Submit Project Proposal													
Prepare & Submit 1st Term Progress Report													
Prepare & Present 1st Term Progress													
Design MI-BCI													
Data Collection													
Prepare & Submit 2nd Term Progress Report													
Prepare & Present 2nd Term Progress													
Frequency Band Analysis													
Testing & Evaluation													
Final Report													
Final Presentation													
Project Demonstration													

1.6 Project Budget

The project primarily comprises of simulation techniques. However, the budget is be taken into account with the intention of hardware implementation.

1.6.1 Overall Budget

EEG data recording is done using a licensed EMOTIVE EPOC+ 14 channel wireless EEG headset. MATLAB software is needed for signal processing, executing the algorithms, and analyzing the outcomes. A suitable laptop is also required to run the highly advanced MATLAB software.

Table 1.3 Overall Budget

Sl	Item	Justification	Price (BDT)
1.	EMOTIVE EPOC+ headset, license	To record data EEG headset is required. Along with MATLAB software a compatible laptop is required.	20,800
2.	Compatible laptop		80,000
3.	MATLAB software license		80448
4.	Interfacing microcontroller-based electronics and targeted electrical devices (eg. raspberry pi)		7500
5.	Bluetooth Module		300
6.	Lithium Polymer batteries (4V)		12000
Total (BDT)			2,01,048
In words: Two lac one thousand and forty-eight taka only			

1.6.2 Software Budget

The table below shows the budget for the software license for the headset and the MATLAB software license.

Table 1.4 Software Budget

Sl	Item	Justification	Price (BDT)
2.	EMOTIVE EPOC headset, license		20,800
4.	MATLAB software license		80,448
Total (BDT)			1,01,248
In words: One lac one thousand two hundred and forty eight taka only			

1.7 Organization of this Report

The thesis comprises of the following chapters:

- **Chapter 1**

  Discusses issues relating to the background and motivation of the thesis followed by the objectives, and structure of the general research methodology followed.

- **Chapter 2**

  Provides a detailed description of MI-BCI and electroencephalography, the biomedical signal used in this research, and its related topics as well as a detailed review of related literature.

- **Chapter 3**

  Describes the system designed for this project as well as every process. It also speaks about the nature of the dataset used and the techniques used in each step.

- **Chapter 4**

  Discusses how this project was implemented using the data as well as the working process of the algorithm used.

- **Chapter 5**

  Discussed the results obtained via various performance parameters and what each value means as well as what changes can be made.

- **Chapter 6**

  Elaborates the Complex Engineering Problems and Activities related to this project

- **Chapter 7**

  Addresses the engineering activities undertaken to address the complex engineering problems associated with the current project.

- **Chapter 8**

  Includes the conclusion of this project.

CHAPTER 2

LITERATURE REVIEW AND METHODOLOGY

2.1 Brain-Computer Interface

Brain-computer interface (BCI) is a system that collects, analyzes, and transforms brain signals into commands that are fed into an output device to carry out a desired operations. Electroencephalography, or EEG, is a method that uses a headset with electrodes—special sensor plates—integrated into the headset to record the impulses originating from the CNS. The signals are then analyzed in a computer to identify the desired action after signal acquisition. Relevant features are gathered and translated into commands that operate an output device, or in other words, carry out the command. The user is subsequently provided with feedback to confirm that the command has been carried out correctly. [26][27]

2.2 Electroencephalography

The brain neurons are perpetually active because of metabolism, limb and organ function, brain cell ion exchange, and other factors. The brain experiences repetitive, oscillatory electrical changes caused by these activities that have a very low voltage of only a few microvolts (μV). The term electroencephalogram (EEG) refers to the non-invasive recording of this electrical activity from the scalp. Action potentials are signals generated by nerve cells. Action potentials are assisted in moving across synapse by neurotransmitters, which are particular molecules. A synapse is a physical feature that permits the electric potential to move between two neurons or nerve cells. Neurotransmitters regulate whether the action potential will cross the synapse or not. Such electrical activity is unique to the initiation of several brain activities.

2.3 Regions of the Brain

The brain is divided into several lobes, each of which performs a particular function [5]. The frontal lobe, located at the front of the brain, is responsible for executive functions, decision-making, motor control, and personality. The parietal lobe is located at the top and back of the brain. It processes sensory information, spatial awareness, and manipulation of objects. The temporal lobe is found on the sides and plays an important role in audio interpretation, language comprehension, memory formation, and elements of visual perception. The occipital lobe is positioned at the back and is responsible for visual analysis, analyzing visual information, and color perception. Lastly, the insula lobe, which is situated deep within the brain, is involved in regulating emotions, self-awareness, and certain aspects of sensory processing. These lobes work together to allow the human brain to perform complex cognitive, sensory, and motor processes.

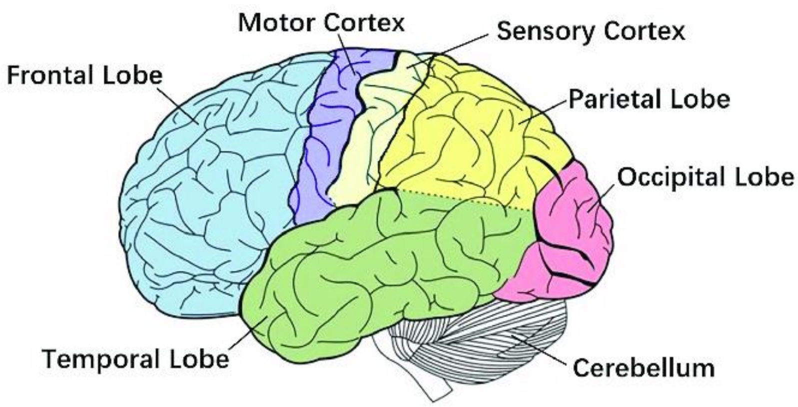


Figure 2.1 Primary Regions of the Brain [6]

The frontal lobe, specifically the primary motor cortex, and the parietal lobe, specifically the somatosensory cortex, play crucial roles during motor imagery tasks in the context of MI BCI. Voluntary movement creation and planning are done by the primary motor cortex in the frontal lobe. When people use motor imagery, the neurons in their primary motor cortex are stimulated, replicating the neuronal patterns connected to actual movement. Then, using methods like EEG, this brain activity can be detected. During motor imagery, the somatosensory cortex in the parietal lobe, which processes touch and body position sensory data, is activated simultaneously. The interaction of these cortical areas enables the mental planning and representation of movements, as well as the production of motor-related signals that MI BCI systems can interpret and utilize.

2.4 Properties of EEG signal

The EEG has a narrow bandwidth and a frequency range of 0.5Hz to 200Hz. 10 to 200 V is the signal strength range [7]. Different brain regions produce distinct waveforms of the signal for a variety of reasons.

Delta waves are the slowest yet have the biggest amplitude waves, with a frequency range of 0.5 to 4 Hz. They follow a rhythm that is linked to deep sleep and healing processes. The amplitudes of delta waves typically range from 20 to 200 microvolts.

The frequency range of theta waves is 4–8 Hz. Theta waves are frequently detected during relaxation, daydreaming, and light sleep. They have a moderate rhythm. Deep concentration and creative thinking include them as well. The amplitudes of theta waves typically range from 10 to 100 microvolts. Theta bands are mostly produced in the temporal and parietal lobes of young people.

During relaxed wakefulness, alpha waves, which have a frequency range of 8 to 13 Hz, are prominent and have a regular rhythm. They are frequently observed when the eyes are closed and are related to mental states of serenity and concentration. It is generated in the occipital region and also the motor cortex. The amplitudes of alpha waves typically range from 5 to 50 microvolts.

Beta waves have a quick and erratic rhythm and have a frequency range of 13–30 Hz. They are connected to concentrated cognitive processes, active thought, and problem-solving. Beta waves range in amplitude from 2 to 20 microvolts, which is quite low compared to other frequency bands.

Gamma waves, which have the fastest rhythm and are found in the frequency range above 30 Hz, are crucial for high-level cognitive functions like sensory integration and information binding. They are related to the development of attention, memory, and complicated mental processes. The amplitudes of gamma waves typically range from 0.5 to 10 microvolts [8].

These frequency bands offer information regarding the oscillatory activity and functional connectivity of many brain regions, along with their distinctive rhythms and amplitude ranges. The amplitude of the electrical activity within the particular frequency bands is reflected in the waves' amplitude.

It's important to keep in mind that these amplitude ranges can change based on individual elements, electrode placement, and recording settings.

Table 2.1 EEG Frequency Bands

EEG band	Frequency
Delta	0.5 Hz-4 Hz
Theta	4 Hz-7 Hz
Alpha	7 Hz-13Hz
Beta	13 Hz-30 Hz
Gamma	Above 30Hz

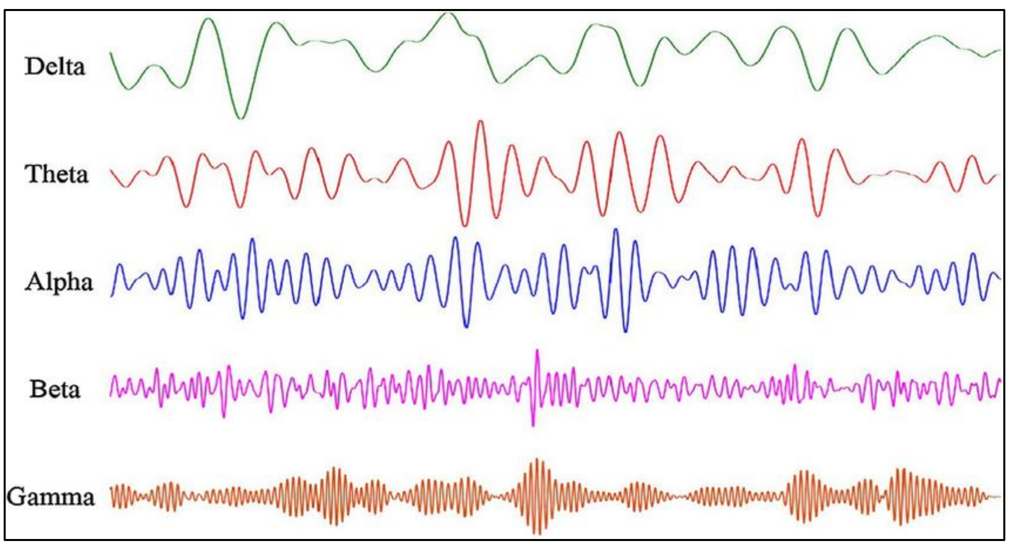


Figure 2.2 Waveforms of EEG Wave Frequency Bands [9]

EEG signals fluctuate in amplitude, which reflects the electrical activity's strength or magnitude. The strength or synchronization of neuronal activity in a specific area of the brain can be deduced from the amplitude of an EEG signal.

Certain EEG signals exhibit rhythmic patterns, such as delta waves—which are unique to sleep—during deep sleep stages—or alpha waves, which are seen in relaxed and awake states and range from 8 to 13 Hz. These rhythms depict the coordinated activity of vast neuronal populations.

Because of the presence of background noise, muscle artifacts, and environmental interference, EEG data have inherent fluctuations. To improve the signal quality and interpretability, preprocessing methods including filtering and artifact removal are used.

2.5 Electrode Placement

The Emotiv EPOC+ 14-electrode wireless EEG headset utilizes a different electrode placement system compared to the traditional 10-20 electrode placement system.

The Emotiv EPOC+ headset is configured specifically to record EEG signals and make the acquired data available for a variety of uses, such as cognitive monitoring and brain-computer interface (BCI) control.

The Emotiv EPOC+ headset has 14 electrodes that are placed on the scalp in 14 distinct locations. Based on their research and development, the manufacturer chose these electrode locations to improve signal acquisition and user experience. The frontal, parietal, temporal, and occipital regions of the scalp are typically covered.

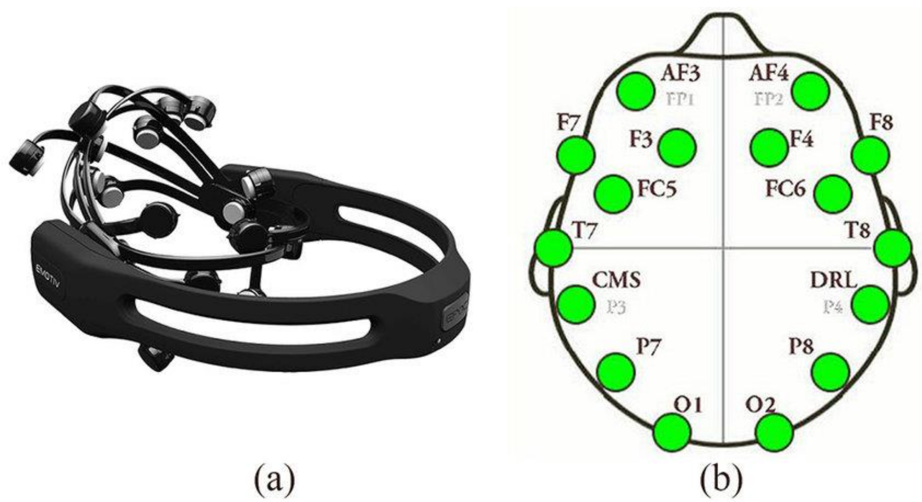


Figure 2.3(a) The Emotiv EPOC+ 14 Electrode Wireless Headset (b) The electrode Placement of the Headset [10]

Despite not adhering to the exact electrode placements specified by the 10-20 electrode placement system, the Emotiv EPOC+ headset has been optimized to record meaningful EEG signals and offer useful features for its intended applications. The Emotiv EPOC+ headset's electrode placement is tailored for the configuration of its sensors and may provide benefits like ease of use, wireless operation, and targeted coverage of brain regions significant to the desired applications.

2.6 Channel Selection

All the 14 channels of the Emotiv EPOC+ headset has been used to acquire data. This decision is based on several factors and considerations. The 14 channels are strategically positioned to cover key areas of the brain involved in motor imagery and related processes.

Using multiple channels improve the spatial resolution, making it possible to localize neuronal activity more precisely while also improving the accuracy and dependability of the recorded EEG signals. This is crucial for capturing the subtle variations in brain signals linked to various motor imagery tasks or targeted brain regions. It provides for better noise reduction, an enhanced signal-to-noise ratio, and reduces the impact of artifacts or interference that could be present in particular channels by simultaneously recording signals from numerous channels.

Each channel of the Emotiv EPOC+ headset helps to collect EEG signals from a particular location of the scalp that corresponds to underlying brain regions. Executive functions, decision-making, and motor control depend on channels over the frontal cortex (for example, AF3, AF4, F3, F4). The parietal cortex's P7 and P8 channels, for example, keep track of spatial awareness, sensory processing, and object manipulation. Language comprehension, memory consolidation, visual perception, and auditory processing are all mediated by channels over the temporal cortex (e.g., T7, T8). O1, O2, and other channels over the occipital cortex, for example, record visual processing, interpretation of visual information, and color perception. The planning, execution, and generation of motor-related signals are all heavily dependent on channels over the sensorimotor cortex (such as C3, C4). Additional pertinent brain regions involved in motor imagery and cognitive processes may be covered by other channels (such AF7 and AF8).

By recording EEG signals from all these channels, a comprehensive picture of brain activity during motor imagery can be obtained, enabling researchers to analyze and extract relevant features for MI BCI applications.

2.7 Literature Review

Ref. No	Datasets	Filtering	Feature Extraction	Classifier	Accuracy	Limitation
[1]	BCI competition II datasets	Delta (<.4) Hz Alpha (8-12) Hz Beta (13-25) Hz Gamma(>25) Hz	DWT, PSD	LDA, KNN	80.00-84.29%	The impact of the method on particular BCI application can be investigated
[2]	BCI competition IV datasets 2a and 2b	band-pass filtered (8-30Hz)	CSP	SVM	95%	Performance evaluation could be done using more criteria
[4]	Publically available	Delta (1-3.5) Hz Alpha (8-12) Hz Beta (14-30) Hz Gamma (>30) Hz Theta (4-7.5) Hz	DWT, DD-DWT	SVM, LDA	94.6%	Real time implementation is not done
[5]	BCI competition III dataset	band-pass filtered (8-30Hz)	CSP	CNN	91.9%	Use a limited number of motor imagery classes
[9]	32-BCI novice	Bandpass filter (8-30Hz)	CSP	SVM	70%	Accuracy is low
[12]	Real time 10 heathy volunteers	FFT	SSVEP, P300	Multi-class LDA	97.5%	Head movement artifact could be removed offline but not in online
[15]	BCI Competition IV dataset 2a	Buttherworth 5^{th} order (μ(8 – 13Hz),β(13 – 30Hz))	CSP	CNN	80%	Reliable information is missing related to motor imagery.
[18]	52 healthy applicants	Alpha & Beta frequency	CCA, SVM	P300, SVM, LDA	84.28±0.87%, >80%, >95%	As the number of channel increases the delay increases

CHAPTER 3
SYSTEM DESIGN

3.1 System Requirements

To ensure the system is able to carry out the tasks necessary at every step of the process, we must meet some requirements. This involves both software and hardware requirements.

3.1.1 Hardware Requirements

Two main hardware components were required for this project: The EEG headset for data acquisition and an advanced computer for data acquisition, signal processing, and the algorithm.

The EEG headset used for this project is the Emotiv EPOC+ 14-channel wireless headset. This headset has 14 strategically placed electrodes at various regions of the brain. It is a wireless headset, and it uses Bluetooth to connect to the computer, making it portable and more

Figure 3.1 Emotiv EPOC+ 14-channel wireless headset components and setup

comfortable than a traditional wired headset. The headset sends data to the computer via the Emotiv Pro software, which comes with the headset. The acquired data from this software can be loaded into a programming software for data processing.

This project utilized advanced software such as the Emotiv Pro and MATLAB, which cannot be run on low-configuration computers. It was necessary to use a computer of high configuration not just for these softwares but also for processing speed.

3.1.2 Software Requirements

To acquire the data collected from the headset, we need the Emotiv Pro Software. This software requires licensing to use, which has to be renewed every month. This software very conveniently displays the connection status of each electrode, EEG quality, and the signal from each channel separately. So, this is very convenient for not only data acquisition but also for reducing hardware-related noise or artifacts.

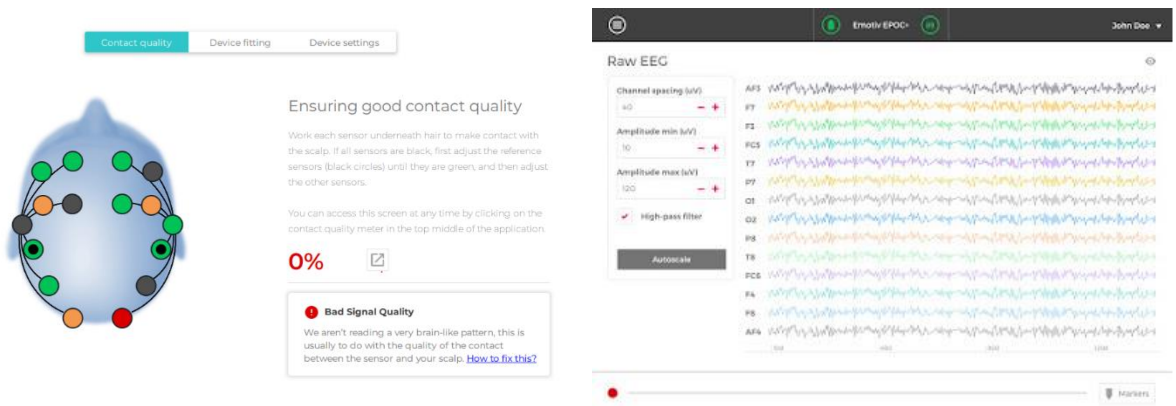


Figure 3.2 Emotiv Pro software Connectivity page and Raw EEG Signal display page

We have used the MATLAB software to process the data and create our algorithm. This is a very large size software which is very convenient for our application. This also has multiple built-in applications and toolkits such as Classification model which is very crucial for performance monitoring.

3.2 System Design

The system is designed such that each required process follows the next, alternating between software and hardware. It has been designed such that the data is collected in the laboratory and then the direction of movement is classified and fed into the algorithm to move the mouse cursor.

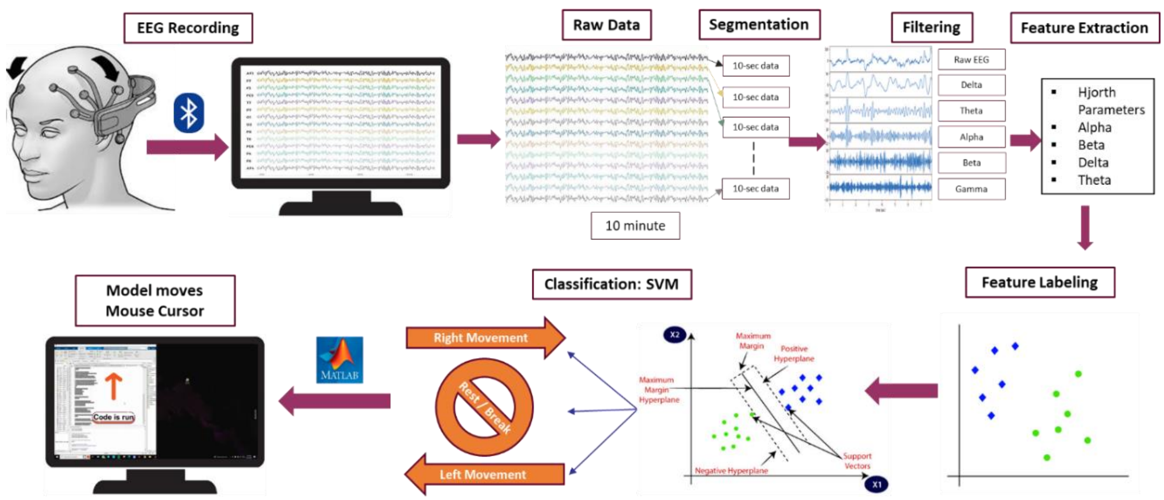


Figure 3.3 Graphical Representation of the System Design

3.2.1 Data Acquisition

The data used for this phase of the project development was recorded at the Biomedical Instrumentation and Signal Processing Laboratory at Independent University Bangladesh, using an Emotiv EPOC+ 14 Electrode Wireless Headset. Participants were briefed on the experiment tasks and data was recorded on the Emotiv Pro software. Two types of data were recorded as follows:

<u>Data Type 1:</u>

Participants were shown a 10-minute-long video which displayed two commands: 1. Relax. 2. Imagine Right Hand Movement. Each of these commands was shown for 10 seconds alternatively for the whole duration of the video. Participants were to carry out these commands as prompted while their EEG signal data is recorded for the duration of the video.

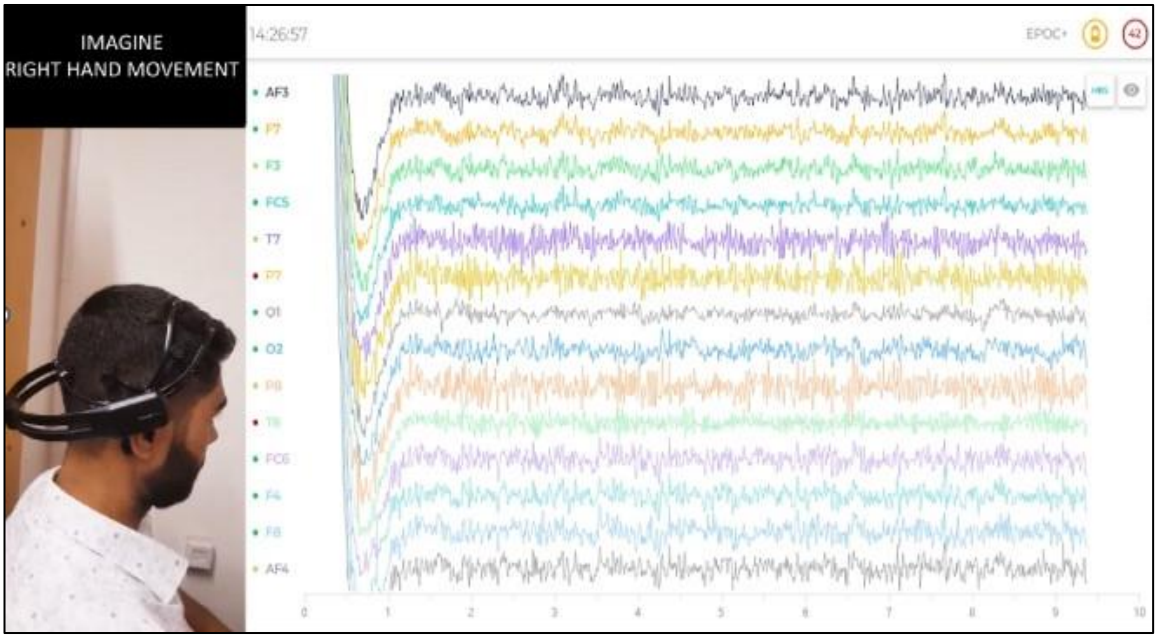


Figure 3.4 Data Acquisition of Data Type 1.

<u>Data Type 2:</u>

A single MI task was carried out and the EEG signal was recorded for 10 minutes. Two separate MI tasks were recorded: 1. Break/Relaxation. 2. Imagine Right-Hand movement. The tasks were undertaken non-stop and without any other tasks mixed in.

3.2.2 Segmentation

The recorded data was segmented into 10-second-long samples before moving on to signal processing. EEG signals are analog data which need to be converted into digital format to be loaded into computers and worked on in software as these are digital systems. The data needs to be processed before undergoing feature extraction and classification.

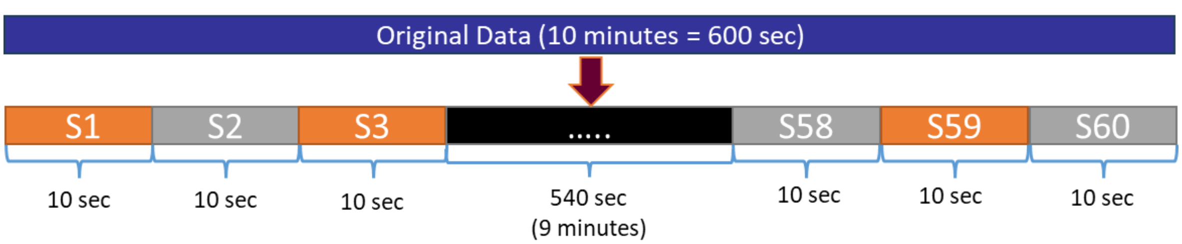


Figure 3.5 Graphical Representation of Segmentation Process

3.2.3 Data Filtering

The Butterworth bandpass filter is a widely used digital filter in signal processing, which is particularly suited to the requirements of this project, which utilizes EEG signal analysis for motor imagery-based brain-computer interfaces (MI BCI). A bandpass filter with a frequency range of 1 to 40 Hz is best suited for this project to focus on the relevant brain activity related to motor imagery tasks.

The Butterworth filter has some advantages over other signal processing techniques. First off, it gives the passband a flat frequency response, which is essential for maintaining the EEG signals' original structure and properties throughout the required frequency range. For the analysis and interpretation of motor imagery-related brain activity to be accurate, this is essential.

Furthermore, effective real-time processing is made possible by the Butterworth filter's implementation as an Infinite Impulse response (IIR) filter, which is essential for applications like MI BCI where prompt feedback and reaction are wanted.

The steepness or roll-off rate, which is the rate at which the filter attenuates frequencies outside the passband, of a Butterworth filter is determined by its order.

Higher-order Butterworth filters have steeper roll-offs, enabling them to accomplish stopband transitions that are more abrupt. As a result, the required frequency range (1–40 Hz) for motor imaging signals is more effectively isolated, and frequencies outside of this range—such as noise and artifacts—are attenuated.

The 5th-order filter is an ideal option because it strikes a balance between preserving the integrity of the selected frequency range and providing enough suppression of undesirable frequencies. A higher-order filter might be able to reduce out-of-band frequencies even more, but because of its added complexity, it might also result in more phase or signal distortion. A lower-order filter, on the other hand, might not offer sufficient suppression of undesirable frequencies.

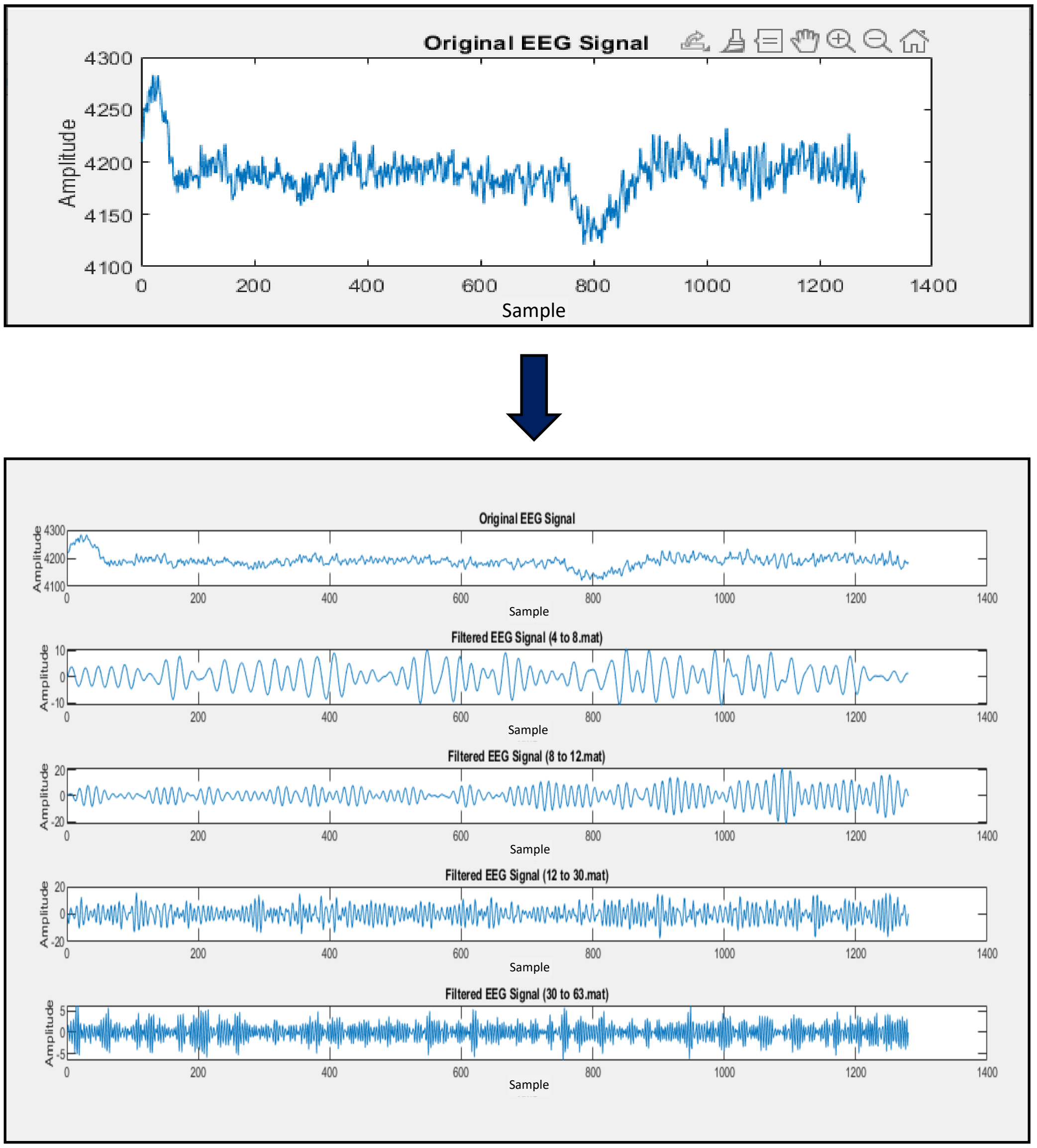


Figure 2.6 Filtration of Original data into each Frequency Band

Later in the process, the frequency range of the filter was set for the different frequency bands: Delta, Theta, Alpha, Beta, and Gamma. The entire process was run for each frequency band, where it was eventually found that Gamma had the best results for the application in this project.

3.2.4. Feature Extraction

In this study, various important elements are extracted from the EEG signals in order to classify and further analyze them for use in motor imagery-based brain-computer interfaces (MI BCI). Hjorth activity, Hjorth mobility, Hjorth complexity, band power in the alpha, beta, delta, and theta frequency bands, as well as variance, skewness, and kurtosis were the features that were retrieved.

The temporal dynamics and complexity of the EEG signals are characterized by statistical measurements called Hjorth activity, mobility, and complexity. The signal's overall power or amplitude is represented by the Hjorth activity, its frequency or waveform changes over time are described by the Hjorth mobility, and the signal's irregularity or complexity is measured by the Hjorth complexity. Equations 3.1, 3.2 and 3.3 shows how each Hjorth Parameter is calculated.

$$Activity = var(y(t)) \tag{3.1}$$

$$Mobility = \sqrt{\frac{var(y'(t))}{var(y(t))}} \tag{3.2}$$

$$Complexity = \frac{mobility(y'(t))}{mobility(y(t))} \tag{3.3}$$

Estimating the power or energy distribution of the EEG signals within particular frequency bands is known as band power analysis. The alpha, beta, delta, and theta frequency ranges are relevant to this project. Theta waves are related to relaxation, daydreaming, and creative thinking, while beta waves are connected to active thinking and cognitive processes, delta waves to deep sleep, and alpha waves to peace and relaxation. We may determine the proportionate energy or power contributions of each band by computing the band power within these frequency ranges.

These features are used as input to machine learning algorithms or classifiers for additional analysis, classification, and interpretation. The extracted features provide a condensed representation of the EEG signals, enabling the system to distinguish between different motor imagery patterns and facilitate accurate control of the mouse cursor using MI BCI techniques.

3.2.5 Classification

Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification and regression tasks. SVM is applicable this project because it can be used to classify motor imagery patterns based on features collected from the data.

SVM can be used to train a classification model that learns to differentiate between various motor imagery states, such as imagining left-hand movement, right-hand movement, or no movement. The SVM model can use the extracted features as input variables.

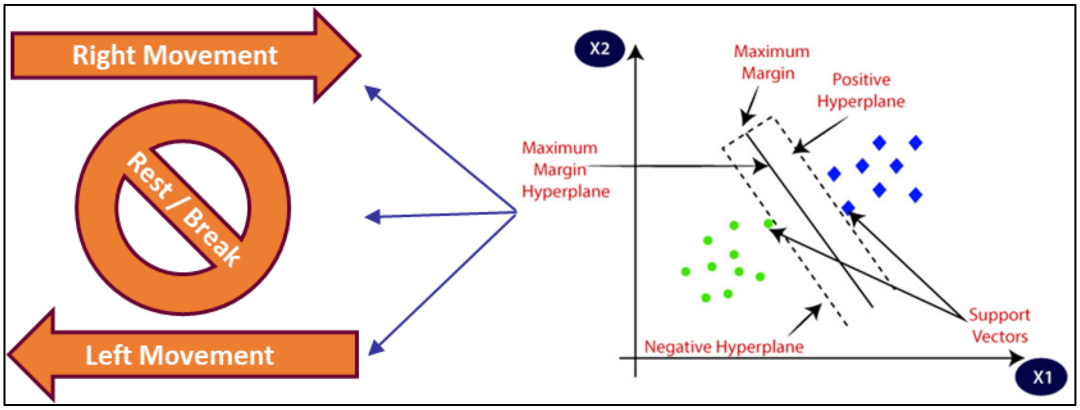


Figure 3.7 Graphical Representation of Classification using SVM

The SVM method refines a decision boundary that separates the various classes of motor imagery patterns in the feature space during the training phase. This decision boundary maximizes the space between the classes, improving the model's adaptability and universality. The SVM algorithm can predict the motor imagery class of new, unseen EEG data after training, allowing the mouse cursor to be controlled according to the user's intended motor commands.

SVM has a number of benefits for this project. Since small sample sizes are frequently used in EEG-based BCI applications, it is capable of handling high-dimensional feature spaces and is efficient in doing so. Additionally, SVM can use kernel functions to capture non-linear correlations between the features and the motor imagery classes, enabling more adaptable decision bounds. SVM is a great option for this project because it has already been widely utilized in BCI research and has shown promising results in accurately classifying motor imagery patterns.

3.2.6 Cursor Movement

Once trained, the classifier can predict the user's intended cursor movement orders. By mapping the classifier outputs to cursor displacement and click actions, the program then translates the input data into corresponding cursor movements on the computer screen. This part of the algorithm is essential for physically impaired individuals to easily navigate the screen and interact with different applications on their own via the continual update of the cursor's position based on the EEG-derived commands.

Once the EEG command is predicted, the algorithm updates the position of the cursor on the screen. The cursor's displacement is proportional to the predicted command's intensity, allowing for precise control. One of the algorithm's objectives is to ensure smooth cursor control with minimal lag between mental commands and cursor movements, so allowing low latency is crucial for providing an immersive user experience.

CHAPTER 4

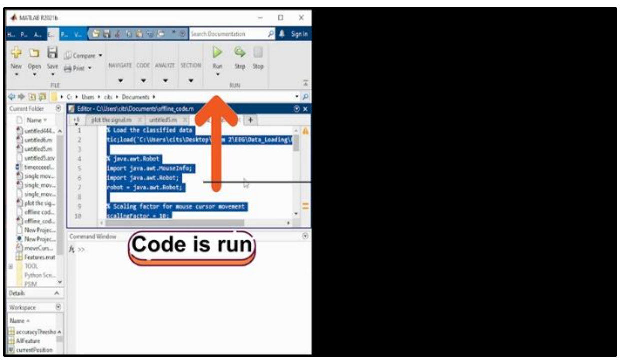
PROJECT IMPLEMENTATION

4.1 Cursor Movement

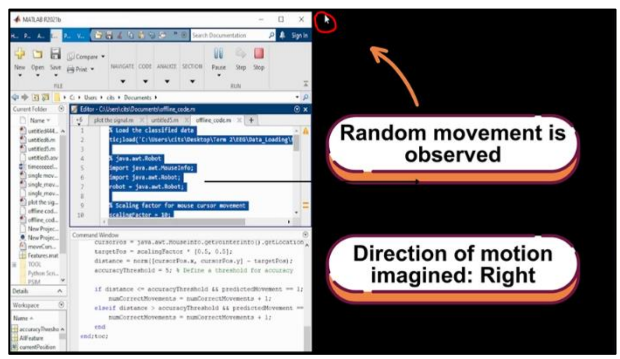
The main objective of this project is to create an algorithm that uses EEG signals and converts the processed signal to commands to move a mouse cursor. Two algorithms were created to achieve this.

4.1.1 Algorithm 1: Directly Using Processed Signal

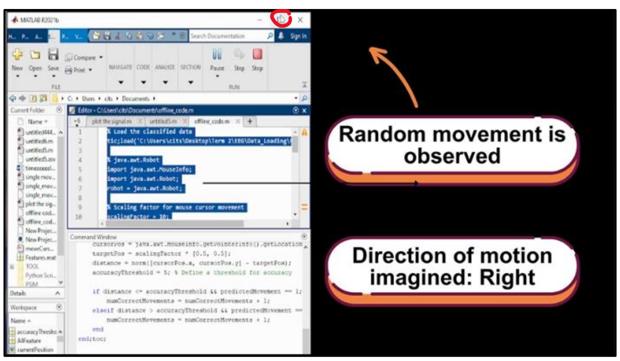
The first algorithm was designed such that after classification, the processed signal was directly translated to cursor movement commands. The input was not attenuated or scaled, and there was no delay in the algorithm, so the result was an erratic movement of the mouse cursor at the very top of the screen.



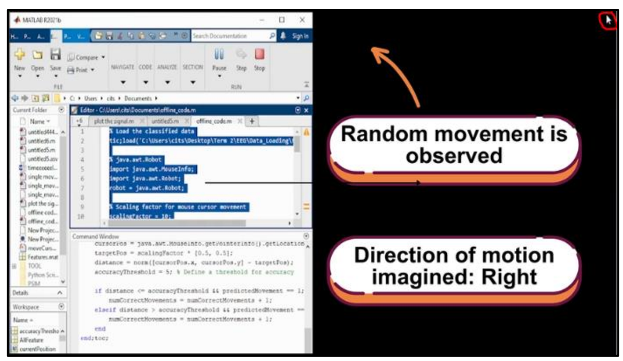
(a)



(b)



(c)



(d)

Figure 4.1 Running the algorithm with Processed Data (a) the code is run (b) mouse cursor at position 1 (c) mouse cursor at position 2 (d) mouse cursor at position 3

As shown in the pictures, the movement imagined was 'Right' but the mouse cursor moves erratically along the horizontal line, and although it does move to the right, sometimes the movement is towards the left.

This shows that the algorithm needed further changes such as a delay in movement, so it gives feedback that can be acted upon by the user. It also needs scaling to make sure the cursor moves along the screen in discrete steps instead of a continual motion, as well as the cursor movement starting from the center of the screen to make sure the cursor can move in steps in any direction commanded.

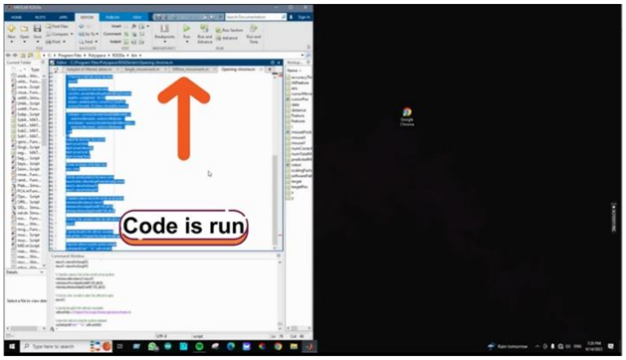
All these were taken into account when designing the second algorithm.

4.1.2 Algorithm 2: Altered Algorithm

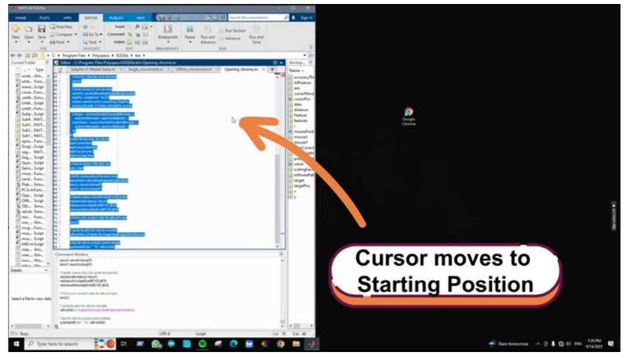
Keeping in mind the results of the previous algorithm, a few changes were made:

- A delay was added between each change in displacement in the mouse cursor movement.
- Scaling was done according to the size of the display screen so that each step taken would cause a fixed displacement.
- Using scaling, the very center of the screen was located and the algorithm was designed such that once the code is run, the cursor will automatically move to the center before moving according to the commands.
- When there was no movement signal detected or when the EEG signal showed rest or break, the command registered was clicking, to enable users to open an application.

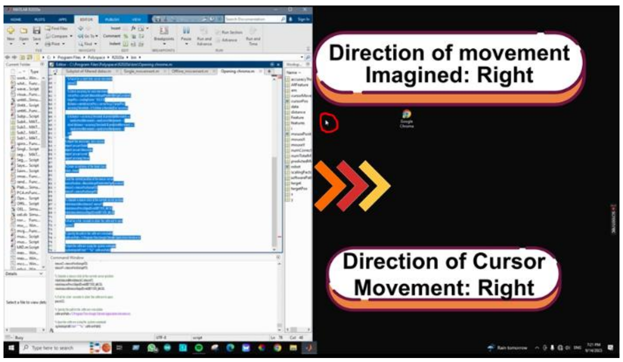
This new algorithm ensured the cursor moved in a much more orderly manner.



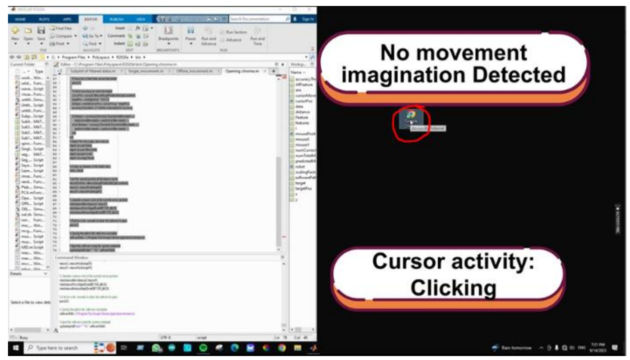
(a)



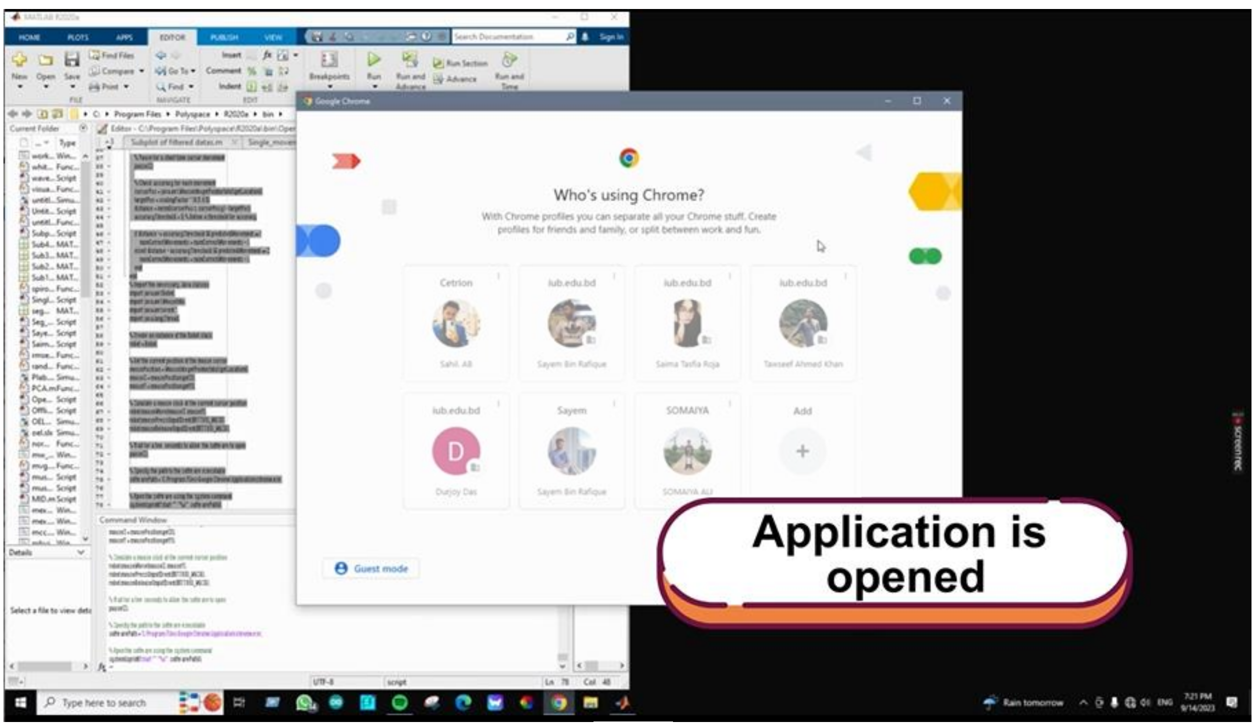
(b)



(c)



(d)



(e)

Figure 4.2 Running the data with the new algorithm adapted for step movement (a) The code is run (b) cursor moves to the starting position (c) cursor starts moving in the direction of the imagined movement (right) (d) cursor stops moving and clicks (e) Application is opened

As shown in figure 4.1.2, the movement imagined was ‘Right’ as well. Once the code is run (a), the cursor moves to the starting position (b) (as indicated exactly by the scaling) and then it starts moving to the right in discrete steps of equal measure (c).

Once the movement command stops and clicking command is prompted (d), the cursor clicks on the application and opens it (e).

This is a successful case of binary classification used to control a computer mouse cursor.

CHAPTER 5

INVESTIGATIONS, RESULTS AND DISCUSSION

5.1 Performance Evaluation Parameters

5.1.1 Confusion Matrix

The classification performed in this project is binary classification using the Support Vector Machine (SVM) method. The possible outcomes were either positive or negative and so the Confusion matrix was 2X2 or 4 cells.

The columns represent the predicted classes, and the rows represent the actual classes. The characteristic entries of the table can be categorized by True Positives (TP) which represent the number of correct positive predictions, False Positive (FP) which is the number of incorrect positive predictions, True Negative (TN) which is the number of correct negative predictions and False Negative (FN) which is the number of incorrect negative predictions. We can calculate the accuracy by adding the true positive and true negative divided by the total number of the matrix. Equation 5.1 shows how the classification accuracy is calculated.

Confusion Matrix

	Actually Positive (1)	Actually Negative (0)
Predicted Positive (1)	True Positives (TPs)	False Positives (FPs)
Predicted Negative (0)	False Negatives (FNs)	True Negatives (TNs)

Figure 5.1 Confusion Matrix Table

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5.1)$$

We want to minimize the false positive and false negative on the other hand we want to maximize the true positive and true negative. Because they directly affect the accuracy of the model prediction.

5.1.2 The ROC Curve

On the other hands, ROC (Receiver Operating Characteristic) curve is a graphical representation of the performance of a binary classification algorithm, which shows the trade-off between the true positive rate (TPR) and the false positive rate (FPR) for different threshold values. The area under the ROC curve (AUC) is a commonly used metric to evaluate the performance of a binary classification algorithm. AUC ranges from 0 to 1, where 0.5 represents a random classifier, and 1 represents a perfect classifier. The closer the AUC is to 1, the better the performance of the classification algorithm.

5.1.3 K-Fold Cross Validation

The Five-fold cross-validation is a frequently used meythod to evaluate model performance in machine learning. The dataset is divided into five equal "folds," or subsets, and the model is trained and tested five times, using a different fold for testing each time and the other four as the training set. For each iteration, performance measures are calculated to assess the model's predictability. In order to produce a more reliable estimate of the model's performance, the outcomes from these iterations are averaged. This approach is a widespread practice in machine learning experiments because it helps prevent overfitting and underfitting, provides a trustworthy assessment of model efficiency, and strikes a balance between computational complexity and accuracy.

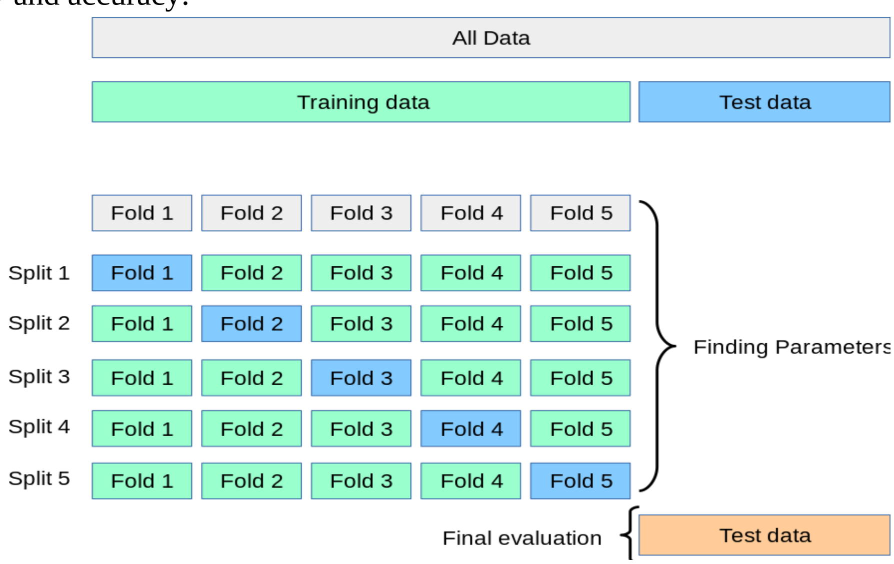


Figure 5.2 Graphical Representation of 5-fold Cross Validation Process

5.1.4 Performance Parameters

Some Performance Parameters used in this project are:

- Sensitivity:

  The model's sensitivity gauges its capacity for identifying true positive cases from false positive ones. It determines the ratio of the number of correctly identified positive instances, or true positives, to all positive cases overall.

- Specificity:

  The model's specificity measures its ability to correctly identify negative cases from all the true negative examples. It determines the proportion of true negatives (negative cases that were accurately identified) to the total number of negative cases.

- Accuracy:

  The ratio of correctly predicted cases (including true positives and true negatives) to the total number of instances in the dataset provides an overall assessment of the model's correctness.

- Precision:

  Precision measures how well a model predicts positive cases. This measure of the model's ability to prevent false positives is calculated as the ratio of true positives to the total number of cases predicted as positive.

Table 5.1 Table showing the highest achieved value for each parameter along with equations for deriving each Parameter.

Parameter	Value	Derivation
Sensitivity	0.9110	TP / (TP + FN)
Specificity	0.9645	TN / (FP + TN)
Precision	0.9667	TP / (TP + FP)
Accuracy	0.9361	(TP + TN) / (P + N)

5.2 Raw Data Accuracy

Out of all the data obtained in the lab, only data from four subjects could be used. The data from these 4 subjects were used for classification and the results are discussed below:

5.2.1 Confusion Matrix

The Confusion Matrix of the four subjects' data are shown below:

Subject 1 (Accuracy:71.1%):

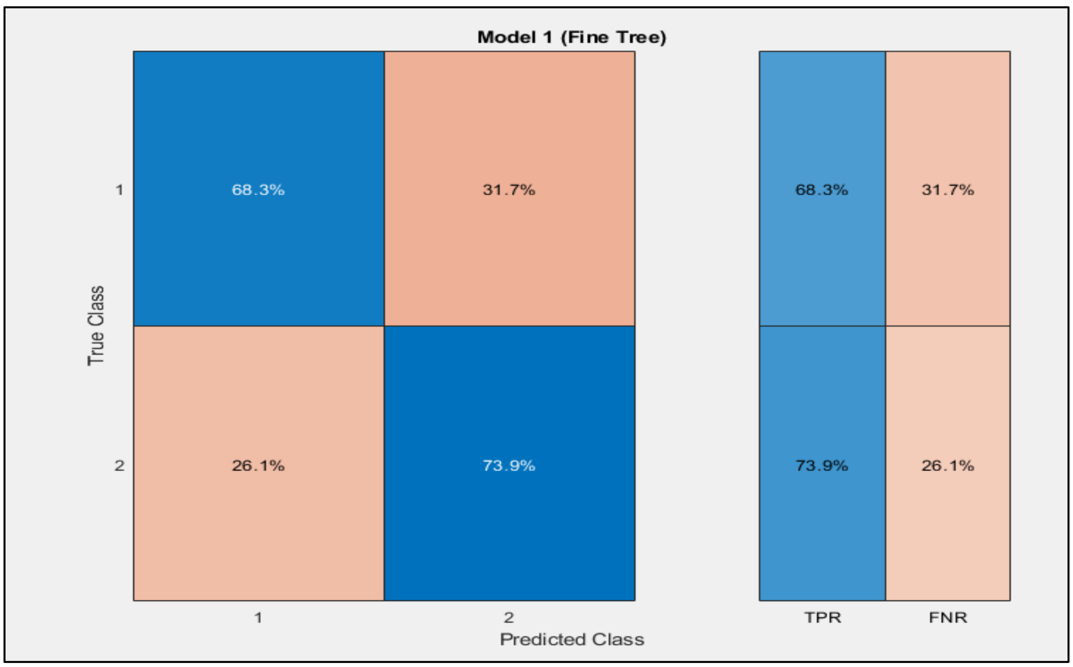


Figure 5.3 Confusion Matrix of Data from Subject 1

Subject 2 (Accuracy:77.2%):

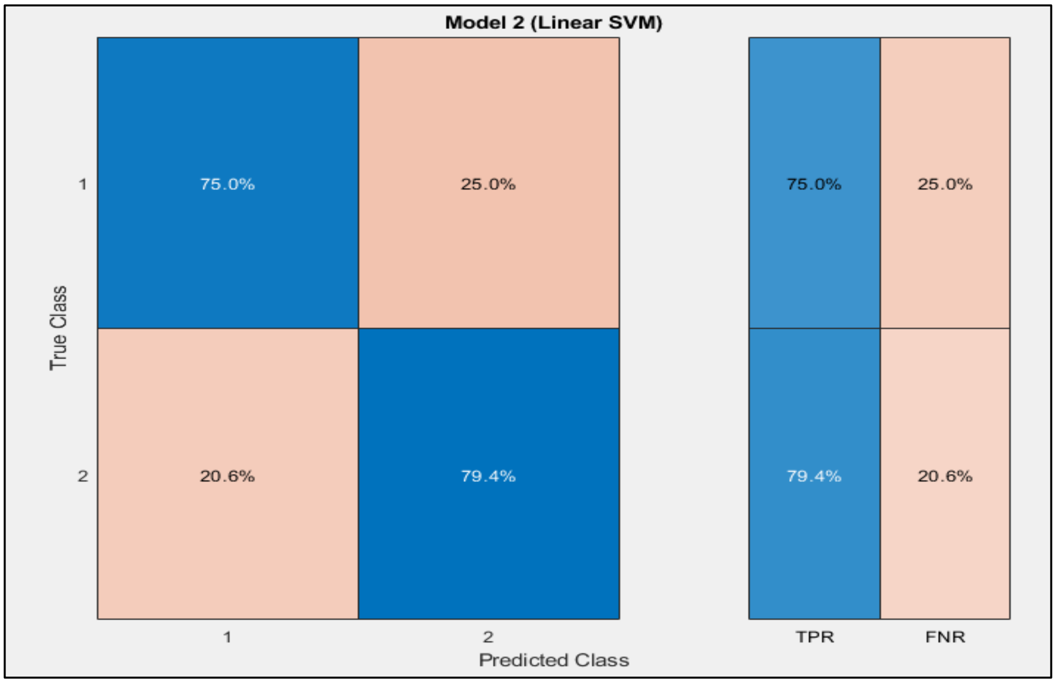


Figure 5.4 Confusion Matrix of Data from Subject 2

Subject 3 (Accuracy: 76.9%):

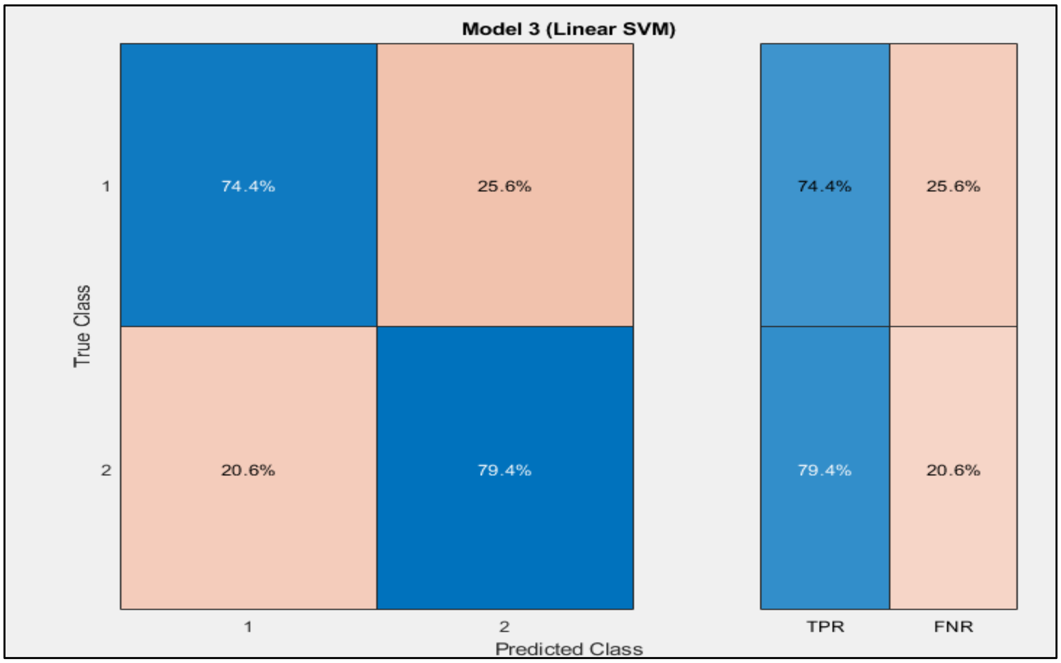


Figure 5.5 Confusion Matrix of Data from Subject 3

Subject 4 (Accuracy:77.2%):

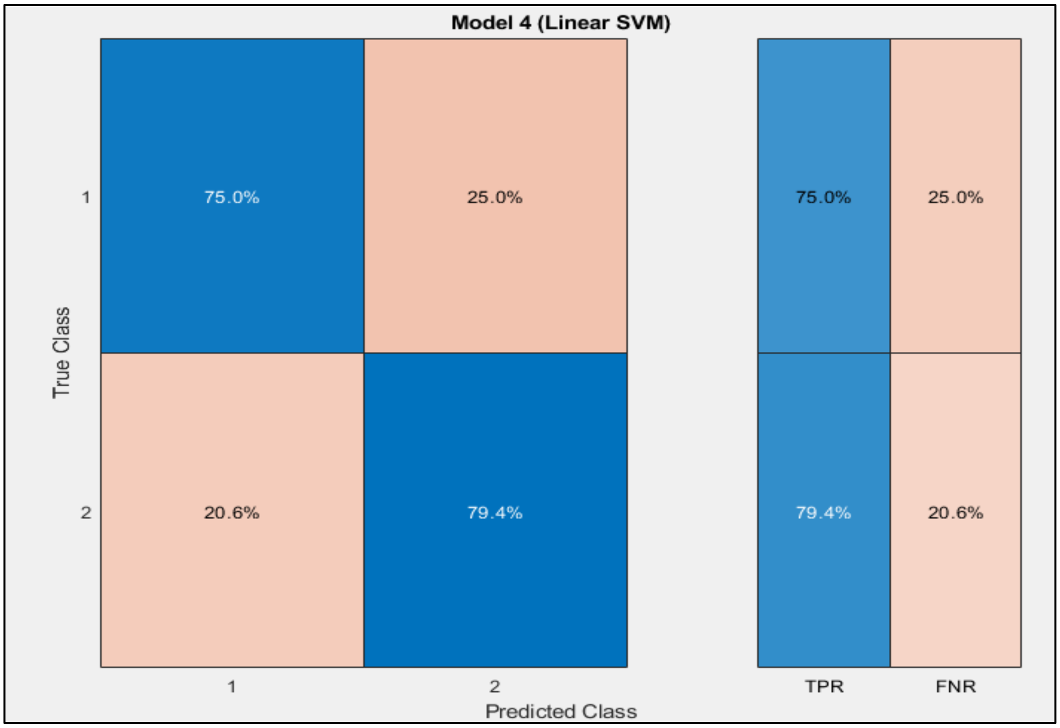
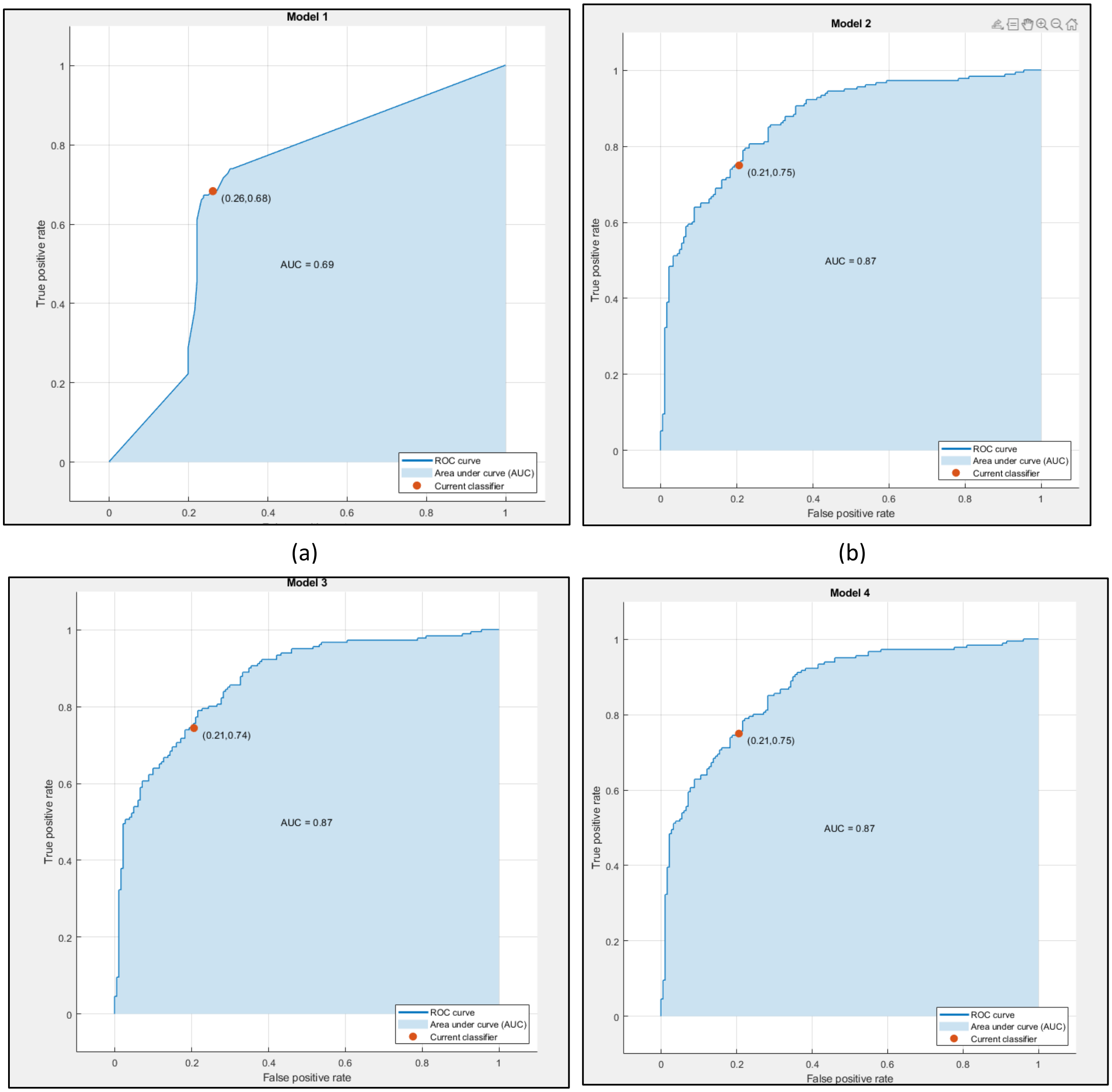


Figure 5.6 Confusion Matrix of Data from Subject 4

Here we can see the accuracy of four different models which are respectively 71.1%,77.2%,76.9%, and 77.2%. We can do the average of the accuracy to get more accurate results.

5.2.2 ROC Curve

The ROC curves of the experimental data are given below:



(a) (b) (c) (d)

Figure 5.7 (a) ROC of data from Subject 1 (b) ROC of data from Subject 2 (c) ROC of data from Subject 3 (d) ROC of data from Subject 4

Here we can see the AUC values of four different models which are respectively 0.69,0.87,0.87.0.87.

So, we can say that the AUC value we get is close to 1, so our model accuracy is high.

5.3 Frequency Bands Classification Accuracy:

Once the algorithm was implemented and the mouse cursor was successfully controlled, the raw data was filtered for each frequency band to see which frequency band was more effective. The results for each frequency band (confusion matrix and ROC curve) are given below:

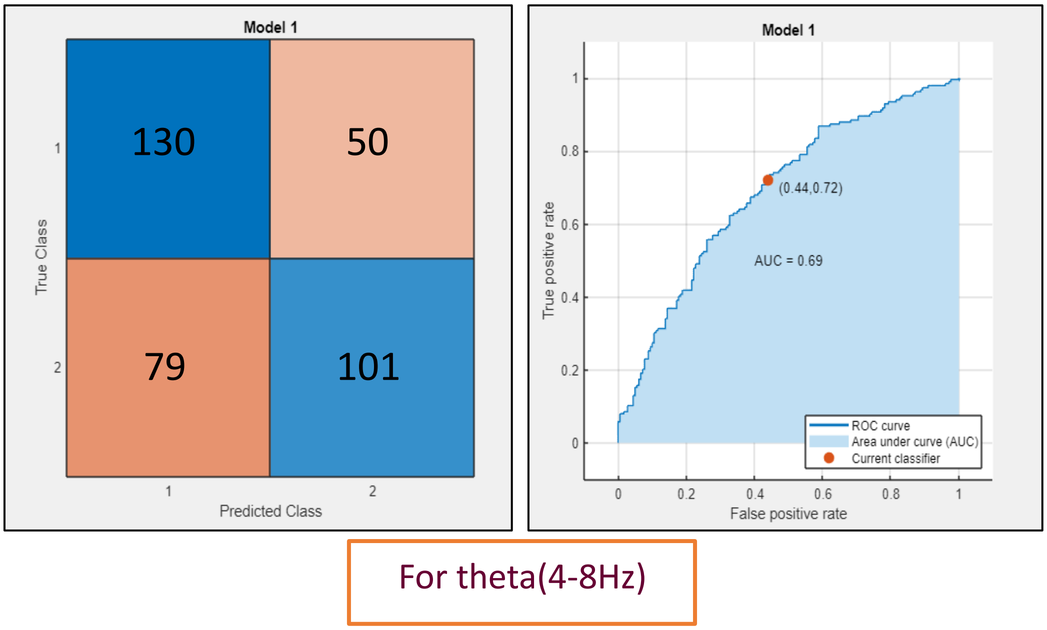


Figure 5.8 Confusion Matrix and ROC Curve of Theta Band

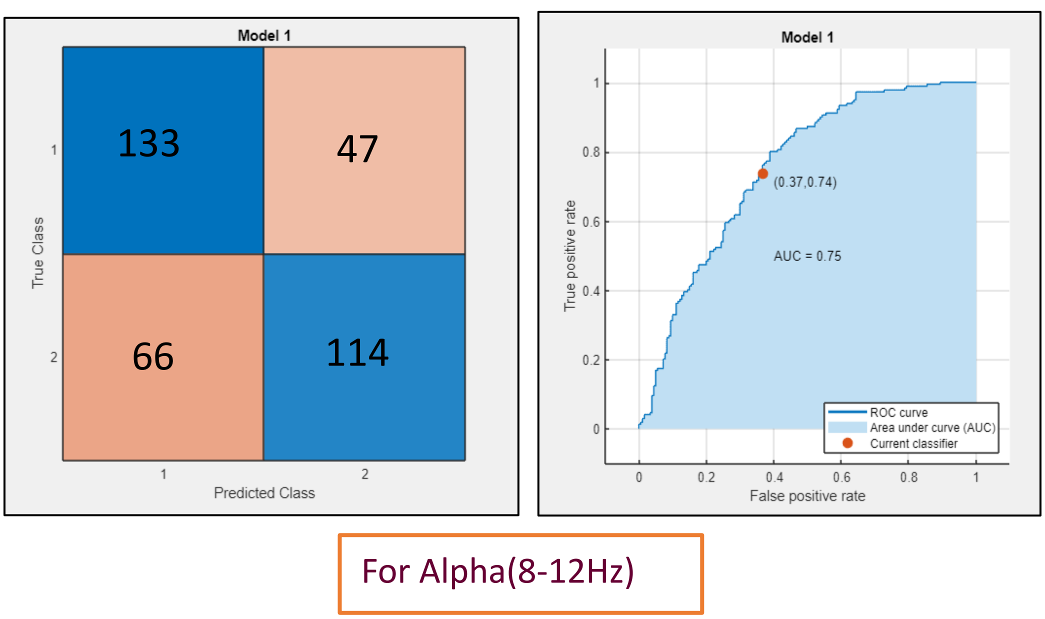
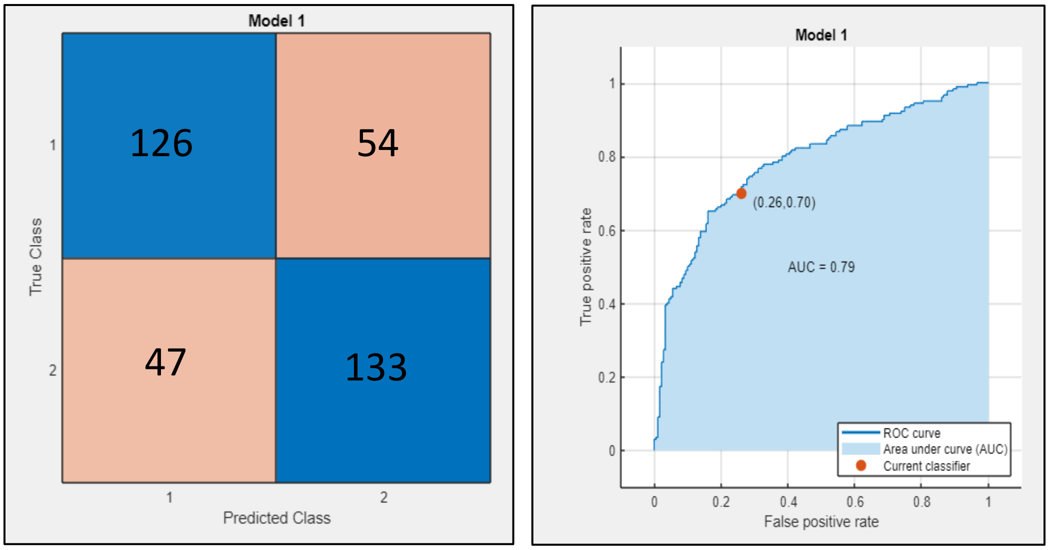
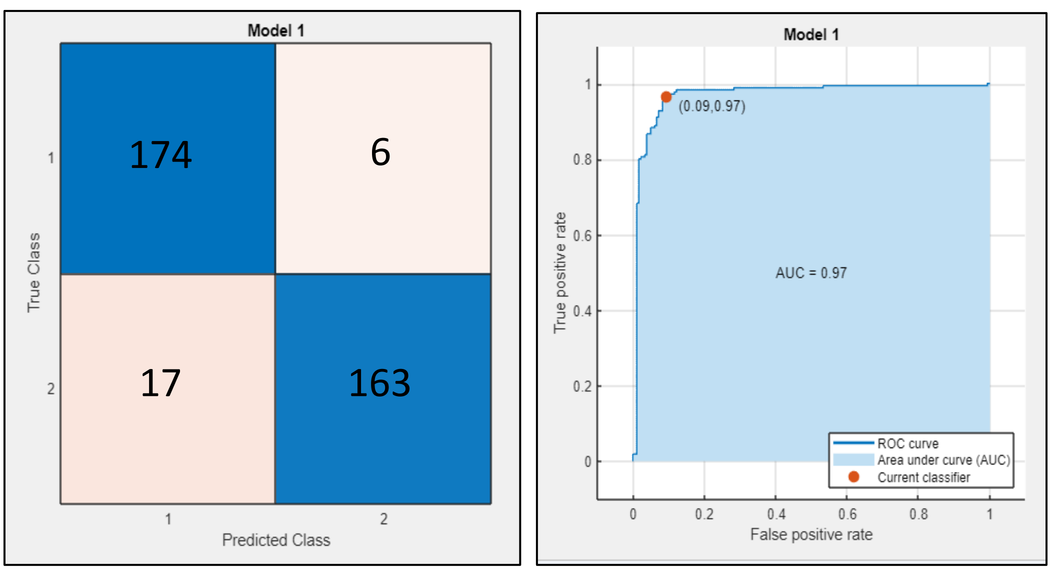


Figure 5.9 Confusion Matrix and ROC Curve of Alpha Band



For Beta(13-30Hz)

Figure 5.10 Confusion Matrix and ROC Curve of Beta Band



For Gamma(30-64Hz)

Figure 5.11 Confusion Matrix and ROC Curve of Gamma Band

The results are given in the table below:

Table 5.2 Comparison of Performance between the Original Data and each frequency bands

Frequency Band	**Classification Accuracy**	**Sensitivity**	**Specificity**	**Precision**	**AUC**
Original Data (0.5-40Hz)	71.10%	72.35%	69.98%	**68.30%**	**0.69**
Theta(4-8Hz)	**63.78%**	**62.20%**	**66.89%**	72.22%	**0.69**
Alpha(8-12Hz)	68.40%	66.83%	70.81%	73.89%	0.75
Beta(13-30Hz)	72.25%	72.83%	71.12%	70.0%	0.79
Gamma (30-64Hz)	**93.60%**	**91.10%**	**96.45%**	**96.67%**	**0.97**

As we can see here, the lowest value of the performance parameters was achieved by the Theta frequency band (4-8Hz) with a classification accuracy of 63.78% and an AUC of 0.69. The same AUC was achieved by the original data (0.5-40Hz), which also had the lowest Precision of 68.30%.

In contrast, the highest values of the performance parameters were achieved by the Gamma frequency band (30-64Hz). The classification accuracy was 93.60% and the AUC value was 0.97, which is very close to 1, and therefore, near perfect. It also achieved a sensitivity of 91.10%, a Specificity of 96.45%, and a Precision of 96.67%, which is much higher than the other frequency bands and therefore the band to be considered for this project.

5.4 System Latency

The system Latency of each step of the process is shown in the table given below:

Table 5.3 Total time of the process for each 10 second segment

Process	**Time(s)**
Initiation Time	10
Data loading	0.201
Data filtering	0.079
Feature Extraction	0.168
Offline Movement	0.488
Single Movement	0.069
Processing Time	**1.005**
Total Time	**11.005**

5.5 Comparative Analysis

There were a few similar systems from our literature review as the usage of BCI has grown over the decades. The table given below shows a comparison with some of these systems:

5.4 Table of Comparison to other similar systems

Reference	Wireless Headset?	Filtering Range	Implementation?	Classification Accuracy
“Classification of multi-class motor imagery EEG using four band common spatial pattern." In 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 1034-1037. IEEE, 2017.	🚫	0.5-32Hz	-	94.64%
"A comparative analysis of signal processing and classification methods for different applications based on EEG signals." Biocybernetics and Biomedical Engineering 40, no. 2 (2020): 649-690.	🚫	0.5-64Hz	🚫	85.50%
"EEG datasets for motor imagery brain–computer interface." GigaScience 6, no. 7 (2017): gix034.	-	8-30Hz	🚫	73.08%
"Multiclass support vector machines for EEG-signals classification." IEEE transactions on information technology in biomedicine 11, no. 2 (2007): 117-126.	✅	0.5-100Hz	🚫	99.95%
Our Work	✅	30-64Hz	✅	93.61%

5.6 Discussion

The overall work presents the classification work which represents the binary classification by using the Support Vector Machine (SVM). This classification work has been evaluated by implementing confusion matrix. This confusion matrix that has been implemented is 2x2 or 4-cell model performance where shown True Positive (TP), True Negative (TN), False Positive(FP) and False Negative(FN). This model represents the actual class and predicted class.

To assess the accuracy model, the true positive and true negative values can be calculated by doing the addition and division of the using matrix. This working process has been done to reduce the false negative and positive on the other side to maximize the true positive and true negative value.

The ROC stands for the receiver operating characteristic curve and this curve is used to assist the performance the binary classification of this project. This curve is mainly used to evaluate the better performance of the result where the AUC works. If the AUC stands as close to 1 then the system can give better performance. The AUC values have been compared to evaluate the result. The average AUC has been shown to obtain the overall performance where the lower accuracy shows the low AUC value, and the heights accuracy shows the higher AUC value.

The five-cross validation method was used to evaluate the model's performance. This work process has been implemented to do the training and testing mode of each model for the better accuracy. Performance measures are calculated for Each iteration and the outcomes are averaged to provide a more reliable model's efficiency.

Lastly the discussion ends by showing the highest and lowest accuracy from different frequency bands by doing comparison. The Theta frequency bands (4-8 Hz) has the lowest accuracy with the lower AUC and precision values. On the other hand, the Gamma (30-64 Hz) has achieved the highest accuracy value with the AUC, sensitivity, specificity and precision values. That is why the Gamma frequency band is more relevant and considered in this project system.

CHAPTER 6

SOCIO-ECONOMIC IMPACT AND SUSTAINABILITY

6.1 Impact of the Project on Societal, Health, Safety, Legal and Cultural Issues

The impact of this project on various aspects is significant. Societally, it contributes to a more inclusive society by empowering individuals, especially those with disabilities, to control a mouse cursor using EEG signals. This technology enhances accessibility, allowing a broader demographic to engage with digital interfaces.

From a health perspective, the project can alleviate physical strain by providing an alternative to conventional mouse control. This is particularly beneficial for individuals with mobility issues or conditions that limit their ability to use traditional input devices comfortably.

In terms of safety, the project promotes a safer and more ergonomic work environment by reducing the need for repetitive physical movements associated with standard mouse usage. It potentially mitigates issues like carpal tunnel syndrome and other strain-related injuries.

On the legal front, ensuring data privacy and obtaining informed consent from users regarding EEG data collection and usage is crucial. Adhering to legal requirements and maintaining transparency in data handling is imperative to mitigate legal risks.

Lastly, culturally, the project represents an advancement in human-computer interaction, showcasing how technology can adapt to and accommodate diverse abilities. It fosters a culture of inclusivity and technological progress that aligns with the evolving societal norms of accessibility and equality.

6.2 Impact of Project on the Environment and Sustainability

This project can be termed as 'green' since there is no harmful byproduct released in the surrounding. And it ensures to fulfill four out of seventeen UN's sustainable development goals (SDG) which were adopted by the UN in 2016. These goals are:

Figure 6.1 UN Sustainable Development Goals that this project meets

Here Goal 3 aims to ensure that everyone has access to healthcare and can lead healthy lives. The BCI system has immense potential to enhance the quality of life for the average person. Also the BCI system can significantly reduce the time required to perform specific tasks since one simply needs to imagine a command to initiate an action.

Goal 8 aims to promote sustainable economic growth that creates jobs and reduces poverty. This includes promoting sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all, reducing informality and protecting labor rights.

Goal 9 aims to build resilient infrastructure and upgrading the infrastructure, fostering innovation, promoting research and development, and promoting the development of new technologies. This innovation can be integrated into robots and machinery, offering substantial benefits on an industrial scale, such as saving time in production while maintaining high quality. Furthermore, implementing MI BCI in the gaming industry can revolutionize the gaming experience, making it more enjoyable and interactive. Importantly, this technology promotes inclusivity by enabling people with disabilities to engage in everyday activities, ultimately boosting their confidence and reducing societal inequalities they may face. For example, it could empower an individual to start their own online business.

Goal 10 aims to reduce income and wealth inequalities within and among countries. This includes reducing income inequality, ensuring equal opportunities for all, eliminating discrimination, and ensuring that everyone has the opportunity to benefit from economic growth. The stakeholders involved in MI BCI include individuals with special needs, healthcare professionals, rehabilitation engineers, and many others. The potential of MI BCI to positively impact daily life is substantial and still in its nascent stages. There's much to explore regarding its applications, particularly in the healthcare system, which holds promise for long-term sustainability and potential direct involvement in ensuring environmental sustainability.

CHAPTER 7

ADDRESSING COMPLEX ENGINEERING PROBLEMS AND ACTIVITIES

7.1 Addressing Complex Engineering Problems

To effectively tackle the complex engineering challenges of this project, we begin by building a solid foundation in engineering courses related to the project, such as signal and systems, and gaining proficiency in essential tools like MATLAB and signal processing. A thorough literature review follows, helping identify the existing research gaps. In this project, our focus is on removing the artifact and to controlling the mouse cursor by using EEG signals.

We have acquired knowledge about the artifact removal, signal processing, and classification methods relevant to MI BCI. Initially, we immerse ourselves in understanding BCI, particularly MI BCI, its applications, societal impact, and the potential beneficiaries of the project. We also work on acquiring knowledge about applicable codes for ethical practices and efficient system analysis, including IEEE Code of Ethics, IEEE P2731, ISO 9241-210:2019, ISO 9241-11, and IEEE P360 standards, ensuring ethical conduct and practical usability of the system.

All of these standards aim to provide guidelines and best practices to ensure that technology is developed in an ethical, user-centered, and effective manner, taking into account the safety, health and welfare of the public, and the preservation of data privacy and security.

The stakeholders in this project encompass people with special needs, physiotherapists, rehabilitation engineers, healthcare professionals, athletes, and more. Understanding these interconnections and stakeholders is vital for the project's success.

Table 7.1 Complex Engineering Problems regarding this project

Complex Engineering Problems		Addressing the complex engineering problems in the project
WP1	Depth of knowledge required (WK3-WK5, WK8)	WK3-Knowledge of Signal and Systems, Numerical technique Lab, WK4- Digital Signal Processing (DSP), DSP Lab, Biomedical Signal Processing, EEG signal processing MATLAB-BCI LAB WK5-Engineering Design, WK8-literature review including Journal and Conference papers.
WP2	Range of conflicting requirements	Choice of signal processing algorithm (tradeoff between computational time and performance accuracy).
WP3	Depth of analysis required	In-depth knowledge of feature extraction, raw EEG signal extraction methods and classification methods for EEG signals is required.
WP4	Familiarity of issues	MI BCI, EEG signal processing and performance evaluation and applicable artifact removal methods.
WP5	Extent of applicable codes	7.8 IEEE Code of Ethics, IEEE P2731, ISO 9241-210:2019, ISO 9241-11, IEEE P360, standard for MI BCI in particular
WP6	Extent of stakeholder involvement	People with disability, who have trouble using their upper limbs, amputees, paralyzed individuals, and many more.
WP7	Interdependence	There are many subsystems- EEG signal collection, the signal preprocessing system, artifact removal method application, feature extraction, BCI classification method.

7.2 Addressing Complex Engineering Activities

Range of resources that we have been used in our project are the human team including a supervisor and involved students, available datasets along with a computer capable of handling memory-intensive software like MATLAB. Various algorithms and necessary software are also needed for different stages of the project, including data input, preprocessing, artifact removal, and classification. These stages are interconnected and highly dependent on one another, emphasizing the project's intricate nature.

The groundbreaking aspect of this project lies in the ability to control electronics and machines using brain signals. This innovation holds immense promise for improving the usability of BCI in healthcare systems, prosthetics, and beyond. The research conducted will address a critical research gap by investigating artifact removal techniques for MI BCI, pushing the boundaries of knowledge in this field.

However, it's essential to be mindful of legal considerations, particularly regarding the handling of personal data and EEG signals from subjects. Sharing such data without proper consent could result in legal complications.

In the project, there are complex engineering problems and activities, outlined in Table 6.1 and Table 6.2, which provide a structured view of the challenges and tasks associated with this innovative venture.

Table 7.2 Complex Engineering Activities required for this project

Complex Engineering Activities		**Addressing the complex engineering activities in the project**
EA1	Range of resources	Human resource, Available datasets, electronics and software to carry out the project such as- PC/Laptop compatible to run necessary software applications (MATLAB, classifiers)
EA2	Level of interactions	The algorithms used for each stage such as the Data input, preprocessing, noise removal, and classification is interdependent. Considering these stages as subsystem, there is a high level of interaction.
EA3	Innovation	Making MI BCI more effective in applications. Controlling devices using brain signals
EA4	Consequences to society / environment	The project will have an impact on the usability of MI BCI in healthcare system, economy, education, equality etc. The research done will aid stepping further into filling the research gap of investigating noise removal techniques, classification methods for MI BCI. Legal issues to be faced upon sharing personal data of subjects without permission.
EA5	Familiarity	Gaining knowledge of MI BCI, EEG signal processing(WT, EMD, STFT etc.) and performance evaluation.(confusion matrix, classifiers).

CHAPTER 8
CONCLUSIONS, LIMITATIONS AND FUTURE WORKS

8.1. Conclusion

This thesis work illustrates a system which is designed to move the mouse cursor using the EEG signal using Motor Imagery Brain-Computer Interfaces (MI-BCI). After an initial filteration of 0.5-40Hz and achieving an average classification accuracy of 71.10%, a highest accuracy of 93.60% was achieved by filtering the gamma band, which is quite high. It also had an AUC value of 0.97, which is near perfect.

The algorithm was also implemented using recorded offline EEG data and it successfully moved the mouse cursor in the desired direction, as well as click open an application. This shows a strong potential for this project.

8.2. Limitations

There were few limitations identified in this project. One of limitation of this study is the utilization of small amount of dataset as well as the less number of subjects participating during data collection.

Another limitation can be highlighted that the utilized dataset was acquired from the healthy subjects. The main motivation of this project was to develop an EEG-based mouse cursor system to assist the physically impaired individuals. Our current implemented system's performance was conducted on the healthy subjects.

In this project the system was designed with binary classification which refers the to two movement such as left-break and right-break. This reduces the computational complexity but on the other hand, it is important to acknowledged that movement in multiple directions can be achieved by using multiclass classification which requires higher computational complexity.

Using the Emotiv EPOC+ 14-channel wireless EEG headset requires the software Emotiv Pro, which is a licensed software that must be renewed every month. Using this for multiple months can get quite expensive, as well as it means the headset is rendered unusable when the license expires.

8.3 Future Works

Our future aim with this project is to increase the performance evaluation in terms of different stages of research and implementations.

As our designed system has been implemented using offline dataset to move the cursor successfully, now we are aiming to implement this system with data obtained in real-time. We also plan on using data from individuals of the targeted class i.e. physically impaired people, to check for performance quality when it came to the targeted group.

We are also aiming to modify the system by using multiclass classification which will enable the mouse cursor control to move in multiple directions and provide versatile control options.

Lastly, we also plan on experimenting with feature extraction to check for better classification performance with alternate features.

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