Software Requirement Specification Document for MindMend : BCI-based Machine learning and Deep learning Algorithms for Stroke Rehabilitation

Abdelrahman Ayman Shorim, Mina Antoun, Habiba Mohamed Salem, Shehab Eldeen Mohamed Sadek, Habiba Amr Ahmed
Supervised by: Dr. Walaa Hassan, Eng. Youssef Talaat

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Table 1: Document version history

Version	**Date**	**Reason for Change**
1.0	4-Jan-2024	SRS First version's specifications are defined.

GitHub: https://github.com/Abdelrahman-Shorim/BCI-based-ML-algorithms-for-Stroke-Rehabilitation

Contents

Abstract

In the field of neurorehabilitation, brain stroke fighters face an intimidating challenge on their path to recovery, journeying through the complex environment of physical therapy and motor functionality restoration. As a consequence, of a stroke that affects the lives of millions, a provoking thought arises: the cutting-edge Brain-Computer Interface (BCI) technologies may serve as the indispensable key to unlocking new frontiers in stroke rehabilitation. BCI technologies have shown promising results in stroke motor rehabilitation yet researches and clinical settings paid less attention to non-motor deficiencies including cognitive impairments. The proposed system is BCI-based that introduces an inclusive treatment plan for motor and cognitive functions after a brain stroke. The system aims to develop restorative neuroplasticity for stroke patients and provide a platform that goes beyond physiotherapy and enhances motor and cognitive functionalities to improve their quality of life and refine clinical results.

1 Introduction

1.1 Purpose of this document

The purpose of the Software Requirements Specification (SRS) document is to introduce the proposed system's features, describe the objectives, explain its objectives. It is a document proposed to the developers and stakeholders of this application.

1.2 Scope of this document

This document covers the application's detailed description, functional and non-functional requirements, basic interface and data designs, and an analysis of the classes needed and the relations between them.

1.3 Business Context

According to the World Health Organization, strokes exert influence on 15 million people each year alongside being the leading cause of long-term disability. As a consequence, there is a growing market demand for innovative and non-invasive rehabilitation solutions. Another key thing to mention is that the healthcare industry is witnessing a shift towards technology driven solutions as stated in [1], and it is a must to implement advanced technologies to cope with the healthcare trends. Coupled with what has been stated, patient satisfaction is one of the most significant motives for the project, and according to preliminary studies, stroke patients using BCI technology for rehabilitation report higher satisfaction rates compared to traditional rehabilitation methods.

2 Similar Systems

2.1 Academic

Suleman Rasheed and Wajid Mumtaz [2] proposed a BCI-based system that evaluates and compares the performance of some feature extraction techniques for motor imagery tasks in EEG-based brain controlled prosthetics, both within-subject and cross-subject classification. They helped in solving the issue by comparing the efficiency of deep learning, spatial pattern-based techniques (filter bank common spatial patterns and common spatial patterns), and feature extractors such as wavelet transform and power spectral density techniques (EEGNet). The dataset they used was completely new, taken from real hemiparetic stroke victims. According to the researchers' main conclusions, all techniques for within-subject classification achieved an accuracy of approximately 80% or higher, with the FBCSP approach exceeding the others and providing the greatest average precision of 84.8The deep learning-based EEGNet model performed better for cross-subject analysis, The remaining techniques (77% accuracy). The first six individuals performed much better with moving window CSP and PSD based approaches; however, subjects 7 and 8 showed very poor performance compared to other algorithms. Our only concern regarding this paper is that the study did not evaluate the algorithms on other motor imagery tasks or other EEG data. Ergo, further research must be made to validate the generalizability of algorithms to other datasets and motor imagery tasks.

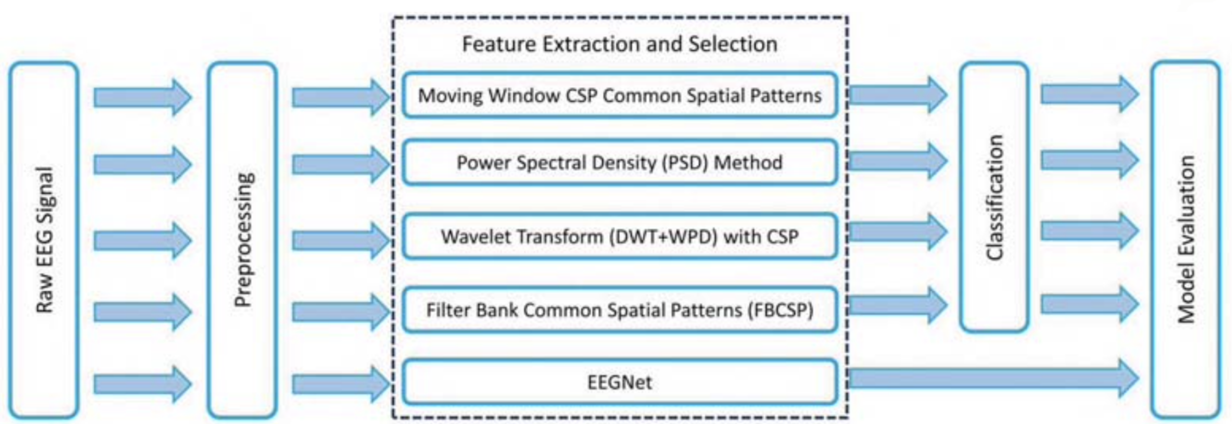

Figure 1: Suleman Rasheed and Wajid Mumtaz's proposed EEG processing pipeline [2]

Tamás Karácsony et al. [3] presented an interesting solution using BCI technology coupled with Virtual Reality (VR). They aimed to find the optimal configuration of online experiments using deep learning and Convolutional neural networks (CNN). The researchers trained their proposed system on the PhysioNet EEG motor movement/imagery dataset, which contains 1500 labeled EEG recordings obtained from 19 subjects. They improved the signal quality using filtering and standardization techniques in the pre-processing phase and achieved better accuracies than previous papers due to their optimization of the CNN hyperparameters and training strategies. Regarding the statistics of their results, all subjects achieved 100% accuracy in reaching their goal due to the low activation threshold and in the real-time performance of 3-class trials, the highest achieved goal accuracy was 87%.

Figure 2: Tamás Karácsony et al VR game for Stroke Rehabilitation [3]

Wei Wang et al.[4] proposed an entertaining solution that aids the direct participation of the motor nervous system, this solution guides stroke patients through their rehabilitation process. They created an upper limb rehabilitation training system based on Virtual Reality (VR) and Motor Imagery (MI)-Brain Computer Interaction (BCI) which was developed by Unity3D, to build a virtual game for the patient which provides a virtual environment for training with real-time feedback from the game. The authors did not mention a dataset, but they conducted 40 trials and explained how the game works, it consists of 4 modes and each mode has several simulated rooms, for example the Beach mode has rooms for training a move such as the grip of the hand, and after the patient enters the room, they get immediate response from the game which calculates the preferred treatment. Finally, they concluded that VR can lead the patients to imagine motion better, which helped in the process of rehabilitation.

Figure 3: Training end interface [4]

2.2 Business Applications

2.2.1 recoveriX

recoveriX is the first BCI system that combines the imagination of movement with visual and tactile response in real time. If the patient imagines a movement of a certain joint and it affects the virtual avatar, with tactile feedback through electrical muscle stimulation in real life at the same time. This encourages the patients to image the movement correctly. [5]

Figure 4: Illustration of the recoveriX system

2.2.2 IpsiHand

IpsiHand is a wearable robotic handpiece that connects the healthy parts of the brain activity to a disabled arm using BCI (Brain Computer Interaction), to use the idea in the brain to control the robotic hand, the EEG robotic hand senses the signals being sent from the brain, then it guides the robotic hand movement to move the disabled hand to improve motor function and open new paths to a new untrained part of the brain to later control that hand. It's used with a headset and a tablet to monitor the brain signals. [6]

Figure 5: IpsiHand robotic hand

3 System Description

3.1 Problem Statement

In theory, patients that suffer from disabilities like partial paralysis caused by a brain stroke, find it hard to practice their daily tasks. Consequently, patients tend to visit traditional rehabilitation centers. The traditional solution is basically going to a physiotherapist who helps patient somehow improve their muscle strength and coordination. Patients face challenges with the traditional ways of rehabilitation from their high cost to the slow treatment progress. As a result, a BCI and Motor Imagery EEG-based system is introduced as a modern and advanced user-friendly alternative for both patients and doctors in rehabilitation centers.

3.2 System Overview

The system should go through 6 main steps as illustrated in figure1 :

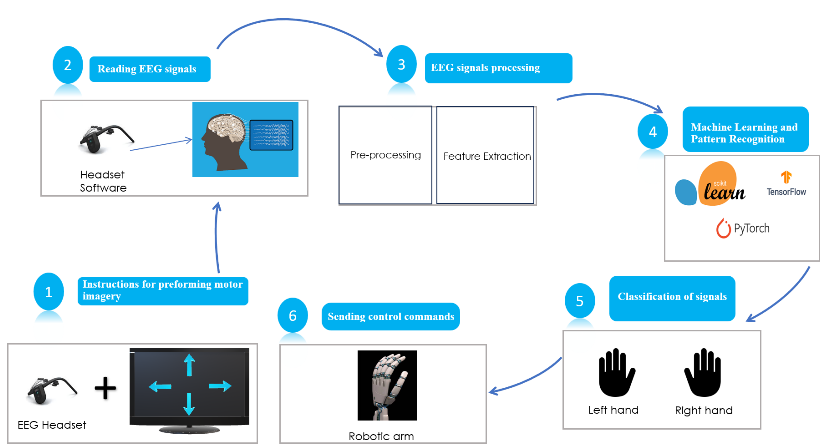

Figure 6: System Overview

3.2.1 Instructions for performing motor imagery

The system should provide certain movements for the patient on a computer screen, to help the patient be able to imagine his desired movement.

3.2.2 Reading EEG signals

The system should be able to connect to the headset via headset software and then visualize the brain signals on the computer.

3.2.3 EEG signals processing

For processing the EEG signals should be filtered from the noise. In order to visualize, analyze, and process the EEG signals to be able to understand it even more. Then extract the features needed for the model.

3.2.4 Machine learning, Deep Learning and pattern recognition

To decipher the user's intentions or cognitive states from the EEG data, machine learning and deep learning algorithms, and pattern recognition techniques are used. These algorithms identify EEG signal patterns that correspond to motor commands or mental processes. Scikit-learn, TensorFlow, and PyTorch are three well-liked machine learning libraries that are employed in BCI applications.

1. Machine Learning Models:

    - SVM: Support Vector Machine is a supervised machine learning algorithm that can be used for classification and in regression tasks. It is a powerful algorithm used with data that is not linearly seperable. It aims to find a plane that seperates the data into several differnet classes. Its margin is the distance between the hyperplane and the nearest datapoint from each class. They are proven to handle high-dimensional data, and they are effective for classification in real-life applications. [7]
    - Random Forest: Random Forest is a machine learning algorithm that can be used for classification. It constructs multiple decision trees while it trains the model to finally choose an output which is the mode of the results of these trees or the mean of all predictions. Each tree is trained on a random set of input which is a subset from the original data based on important features. It is used due to its robustness and ability to handle high-dimensional data. It is used in many fields as finance and healthcare. [8]

2. Deep Learning Models:

    - Convolutional Neural Network: The Convolutional Neural Network (CNN) is a feed-forward neural network designed for feature extraction through filter optimization. The typical structure involves Convolutional layers for pattern recognition, Pooling layers for downsampling, and Fully Connected layers for classification [9]. The proposed model implements this design by utilizing a sequential structure, starting with Convolutional layers with ReLU activation, along with MaxPooling layers for spatial reduction. The transition to Fully Connected layers occurs via a Flatten layer, leading to a final

Dense layer that produces class probabilities with softmax activation. This architecture provides a versatile foundation for EEG classification tasks.

- EEGNet: EEGNet is a deep learning architecture designed specifically for analyzing electroencephalogram (EEG) data. The architecture of EEGNet typically involves convolutional layers to capture spatial patterns in the EEG data efficiently. It often incorporates techniques like depthwise separable convolutions and other specialized layers to handle the unique characteristics of EEG signals. EEGNet aims to provide an effective and computationally efficient solution for processing EEG data, enabling applications in real-time or resource-constrained environments [10].
- Multi-Layer Preceptron: A Multi-Layer Perceptron (MLP) is a type of artificial neural network that consists of multiple layers of nodes, or artificial neurons. It is a feedforward neural network, meaning that information flows in one direction, from the input layer through the hidden layers to the output layer G data, enabling applications in real-time or resource-constrained environments [11]. The model we employed in our code has an input layer, two hidden layers, and an output layer, making it a three-layer MLP. The activation functions used in the hidden layers are Rectified Linear Unit (ReLU), and the output layer uses the Softmax activation for multi-class classification.
- Recurrent Neural Network: Recurrent Neural Network (RNN) is designed for sequential data processing, incorporating Simple Recurrent layers for capturing temporal dependencies and Fully Connected layers for classification.[12] The proposed model implements this design with a sequential structure, starting with Simple Recurrent layers featuring ReLU activation, followed by a transition to Fully Connected layers. Class probabilities are generated using softmax activation in the last Dense layer.

3.2.5 Classification of signals

After the machine learning techniques, the models should classify the intended movement by the patient. The signals should be classified as left-hand motor imagery, right-hand motor imagery as the system had shown to the patients in the first step. Then the classification should be sent to the robotic arm.

3.2.6 Sending control commands

After the algorithms have identified the EEG signal patterns, and the model has classified the signals(e.g. left-hand motor imagery, or right-hand motor imagery or feet). The system should send motor commands to the Robotic arm, that will be able to make the intended movement of the patient.

3.3 System Scope

The system should contain the following:

- The system is designed to help the patient through visuals on a computer screen to perform some mental practices.

- The system is designed to record the headset readings and compute the values of brain-computing interface (BCI) channels.
- The system is designed to segment the epochs, each representing a specific MI task (left-hand motor imagery, right-hand motor imagery).
- The system is designed to use Deep Learning, Machine learning models, and BCI and Motor imagery technology.

3.4 System Context

The system interacts with various types of users: patients and doctors. Also, the system interacts with various systems in order to meet the needs of the system as demonstrated by figure 7. The Microsoft SQL Server is used to manage all the data related to the system which is modeled in section 7 . Furthermore, the headset API should be used to connect the headset with the system in order to be able to read the brain signals from the patient and send them to the system. Then the system will be sending the brain signals into a model that will be able to classify the brain signals as in right hand movement or left hand movement. Also, the Arduino software is used to be able to send the movement commands to the robotic arm.

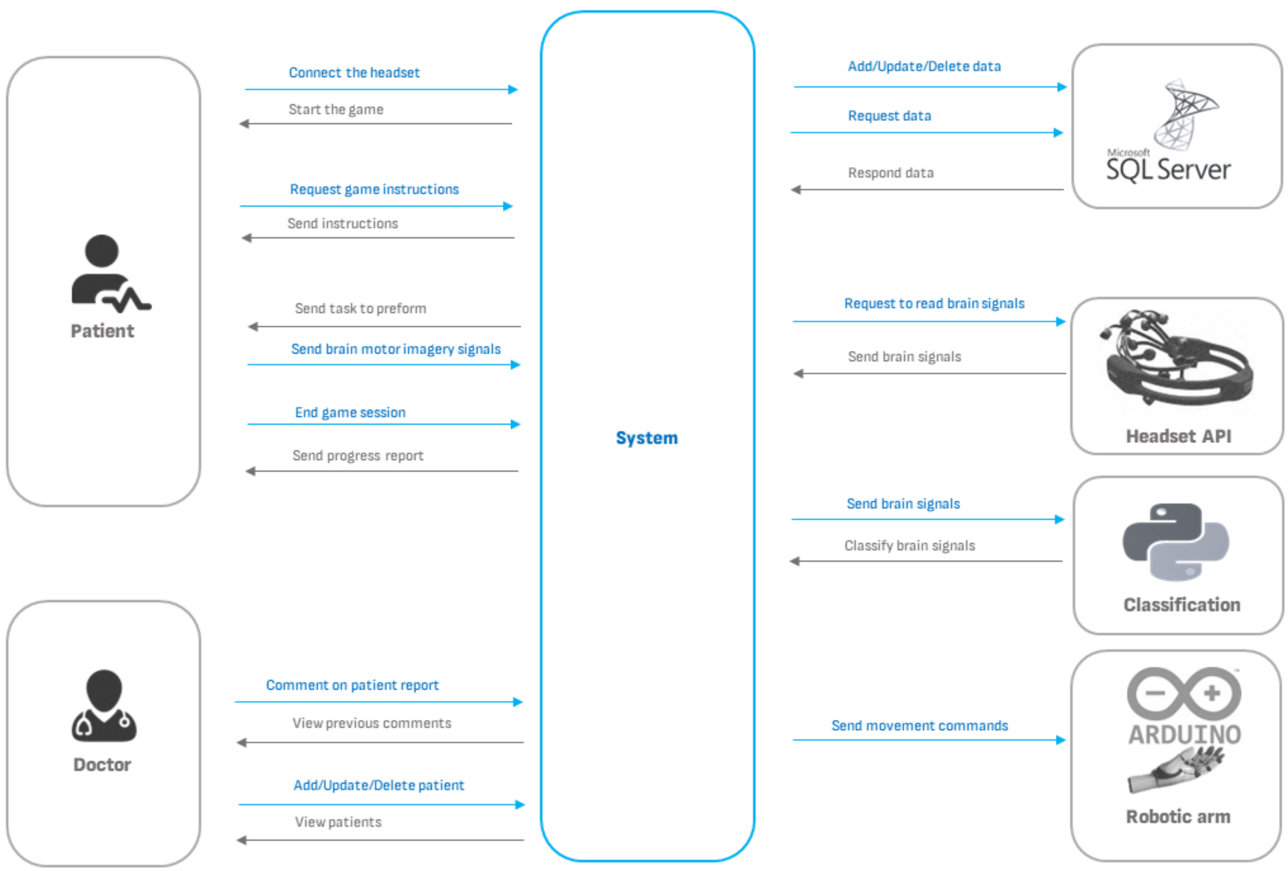

Figure 7: System Context

3.5 Objectives

- To create a user friendly system that can be accessed on desktop or web environments to support stroke patients on their rehabilitation journey and allow doctors to monitor the patients.
- To personalize treatment for each patient
- To ensure that the patient enjoys the game and uses it as an engaging tool during physiotherapy sessions.
- To optimize the BCI accuracy.
- To allow doctors to track the progress of each patient, and decide the course of treatment depending on that.

3.6 User Characteristics

The system is mainly for stroke patients to train their brain to be able to use the damaged parts. Consequently, the system will also be used by doctors to track the progression of the patient's treatment. The system is designed to be user-friendly.

However, patients must have:

- Already been diagnosed as a stroke patient.
- A basic knowledge of how the game works.
- In order to make rehabilitation procedure at home, the patients must have a headset and a helper to be able to connect to the game.

Furthermore, doctors must have:

- A brief understanding of the game to be able to track the progress of the patient.
- Basic knowledge of how to use the system to be able to track the patient's progress and be able to retrieve the patient's data.

4 Functional Requirements

4.1 System Functions

The below use case diagram in figure below demonstrates the system functional requirements. The system is composed of three user types: stroke patient, doctor and admin.

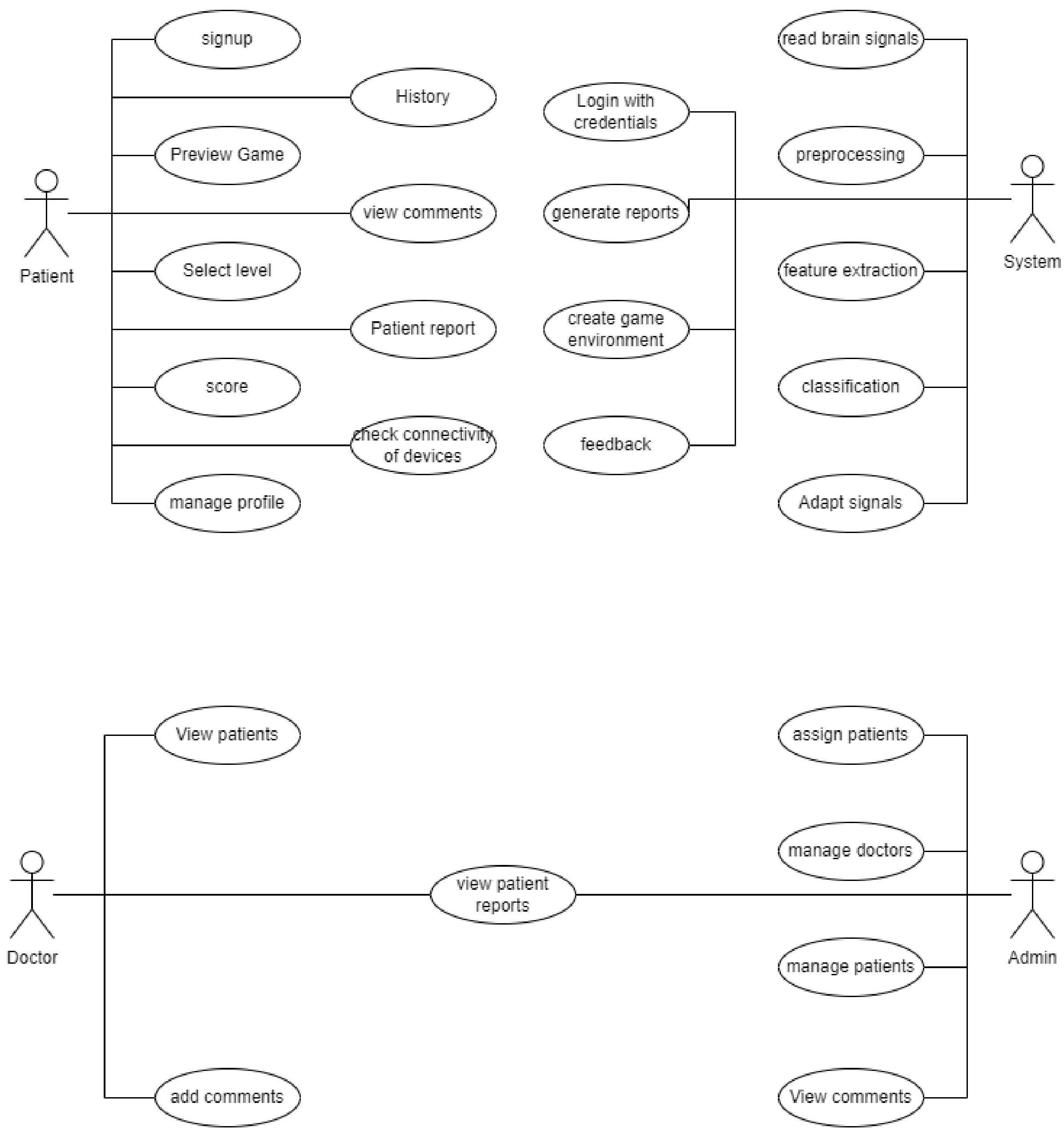

Figure 8: Use-case diagrams

1. The patient shall be able to create an account with his information when accessing the system. (P01)
2. The patient shall be able to view a description for the game and a description for it's levels. (P02)
3. The patient shall be able to view and select a level to play. (P03)
4. The patient shall be able to view his score that is calculated according to his performance. (P04)
5. The patient shall be able to add/update his account information into the system. (P05)
6. The patient shall be able to view a history of his played game, each game played is viewed as a detailed report. (P06)
7. The patient shall be able to view the comments/feedback given by his doctor after viewing the patient report. (P07)
8. The patient shall be able to view a full report of the game played. (P08)
9. The patient shall be able to check the connectivity of the connected devices before starting a game. (P09)
10. The system shall be able to read brain signals acquired from EEG headset. (S01)
11. The system shall perform some preprocessing techniques on the data acquired from the headset. (S02)
12. The system shall perform feature extraction techniques to extract Motor imagery signals from the preprocessed data. (S03)
13. The system shall give a classification result using classification algorithms. (S04)
14. The system shall generate a detailed report of every game for each patient. (S05)
15. The system shall create the game environment for the patients to play. (S06)
16. The system shall give a feedback to the robotic arms giving instruction to which arm should be moved. (S07)
17. The system shall adapt the model when having continues miss classification with a patient. (S08)
18. The Doctor shall view list of patients that are assigned to him. (D01)
19. The Doctor shall add his comments of the game/progress to the patient if needed. (D02)
20. The admin shall assign a patient to a doctor for constant supervission. (A01)
21. The admin shall be able to add/edit/delete/view doctors into the system and view patients assigned to each Doctor. (A02)

22. The admin shall be able to add/edit/delete/view patients into the system. (A03)
23. The admin shall be able to view the comments posted from the doctors to the patients for monitoring. (A04)
24. The Admin and the Doctor shall be able to view a full detailed report of a patient. (AD01)

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4.2 Detailed Functional Specification

Name	Preview Game
Code	P02
Priority	Extreme
Critical	This is one of the most crucial functionalities in the system as the patient has to preview the game that he will play for rehabilitation purposes
Description	The patient is presented with a game and level descriptions. The patient should then select a level to start his rehabilitation session
Input	None
Output	List of game levels with their descriptions
Pre-Condition	- The patient must be logged in
Post-Condition	The levels with their descriptions will be overlaid onto the screen for the patient
Dependency	None
Risk	None

Name	Patient Report
Code	P08
Priority	Extreme
Critical	This is one of the most crucial functionalities in the system as the patient, doctor, and admin have to view the full report of the patient.
Description	After the patient finishes the game session. A full report must be generated of that session as it acts as a progress indicator of the patient recovery. If there is no game session recorded then "No game sessions available yet" will be displayed
Input	PatientID and GameID
Output	Report showing details of the game played by the patient
Pre-Condition	- The patient/doctor/admin must be logged in - At least one game session is played by the patient
Post-Condition	A full report will be overlaid onto the screen for the patient/doctor/admin
Dependency	None
Risk	None

Name	History
Code	P06
Priority	Extreme
Critical	This is one of the most crucial functionalities in the system as the patient, doctor, and admin have to view the History of all game sessions played
Description	After the patient finishes multiple game sessions. A history for these games is generated. The doctor uses this history to observe the improvements over time
Input	PatientID
Output	List of all game sessions played
Pre-Condition	- The patient/doctor/admin must be logged in - At least one game session is played by the patient
Post-Condition	A List of reports will be overlaid onto the screen for the patient/doctor/admin
Dependency	None
Risk	None

5 Design Constraints

5.1 Standards Compliance

- The system must adhere to industry standards, ensuring compatibility and readability.
- The user must have an internet connection to access the system.

5.2 Hardware Limitations

- The EEG Hardware number of channels might affect the system performance(Using headsets of more or less channels than the international 20-30 placement standard).
- The EEG Hardware must be compliant with the 10-20 Electrode placement system.
- The system's non-invasive approach may not achieve the same level of medical accuracy as invasive methods.
- The Robotic arm is with a standard size that cannot fit in all people's hands.

5.3 Other Constraints as appropriate

- The dataset currently in use is acquired from 22 EEG channels, while the headset purchased is only 14 EEG channels. As a consequence, some channels maybe dropped from the dataset.
- The system supports the classification of Left-hand and Right-hand motor imagery.
- Only supported in English currently.

6 Non-functional Requirements

6.1 Reliability

The game session shall be stable and smoothly functional, where it shall not crash while running and interrupt the rehabilitation session.

6.2 Maintainability

The application shall be built to be easy to maintain and allow ease of addition or removal of features by following the SOLID Principles (Single Responsibility Principle (SRP), Open/Closed Principle, Liskov Substitution Principle (LSP), Interface Segregation Principle (ISP), and Dependency Inversion Principle (DIP)).

6.3 Scalability

The application shall have the ability to extend any future functionality additions without greatly affecting the performance by applying the Dependency Injection principle leading to loosely coupled application.

6.4 Security

All passwords shall be hashed, admin privileges shall only be accessible from admin accounts, and doctor privileges shall only be accessible from doctor accounts.

6.5 Usability

The system shall provide an easy to understand UI (User Interface) and a satisfactory UX (User Experience). This shall be accomplished through:

- The user interface shall be intuitive and responsive.
- The game session shall be simple to understand.

6.6 Assurance

For the accurate implementation of game instructions and electrodes placement instructions, the system is required to present:

- Cautionary messages corresponding to the importance of the instructions.
- Alarm messages in cases where the user does not adhere to instructions properly in game or in electrode placement.

7 Data Design

7.1 Dataset

We used the "BCI Competition – Graz data set A" which is a benchmark dataset in the field of brain and human computer interfaces. Data was acquired from 9 subjects, and 2 sessions were recorded for each subject. Each session consists of 6 runs, and each run consists of 48 trials, 12 for each of the 4 classes (tongue, feet, right hand, left hand). Total 288 trials per session. The dataset was already pre-processed using Bandpass filtering (0.5Hz, 100Hz) and Notch filtering (50Hz). The former pre-processing technique is used to filter a frequency band inside a signal while minimizing frequencies outside of that range and the latter technique is used to eliminate a specific range of frequencies such as powerline interference. Data was recorded using 22 EEG channels and 3 EOG channels (measures the influence of eye movement). Dataset is available for download at this webpage. [13]

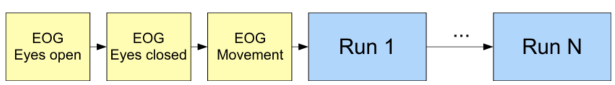


Figure 9: Time Scheme for one session

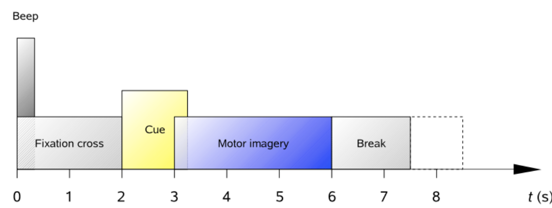


Figure 10: Timing scheme of the paradigm

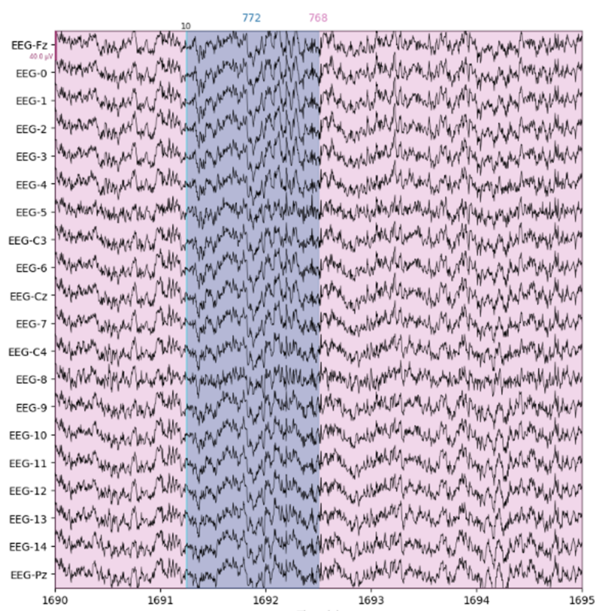


Figure 11: EEG Graph sample

Data sample at t=1690s with events 772,768 (class 4, new trial).

Each row represents a channel and its corresponding microvoltage.

```python
fig = mne.viz.plot_events(events[0], event_id=event_dict, sfreq=raw.info['sfreq'],
                          first_samp=raw.first_samp)
```

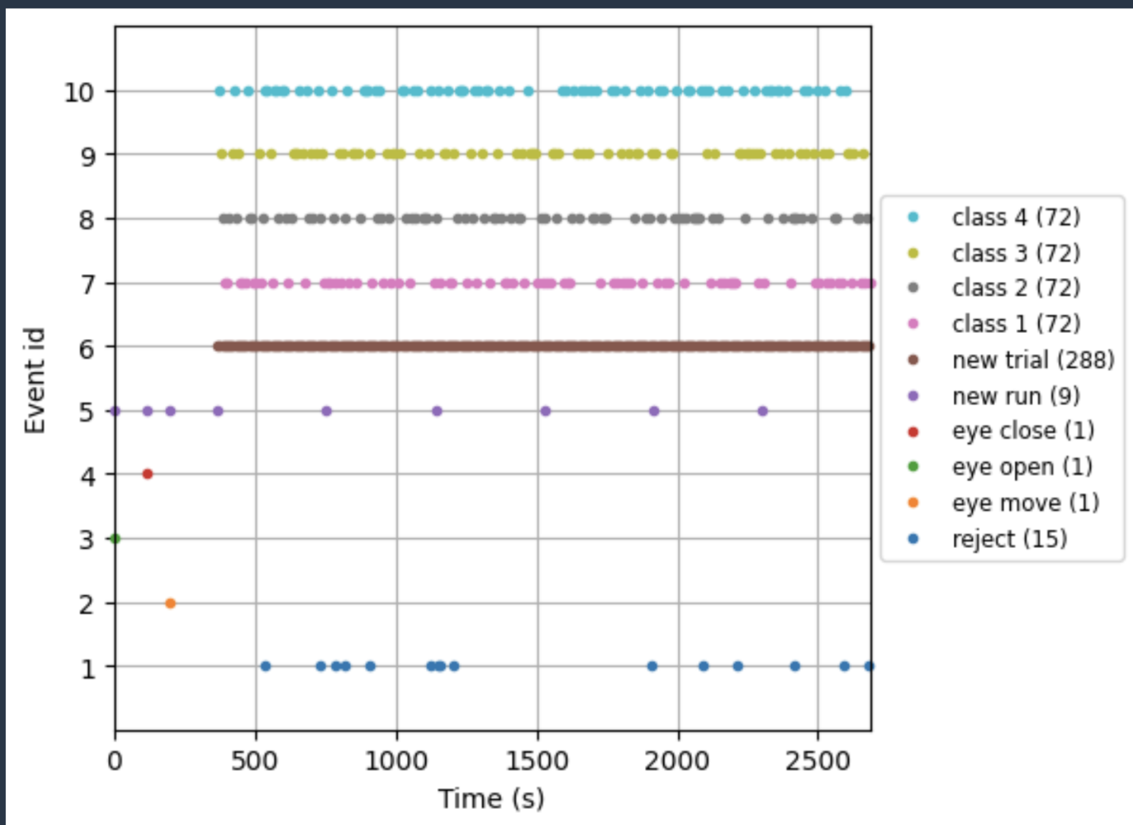


Figure 12: Dataset Events

```python
df.sample(n=5)
```

[120] Python

	patient	time	label	epoch	EEG-Fz	EEG-0	EEG-1	EEG-2	EEG-3	EEG-4	...	EEG-8	EEG-9	EEG-10	EEG-11	EEG-12	EEG-13	EEG-14	EEG-Pz
57555	1	0.176	right	599	-8.505313	-8.954156	-9.746674	-11.318564	-7.827353	-7.357852	...	7.238001	3.106391	-0.469330	-3.419676	2.242508	7.038933	10.361123	10.436243
10467	1	-0.040	left	116	-0.349138	-4.182146	-1.442137	-2.174559	0.238677	-1.983002	...	-1.331335	1.309140	2.927980	2.124194	1.363602	0.026463	3.508284	3.001222
27653	1	0.364	foot	293	-2.087146	5.992030	4.204170	1.409699	1.067902	-0.137777	...	0.444404	2.566550	2.412553	-0.109607	-1.749105	-3.707864	-3.503162	-6.541774
52139	1	0.220	foot	544	0.680008	3.220949	5.236048	6.575066	-0.089974	-0.910662	...	-8.418925	-1.233678	2.246264	4.914909	-1.601767	-6.955959	-1.274995	0.120363
23910	1	0.668	tongue	255	-4.644221	-2.520197	-1.953040	2.097817	-3.605684	0.745653	...	0.636729	1.814238	-0.940795	6.636954	5.091356	6.402204	-2.544611	-1.177424

Figure 13: Sample of the dataset in CSV format

7.2 Database

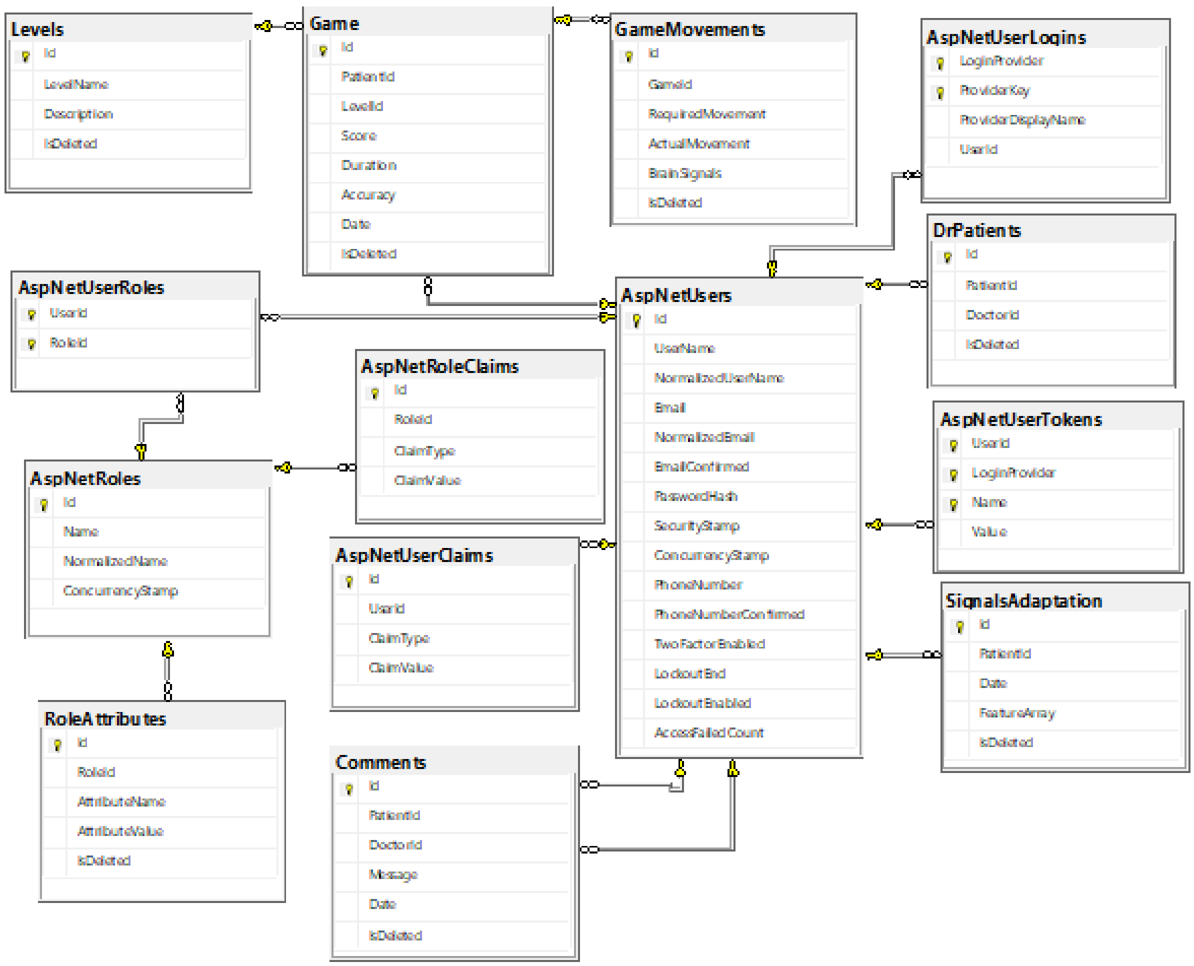


Figure 14: Database schema

8 Preliminary Object-Oriented Domain Analysis

Initial Class Diagram is shown in figure 15.

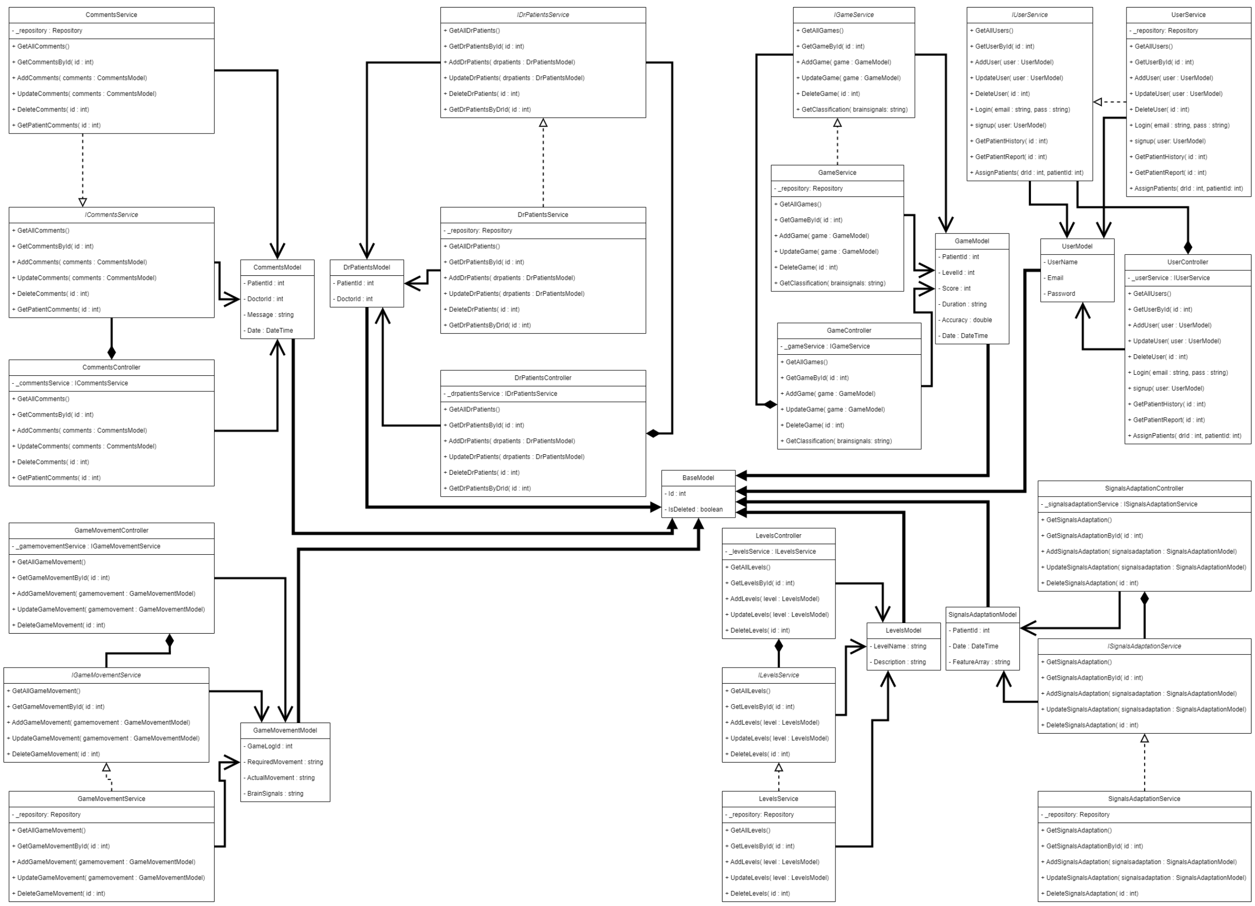


Figure 15: Initial UML Class Diagram

9 Operational Scenarios

Scenario 1: Patient Account Creation

1. **Initial assumption:** The patient has access to a stable internet connection and a device capable of running the system.

2. **Normal:** The patient initiates their journey with the system by creating an account. The user interface guides them through the input of vital personal information and relevant medical history, establishing a robust profile for personalized stroke rehabilitation.

3. **What can go wrong:** In the event of connectivity issues, the account creation process may experience delays or interruptions.

Scenario 2: Patient Calibration Process

1. **Initial assumption:** The patient is wearing the EEG headset and is in a quiet environment conducive to calibration.

2. **Normal:** The patient follows the on-screen instructions for calibration, adjusting the headset for optimal signal reception. Visual and auditory cues guide the patient to ensure accurate calibration.

3. **What can go wrong:** Users may struggle to achieve proper headset positioning, leading to inaccurate calibration.

Scenario 3: Game and Level Description Viewing

1. **Initial assumption:** The patient has successfully logged into the system and possesses a basic understanding of navigating the user interface.

2. **Normal:** As the patient explores the system, they delve into comprehensive descriptions of available games and their associated levels. This feature enhances user understanding, providing context to the therapeutic exercises embedded in the gaming experience and after that the patient eventually starts the game.

Scenario 4: Feedback to Robotic Arms

1. **Initial assumption:** The robotic arm is properly calibrated and responsive to real-time feedback signals from the system.

2. **Normal:** The system coordinates an exact feedback mechanism, providing precise instructions to robotic arm for the necessary limb movements. This real-time guidance amplifies the therapeutic effectiveness of the rehabilitation process.

3. **What can go wrong:** Feedback disruptions may arise, potentially resulting in miscommunications with robotic arm.

Scenario 5: Score Viewing

1. **Initial assumption:** The patient has successfully completed a gaming session and is eager to assess their performance.

2. **Normal:** Post-game, the patient eagerly reviews their performance score, gaining insights into their progress and achievements. This real-time feedback mechanism contributes to the motivational aspect of stroke rehabilitation through gamification.

Scenario 6: Detailed Patient Report Viewing

1. **Initial assumption:** Doctors have authorized access to detailed patient reports, ensuring confidentiality and privacy.

2. **Normal:** Doctors access comprehensive reports detailing a patient's entire gaming experience. This detailed insight serves as a crucial reference point for informed decision-making and ongoing rehabilitation strategies.

Scenario 7: Doctors adding Comments to Patient

1. **Initial assumption:** Doctors have reviewed the patient's gaming progress and are ready to provide constructive feedback.

2. **Normal:** Doctors actively engage with patients by adding comments and feedback on their gaming progress. This interactive feature fosters a collaborative approach to stroke rehabilitation.

Scenario 8: Patient viewing Doctor's Feedback

1. **Initial assumption:** The patient sees the feedback provided by their supervising doctor and actively seeks guidance for ongoing improvement.

2. **Normal:** The patient eagerly accesses feedback and comments from their supervising doctor, creating a collaborative dynamic between medical professionals and patients. This feedback loop ensures personalized guidance and support.

Scenario 9: Patient Progress Calculation

1. **Initial assumption:** Doctors rely on the system-generated reports and patient self-reports to assess progress.

2. **Normal:** Doctors regularly review system-generated reports and engage in subjective assessments to validate patient progress. A collaborative approach ensures that doctors and patients are on the same page regarding rehabilitation goals.

3. **What can go wrong:** Doctors may observe discrepancies between patient-reported progress and system-generated reports. Incorporating periodic check-ins and subjective assessments can help doctors validate progress.

10 Project Plan

A Full view of the Project's Time plan is shown in figure: 16 and broken down in figures: 17,18,19,20

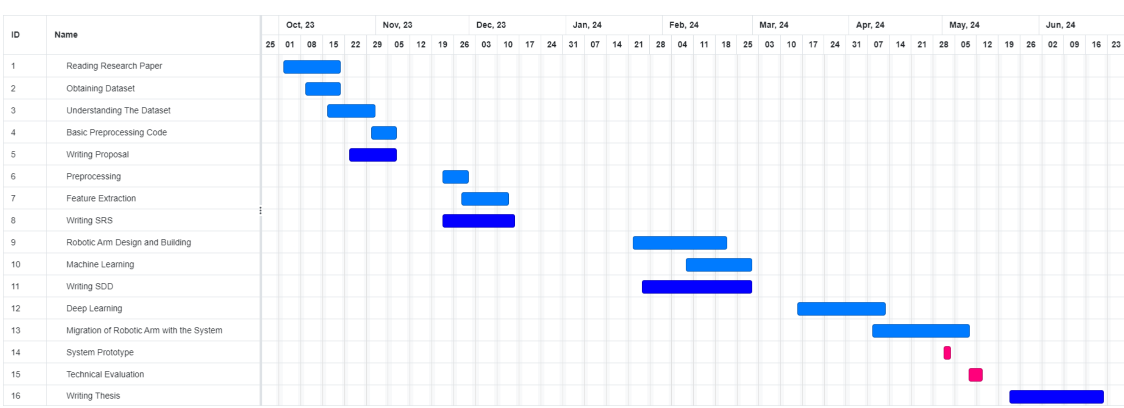


Figure 16: Time Plan throughout the year

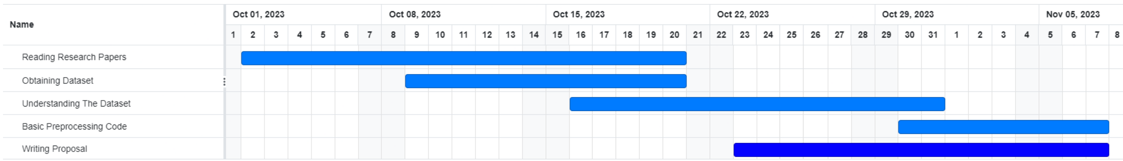


Figure 17: Time plan part 1

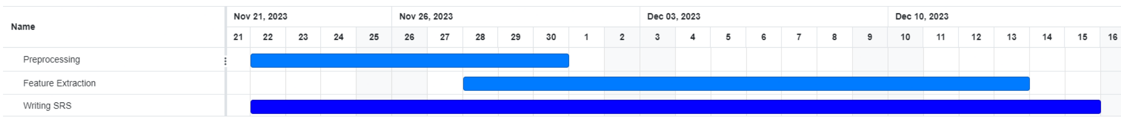


Figure 18: Time plan part 2

Figure 19: Time plan part 3

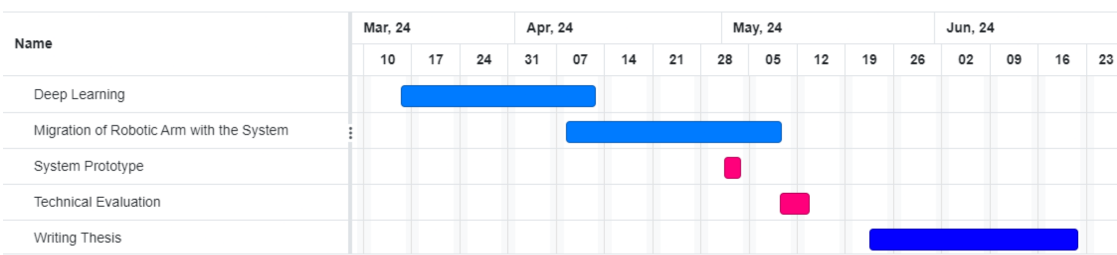


Figure 20: Time plan part 4

11 Appendices

11.1 Definitions, Acronyms, Abbreviations

Table 2: Abbreviations and Definitions

Abbreviation	**Definition**
API	Application Programming Interface
BCI	Brain Computer Interface
CSP	Common Spatial Pattern
CNN	Convolutional Neural Network
DL	Deep Learning
EEG	Electroencephalogram
FBCSP	Filter Bank Common Spatial Pattern
MI	Motor Imagery
ML	Machine Learning
MLP	Multilayer Perceptron
RF	Random Forest
RNN	Recurrent Neural Networks
SRS	Software Requirement Specification
SVM	Support Vector Machine
VR	Virtual Reality

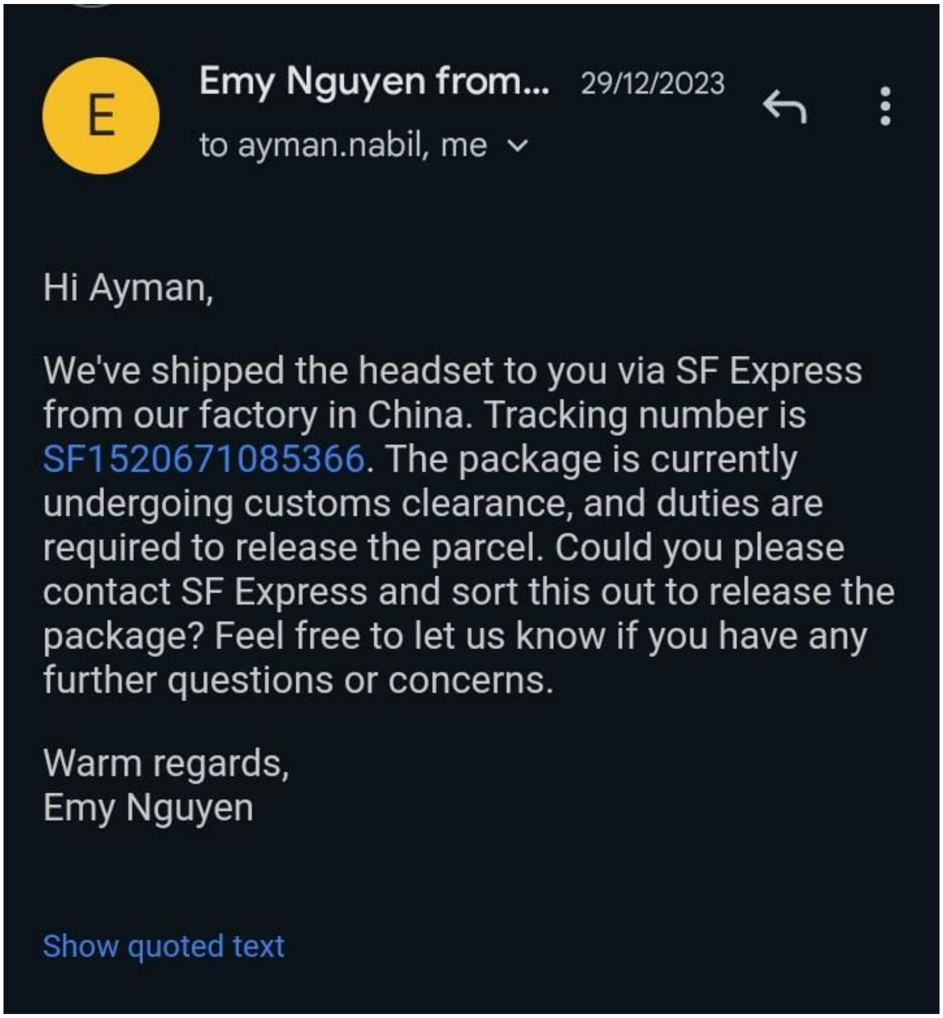
11.2 Supportive Documents

11.2.1 Zawam Rehab

Zawam Rehab - Physiotherapy and Rehabilitation Center was contacted. Through a meeting with one of the team members, physiotherapists shed light on the significant business needs for such a project and discussed some aspects regarding the acquisition phase which will be taken into consideration.

11.2.2 Emotiv

Figure 21 is an email for contacting Emotiv company for successfully purchasing the Headset.


Emy Nguyen from... 29/12/2023
to ayman.nabil, me

Hi Ayman,

We've shipped the headset to you via SF Express from our factory in China. Tracking number is SF1520671085366. The package is currently undergoing customs clearance, and duties are required to release the parcel. Could you please contact SF Express and sort this out to release the package? Feel free to let us know if you have any further questions or concerns.

Warm regards,
Emy Nguyen

Show quoted text

Figure 21: Emotiv mail

11.2.3 El-Demerdash hospital

The Epilepsy Research lab in El-Demerdash hospital was visited, where doctors guided the team through things related to the biological and psychological point of view of the project. They also showed the team how the traditional way of acquiring brain signals is done and what each signal represents. They agreed on the fact that the success of this project will definitely help patients with motor disabilities and can also be used by physiotherapy students in their training year.

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