Software Requirement Specification Document for Brain Decoding using EEG signals: Turning thoughts into text

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Table 1: Document version history

Version	Date	Reason for Change
1.0	12-Dec-2022	Specifications for the SRS First Version are outlined.
1.1	14-Dec-2022	New use case for both Users and Administrators. The remaining functional requirements have been identified. identified limitations imposed by the hardware
1.3	17-Dec-2022	Non-Functional Requirements updated. Removed additional unnecessary user interface design constraints.

GitHub: https://github.com/hadywk/EEG_Decoding

Contents

Abstract

Electroencephalography (EEG) is a method of recording brain activity. During this non-painful examination, tiny sensors are placed on the scalp in order to recognize electrical impulses generated by the brain. A Headset records these signals, which are then analyzed by a physician. The capacity to type using direct brain control, which enhances the decoding accuracy of EEG signals for the range of brain functions, is one of the most exciting and contentious EEG-based BCI applications. BCI (Brain-Computer Interface) makes possible the translation of thought to text. A fresh and growing field The electroencephalogram (EEG) represents electrical activity at the surface of the brain.

1 Introduction

1.1 Purpose of this document

This document's intended function is to describe its characteristics. The documentation is not only a record of the product's approval for the necessary functions but also a useful resource for developers. Here you will learn about the software implementation. The software's implementation of the techniques and methodologies is also discussed. Furthermore, BCI (Brain-Computer Interface) research into translating mental operations into physical actions remains in its infancy. Focusing on how people (users) communicate with computers. The brain-computer interface (BCI) mediates communication between the mind and an external system. The primary idea behind this project is to translate mental activity captured by a wireless Electroencephalography (EEG) headset into text. The suggested system uses electroencephalogram (EEG) signals as a means of communication between human brains and digital devices.

1.2 Scope of this document

The Brain-Computer Interface (BCI) allows people to communicate with others or operate devices like computers, prosthetic limbs, or robots using mental activity alone, rather than through the use of physical gestures (EEG). This initiative aims to help everyone who struggles to find the right words to express their needs by translating their ideas into text.

1.3 System Overview

Gives a high-level description of the product that was established as a consequence of the requirements elicitation process. More than 16000 EEG pictures were collected for analysis before the signal waveform was amplified. After the waveform has been recovered from the EEG signals, it will be digitalized and sent to the computer. Then, start the preprocessing of this digital waveform using deep learning models. With the intention of gleaning exactly what is needed from these preprocessed amplified digital signals. Then, feature selection methods will be used to pick and choose among the extracted signals to get the desired results. Then, classification models will be used to sort them into groups according to the model's predicted performance. The data will then be split up so that it may be used for testing and prediction. A project's precision and correctness will show in the final product.

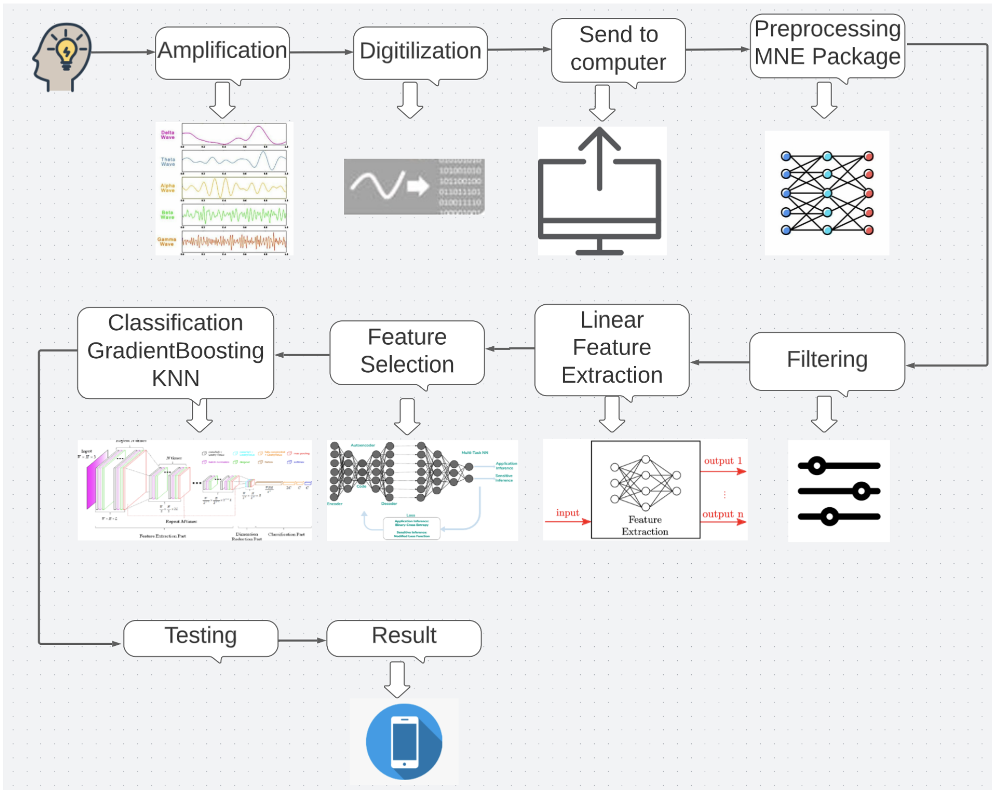


Figure 1: Model of decoding EEG signal

1.4 System Scope

In order to acquire brain signals associated with different states, electroencephalography (EEG) is a helpful technique. We provide BCIs that use a deep learning-based hierarchical approach to feature extraction. Using an EEG Headset to gather information and then beginning the data processing necessary to eliminate redundant entries. Create a straightforward mobile app for those with disabilities. EEG-based BCI may be used on the go to provide true brain-controlled typing. The goal is to develop a method of writing with one's brain by increasing the accuracy with which EEG data can be decoded over a wider range of brain activity. Create a unified deep learning framework to capture the spatial dependence of raw EEG data by using features generated from a convolutional operation and temporal correlation through a recurrent neural network architecture.

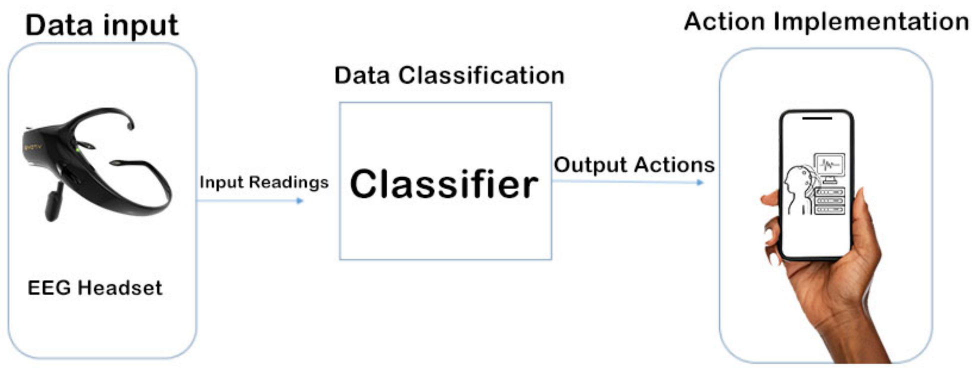


Figure 2: Emotiv Epoc X signals to mobile application

1.5 Business Context

- For those who are unable to express themselves verbally, we will now know exactly what they are thinking.
- Those who have difficulties communicating verbally would benefit greatly from having their thoughts read aloud.
- Eventually, this might lead to inexpensive BCIs that can be used to operate a wide variety of electronic equipment.

2 Similar Systems

2.1 Academic

- **The Thought Translation Device: Structure of a multimodal brain-computer communication system**[1]
  The subsequent study led to the development of a brain-computer interface (BCI) called the Thought Translation Device (TTD), which was intended to assist patients who were completely wheelchair-bound in their ability to interact with the outside world. The portion of the electroencephalogram (EEG) below 1 Hz is referred to as slow electrocortical potentials (SCPs). Birbaumer and colleagues demonstrated that a feedback device known as the Thought Translation Device (TTD) can be utilized to learn the self-regulation of these slow electrocortical potentials. After being recorded and reduced to binary options via a filter, the response from the SCP was then sent to one of the other (application-related) processes operating on a different system. This process was in charge of displaying the user's input. During training, the potential user is tasked with producing SCP changes of a certain polarity. This is done in order to test their abilities. The training application will thus show the response data, the feedback SCP-signal, and the work that has to be done, while also using a grinning and pleased-looking face to highlight the responses that are accurate. Because it

has been shown that the TTD is both successful and beneficial, it is being used in an increasing number of clinical investigations in which researchers need to employ EEG input for the purposes of either communication or treatment.

- **DEEP LEARNING THE EEG MANIFOLD FOR PHONOLOGICAL CATEGORIZATION FROM ACTIVE THOUGHTS**[2]
  They present a Speech-related Brain-Computer Interface (BCI) that makes use of a unique hierarchical feature extraction technique that is based on deep learning to identify phonological groups irrespective of the subject in the study that comes after it. More than that, it is designed to explicitly teach individuals who have speech difficulties a new method to express themselves via the use of their voices, which is a significant benefit. Deep learning strategies are included in the design, including long short-term memory (LSTM), convolutional neural networks (CNN), and deep autoencoders. Our suggested method achieves higher results than those achieved by current algorithms in each of the five binary classification tests by an average of 22.51 percentage points.

- **Think2Type: Thoughts to Text using EEG Waves**[3]
  When a person concentrates their attention on a certain subject, the ionic currents that flow inside the neurons of the brain cause the voltage levels of the neurons to fluctuate. These microvolt EEG signals may be analyzed in a non-invasive manner from a variety of scalp locations. Because of the complex ways in which different people think, it is not possible to utilize non-invasive approaches to detect or categorize EEG waves of alphabets or brain wave activity associated with alphabet letters. As a consequence of this, the participants will have their EEG waves recorded by the sensors so that we may analyze them. At this point, we need to translate the person's objective into morse code. The use of artificial neural networks (ANNs) is prevalent in the process of feature extraction. Extraction of data from long-term memory as well as neural networks (CNN). An artificial neural network (ANN) is built up of artificial neurons, which are essentially a network of linked nodes that are designed to simulate the behavior of genuine neurons found in the brain. By using Gradient Boosting to train an ANN on the acquired qualities, it is possible to make a prediction about the path that the waves will take. When utilizing the XGB model, the accuracy of trained CNN, RNN, and ANN models is comparable to 97% when using the categorical cross-entropy loss that was provided by the supplier.

- **Imagined object recognition through EEG signals using deep convolutional neural network**[4] The process of producing and manipulating mental pictures is referred to as visual/mental imagery, abbreviated as VI/MI. The XGBoost classifier was used to organize three different image-related datasets in order to demonstrate the usefulness of the model for the categorization of visual imagery-related tasks. Integrates Recurrent Learning (RL) with Convolutional Neural Networks (CNNs) by employing CNN and LSM in an incremental fashion (LSTM). Since many studies use raw EEG data for mental task categorization, having a lower number of EEG channels will make the model less able to discriminate between different types of mental tasks. On the publicly available MI-EEG dataset, the model achieved an average classification accuracy of 99.57 percent, which was higher than the performance of the most recent deep learning framework designed for this task by almost 6 percent.

- **Brain-to-text: decoding spoken phrases from phone representations in the brain**[5]

  Researchers working on brain-computer interfaces (BCIs) have been interested in the intriguing prospect of thought-to-thought communication with computers or other people for a long time. Encryption of the Result All of the respondents have noted that Brain-to-Text has much greater phone decoding accuracy than randomized models, which suggests that phone representations might be utilized to represent continuous speech output. The most successful session had an average classification accuracy of more than 50% for a total of 20 phones plus silence.

2.2 Business Applications

- Vibre[6]: is a young company with a focus on improving workplace security via the use of neurotechnologies. They achieve this by analyzing work processes or by keeping tabs on workers' actual levels of tiredness, sleepiness, and lack of focus in the here and now. According to them, the reality of mental exhaustion is often overlooked. When people aren't mentally fit for their jobs, they make costly blunders doing difficult tasks in dangerous circumstances. Devastating outcomes like those shown in the figures, such as botched surgeries, fatal plane accidents, confused air traffic controllers, and preventable traffic fatalities (6). Viber solutions, such as real-time monitoring and evaluation of your vital signs, may help you maintain a greater attention level while doing complicated work in an even more complex working environment, therefore avoiding all of the aforementioned terrible effects. While groups of professionals are participating in a series of activities, we monitor their cognitive load. Over the course of a few days, data about a wide range of users is gathered (totally anonymously). After collecting data, we write a report in which we thoroughly examine the procedure, highlighting any hiccups and underlying problems. In addition, Neuroframe may be used to monitor workers in real-time while they carry out dangerous tasks.

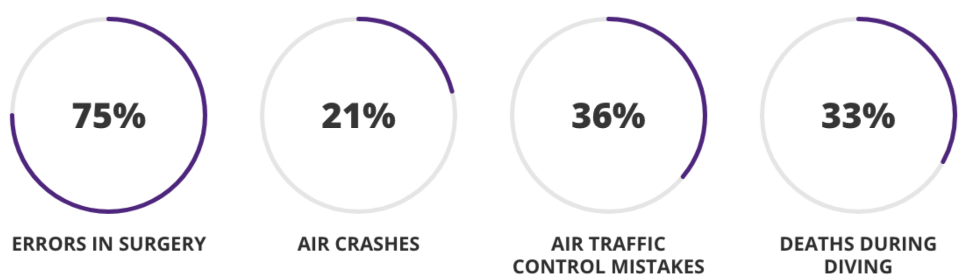


Figure 3: From EEG averaging to classifier

- Neurable:[7] is a billion-dollar company with a focus on mental decoding. By attempting to fully understand the workings of our brains, they attempt to free us from our mental constraints. By offering various goods, they want to hasten the transition from scientific discovery to commercialization of technological advances. One example is the Enten, a receiver for 16 channels of electroencephalogram (EEG) data worn like headphones (7). That operates for more than a day so that you may get an in-depth report on your peak productivity times and locations. The information in this report will allow you to concentrate much more intently on the task at hand. With the present goal of creating the standard brain-computer interface (BCI), neurotechnology is closer than ever before to becoming widely accessible. Therefore, they are competently, ethically, and humanely dedicated to opening this frontier wilderness.

Figure 4: Development of Neurable EEG BCI till reaching Enten in 2020

3 System Description

3.1 User Problem Statement

Since many individuals have trouble communicating with others face-to-face, we utilized EEG signals to help persons with these issues put their thoughts into text. Accurately categorizing the user's intention signals is the primary challenge of the brain typing system. In the wake of data acquisition. The best algorithms should be used to extract features from real-time signals owing to the fact that EEG data has a poor signal-to-noise ratio, which renders it susceptible to background brain processes and environmental impacts. Second, we need to figure out how to utilize these signals to train a model to recognize human intent via the use of precise feature representations and classifications.

3.2 User Objectives

- The user must be able to see into his own head and know what is going on there.
- If the user has a speech impediment, he or she must be able to use it.
- The user has to be able to pick up on the many frequencies his brain impulses emit at.
- For the purpose of user assessment of the newly created approach, there should be both a MI-EEG dataset that is accessible to the general public and a real-world dataset that was gathered by the members of the study group.

- Those with disabilities should be able to access a simple user interface.

3.3 User Characteristics

Target audiences include tech-savvy persons and those with speech impairments. Practitioners of medicine and related fields. For either serious study or leisurely exploration. They should be able to navigate the system's user interface and have a basic understanding of mobile apps.

3.4 System Context

One interface will allow the user to translate their ideas into text using the EEG headset. The system is mainly an interface in which the user will have to wear an EEG headset and pair it with the application for a successful connection, then, the brain signals will be taken directly to the interface and then converted from analogue to digital.

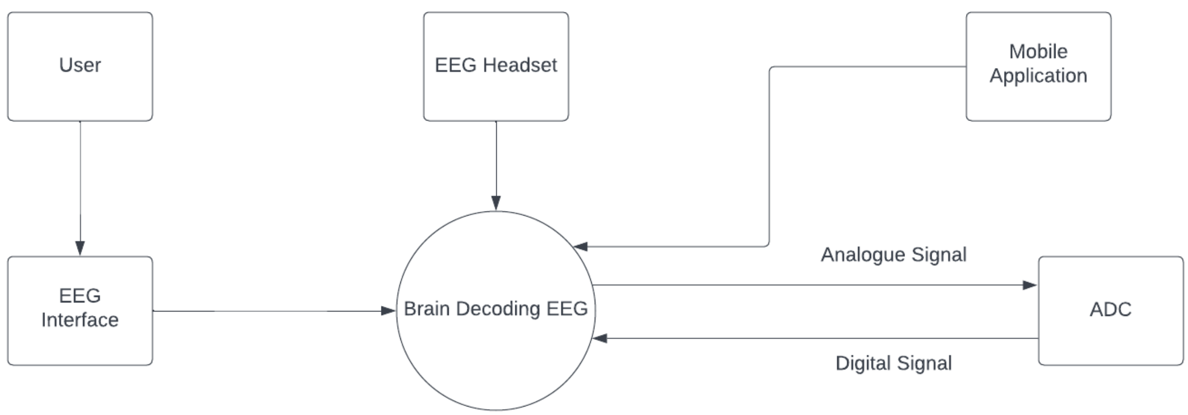


Figure 5: System Context diagram

4 Functional Requirements

4.1 System Functions

1. The model will receive the signals from the headset and then convert the thoughts into text using a mobile application.
2. The model will classify the data using KNN, XGBoost classifiers.
3. The model will receive the incoming signals and then convert them into tasks coming from the brain thoughts.

4.2 Detailed Functional Specification

Table 2: Connect model to headset

Name	connect the model to the headset.
Code	FR01
Priority	High
Critical	It is the component in charge of establishing a connection between both the model and the headset.
Description	Utilized in order to acquire the signals, record the signal values, and then link with the model.
Input	Signals obtained from the user using the headset
Output	Reading signals by using the headset
Pre-condition	The headset should modified and connected by the user
Post-condition	————————————————
Dependency	———————————————
Risk	Issues with the connection of the headset

Table 3: Get Readings from headset

Name	record the reading from headset
Code	FR02
Priority	High
Critical	Utilized for readings to be retrieved from the headset.
Description	The readings from the headset will be retrieved by the system, and then it will utilize those data to translate the ideas into text.
Input	Signals obtained from the user using the helmet.
Output	Records
Pre-condition	Adjusting the headset to your liking is essential.
Post-condition	————————————————
Dependency	FR01
Risk	Issues with the connection of the headset

Table 4: Convert thoughts to text

Name	Convert thoughts to text using the mobile application
Code	FR03
Priority	High
Critical	performs the actions based on the signals received
Description	The Signals, after being translated into job descriptions after the categorization.
Input	Signals obtained from the user using the headset.
Output	Task
Pre-condition	Classifying the signals
Post-condition	————————————————
Dependency	FR01 and FR02
Risk	Problems in headset connection or errors in classifying

5 Design Constraints

5.1 Standards Compliance

Mobile application supported by IOS and Android

5.2 Hardware Limitations

The users need a smartphone to download the application to control the headset.

5.3 Other Constraints as appropriate

The user must have an internet connection to access the application.

6 Non-functional Requirements

- Usability: The application shall have a user-friendly view, and the interface should be easily used by the users.
- Response time: The application shall have a rapid response time for all the user actions.
- Efficiency: minimum use of resources (memory).
- Portability: The system may be accessed over the world wide web. And You may find it on (Mobile Application).
- Availability: In order for users to make use of the program, it must be available at all times.

7 Data Design

7.1 Data Description

The dataset used in the following approach was sampled and collected by the authors of the published paper "EEG data of substantial size and quality for the study of human visual object identification" [8]. The collection contains high-resolution EEG reactions to pictures of items from the natural world. it involves 10 users, with a number of 82,160 tests over 16,740 images with several conditions. Then, the data is split into 16,540 training images, and 200 testing images. Moreover, encoding models were applied to the reprocessed data that perfectly linked each response of the EEG signals to the specified images.

8 Preliminary Object-Oriented Domain Analysis

8.1 Inheritance Relationships

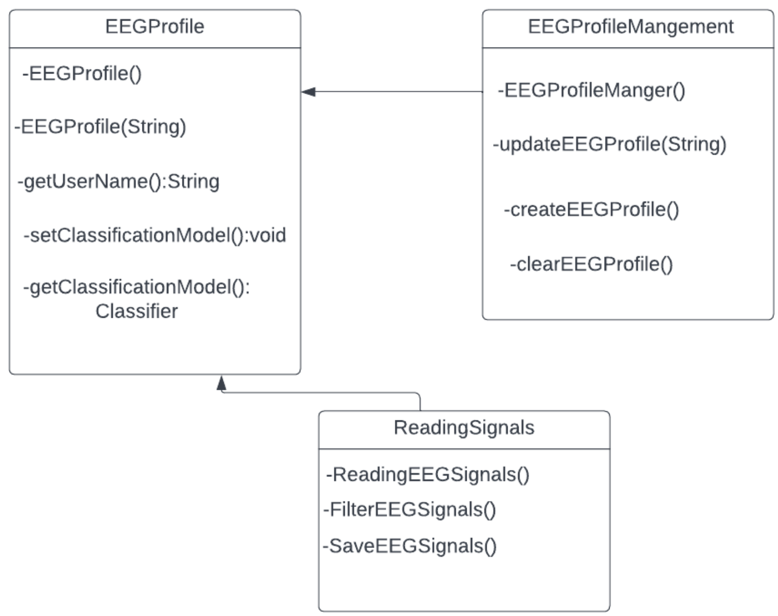


Figure 6: Inheritance Relations

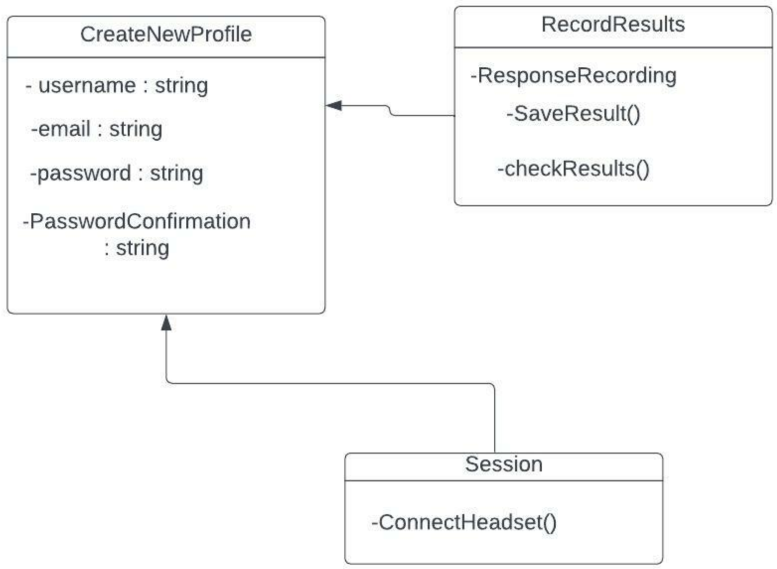


Figure 7: Inheritance Relations

8.2 Class descriptions

Table 5: Class Name - EEGProfile

Abstract or Concrete:	Concrete.
List of Superclasses	————-
List of Subclasses	————-
Purpose	Allow the user to create new EEG profile to use the headset
Collaborations	————-
Attributes	Username, age, gender
Operations	EEGProfile(), EEGProfile(String), getUserName():String, setClassificationModel():void, getClassificationModel(): Classifier
Constraints	————-

Table 6: Class Name - EEGProfileMangement

Abstract or Concrete:	Concrete.
List of Superclasses	————-
List of Subclasses	————-
Purpose	Allow the user to manage the EEG profile to use the headset
Collaborations	————-
Attributes	edit, accept, delete
Operations	EEGProfileManger(), updateEEGProfile(String), createEEGProfile(), clearEEGProfile()
Constraints	————-

Table 7: Class Name - ReadingSignals

Abstract or Concrete:	Concrete.
List of Superclasses	————-
List of Subclasses	————-
Purpose	Reading the signals that coming out from the EEG headset
Collaborations	————-
Attributes	electrodes, headset, channels
Operations	ReadingEEGSignals(), FilterEEGSignals(), SaveEEGSignals()
Constraints	————-

Table 8: Class Name - CreateNewProfile

Abstract or Concrete:	Concrete.
List of Superclasses	———-
List of Subclasses	———-
Purpose	Create a new user profile to save user signals
Collaborations	———-
Attributes	username, email, password
Operations	username : string, email : string, password : string, PasswordConfirmation : string
Constraints	———-

Table 9: Class Name - RecordResults

Abstract or Concrete:	Concrete.
List of Superclasses	———-
List of Subclasses	———-
Purpose	Record the user signals
Collaborations	———-
Attributes	frequency, results, voltage
Operations	ResponseRecording, SaveResult(), checkResults()
Constraints	———-

9 Operational Scenarios

- **Scenario(1): Headband adjustments**
  the user shall wear the EEG headset. Make a decision about where the headband should be placed on your head: in the back or on top. Holding the arm steady, spin the headband by pushing it up or down. And after that, it will lock.

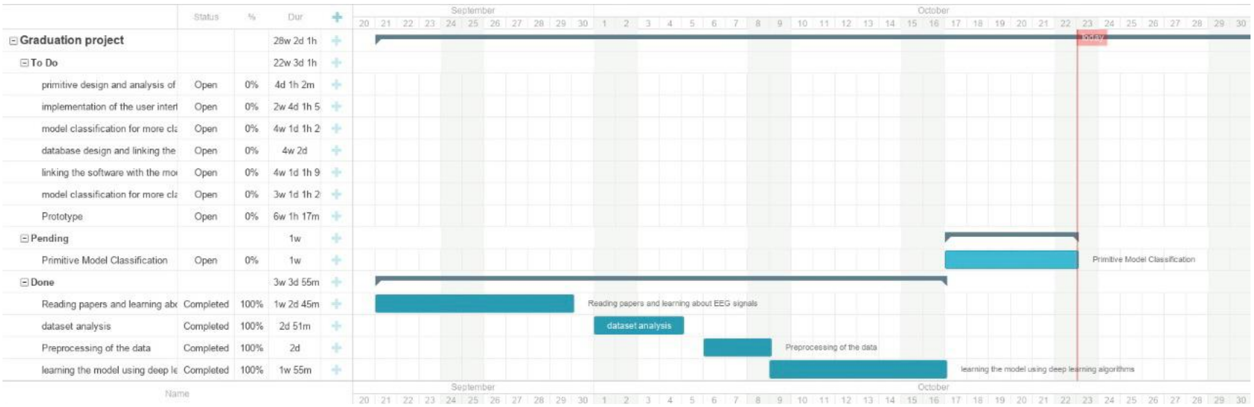
- **Scenario(2): Connecting the EPOC X**
  the user will open the application where the user will need to configure the headset and a successfully connected and make sure the sensors are will fitted on on his/her head.

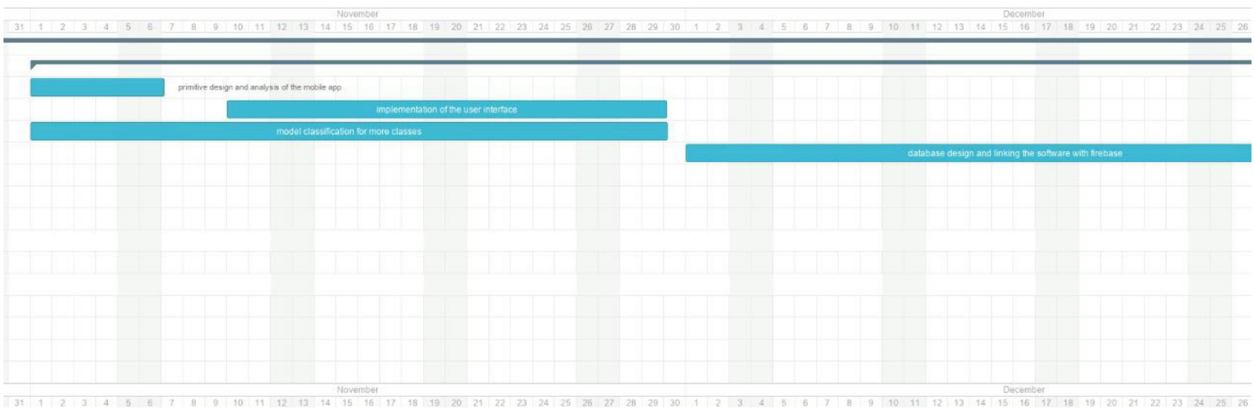
- **Scenario(3): Start trial**
  the user will presented a series of images where what he/she will be expected to realise a certain image, the EEG response of what he/she thought about will be recorded.

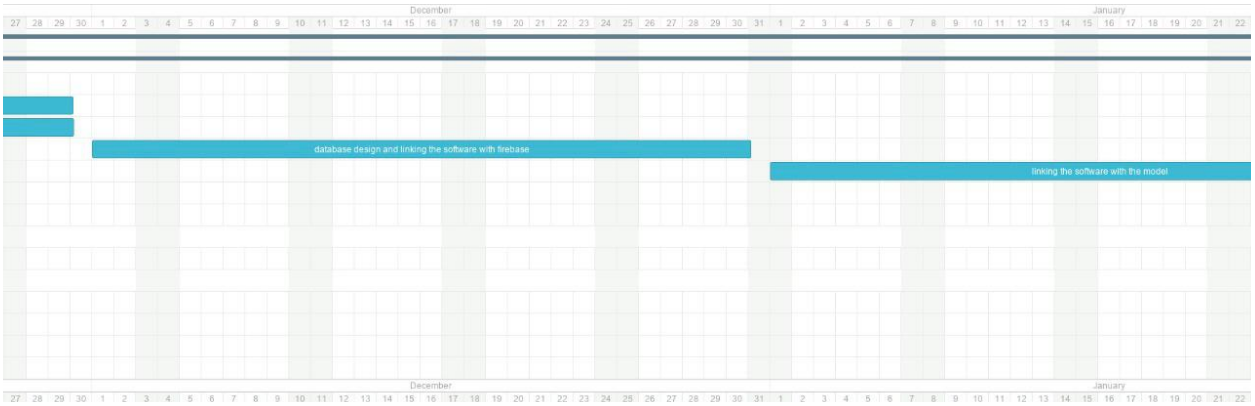
- **Scenario(4): Instructions**
  the user will be asked to perform the experience several trials in order to enhance the accuracy of the trial.

10 Project Plan

Task	Start Date	End date	Duration	Role
Brainstorming ideas	09/21/22	09/30/22	9 days	All
Information collection and research	09/21/22	09/30/22	9 days	All
Collecting dataset by using a headset	———	———	———	Helmy Magdy
Preprocessing of the data	10/06/22	10/09/22	4 days	Mario Shady
Train and test dataset	10/09/22	10/17/22	9 days	Ahmed-Hady-Helmy
Proposal preparation	09/25/22	10/22/22	28 days	All
Classify dataset	10/01/22	10/05/22	5 days	Hady Wael- Helmy Magdy
SRS preparation	11/05/22	12/01/22	26 days	All
SRS presentation	11/05/22	12/01/22	26 days	All
SDD preparation	01/15/22	02/15/22	30 days	All
SDD presentation	01/15/22	02/15/22	30 days	All
Mobile application development	11/10/22	11/30/22	20 days	Ahmed Sameh- Hady Wael
Prototype	02/24/22	04/25/22	31 days	All
Test and validate	04/07/22	04/20/22	13 days	All
Technical evaluation	04/20/22	05/01/22	11 days	All
Thesis	04/30/22	———	30 days	All


Graduation project
To Do
primitive design and analysis of
implementation of the user interf
model classification for more cla
database design and linking the
linking the software with the mo
model classification for more cla
Prototype
Pending
Primitive Model Classification
Done
Reading papers and learning abo
dataset analysis
Preprocessing of the data
learning the model using deep le
Reading papers and learning about EEG signals
Preprocessing of the data
learning the model using deep learning algorithms
Primitive Model Classification


November
December
primitive design and analysis of the mobile app
implementation of the user interface
model classification for more classes
database design and linking the software with firebase



11 Appendices

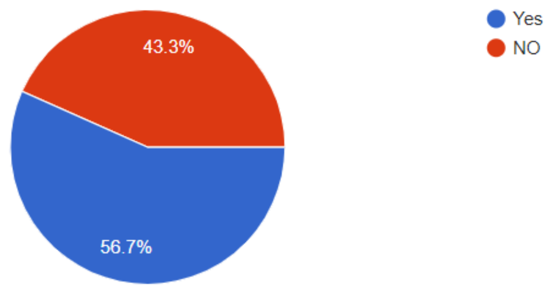
11.1 Definitions, Acronyms, Abbreviations

- EEG: An electroencephalogram is a test that detects electrical activity in your brain by attaching small metal discs (electrodes) to your scalp. Your brain cells communicate through electrical impulses and are always active, even when you're sleeping. On an EEG recording, this activity appears as wavy lines.
- BCI:The term "brain-computer interface" (BCI) refers to a computerised system that reads brain signals, processes them, and then sends the processed instructions to an output device to carry out the intended action.

11.2 Supportive Documents

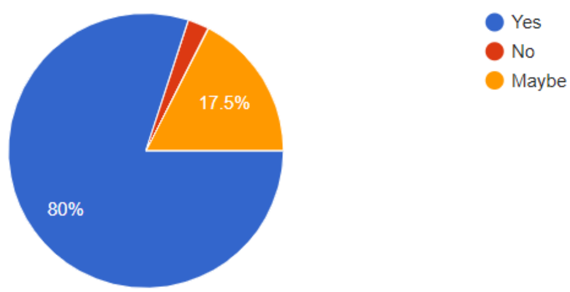
Do you know people with special needs?

120 responses



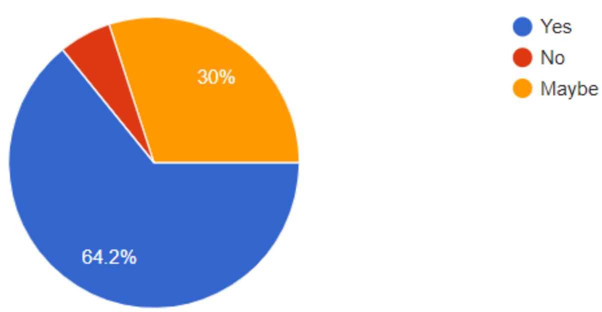
From your point of view, does health condition play a role with special needs people in doing daily tasks?

120 responses



Do you think people with special needs face communication problems?

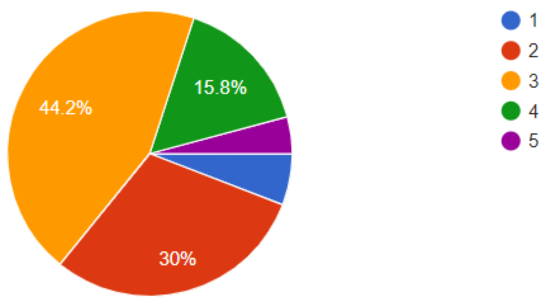
120 responses



How much special needs people are supported in their daily life?

Choose from 1 to 5 (1 not supported at all, 5 completely supported)

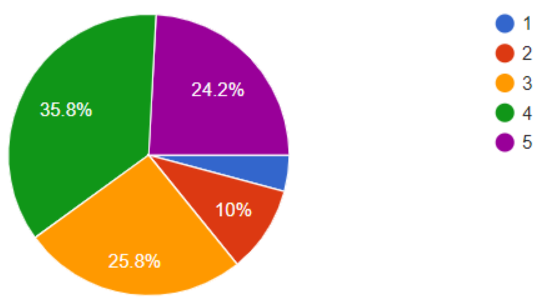
120 responses



Do People with special needs face Social Isolation?

Choose from 1 to 5 (1 completely disagree, 5 completely agree)

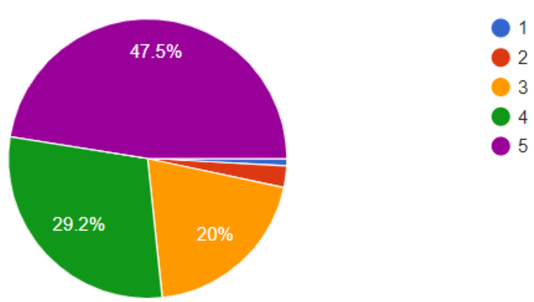
120 responses



Do People with special needs face Emotional Stress?

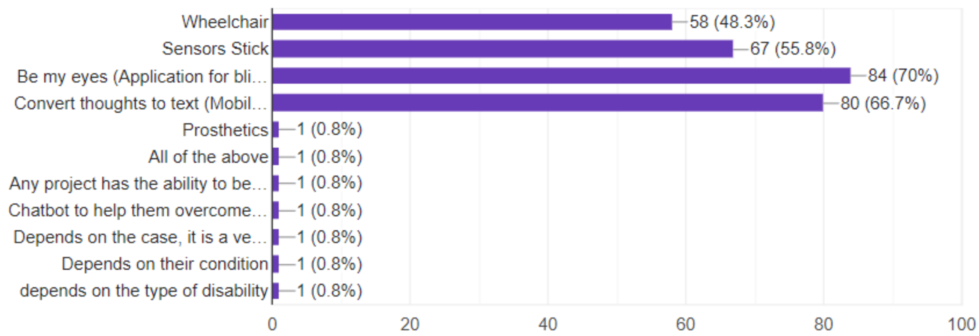
Choose from 1 to 5 (1 completely disagree, 5 completely agree)

120 responses



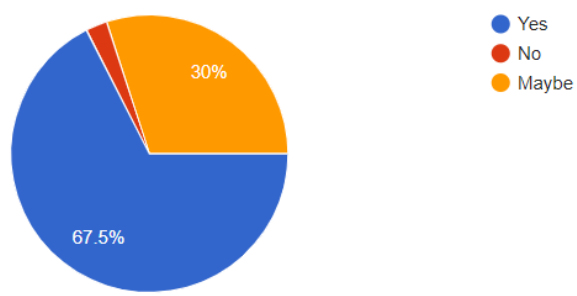
From your point of view, What is the equipment that helps them to live normally?

120 responses



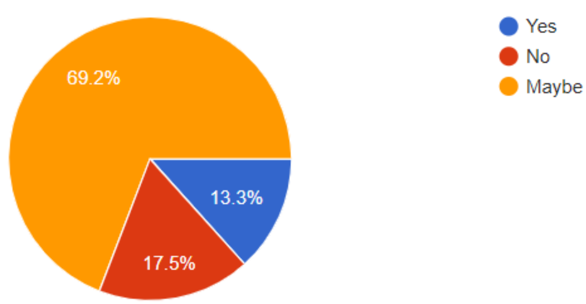
Do you think that converting thoughts into text is useful for people with special needs?

120 responses



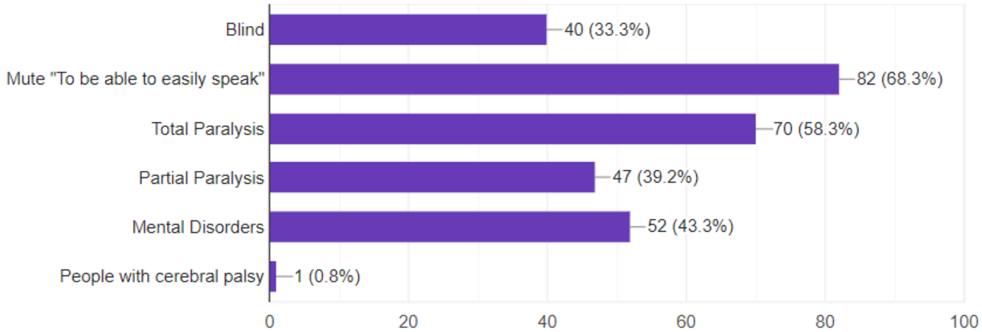
If you know someone have brain problems, would he/she accept brain surgery?

120 responses



Who would benefit the most from turning thoughts into text application?

120 responses



Recommendations or Suggestions to help people with special needs ? (Optional)

13 responses

Greater awareness of the community to accept them and try to modify the things around them to suit their usage

i think raising awareness between normal people about how to treat people with special needs well is the most important target to achieve

it's individual matter based on his/her condition.

People that could communicate with and take care of them.

To let them work in every field

In Egypt anything for special needs costs a lot from schools & hospitals and even sports club ,or if there is something low cost it wouldn't be perfect like private Services , So I really wish that anything will help special needs to be low coats but equals the quality of private services.

Increase people's awareness about special needs through different channels (media, social media, education). Make facilitation in streets, transportation and different places to suit people with special

Recommendations or Suggestions to help people with special needs ? (Optional)

13 responses

education). Make facilitation in streets, transportation and different places to suit people with special needs.

علي اسلوب الشرح وكده bouns بيساعدهم علي انهم يذاكروا حاجة ويشرحوها بأسلوبهم، ويبقي مثلا في app حاسة انه يبقي في

More support and acceptance from community.

Campaigns to raise awareness to treat people with special needs like they are normal human beings instead of treating them as children who don't have a say in what they want (Watch "SBSK" youtube channel, it can help you out to get to know what people with different conditions need.)

We should treat them as normal people like us/ not make them feel as though they are isolated. while trying to understand their conditions more since they are different physically or mentally.

To have an activity or a hobby maybe even a therapist since they will be able to express their feelings easier

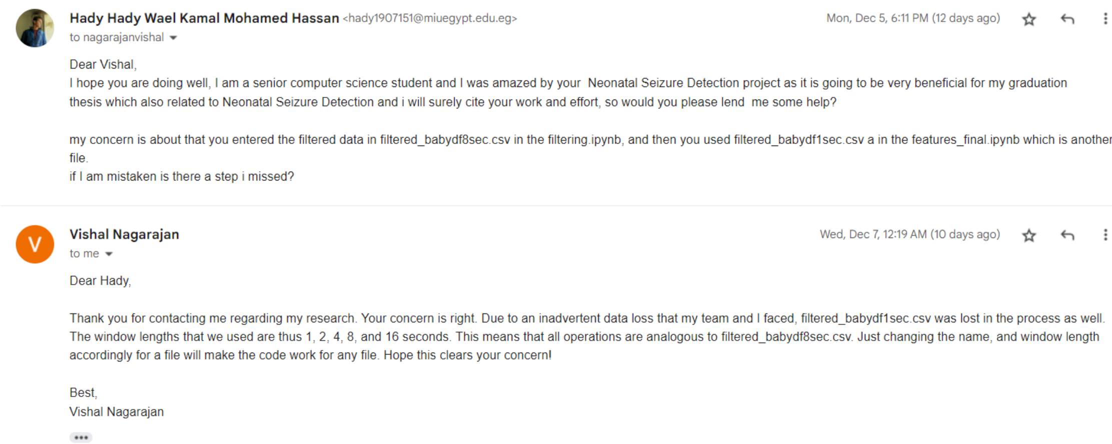
7:07 150 10%

Inquiry about brain typing Research Paper External Inbox

M Mario Mario Shady Samaa... 3 Oct

to xiang.zhang3

Good evening Prof. Xiang,
I am Mario Shady, Computer Science graduate student in Egypt. I was thrilled by your work and your research paper. We intended to cite it in our graduation project. So, I was asking if you can send us the dataset, to help us in our project.
Sincerely,
Mario Shady.


Hady Hady Wael Kamal Mohamed Hassan <hady1907151@miuegypt.edu.eg>
to nagarajanvishal
Mon, Dec 5, 6:11 PM (12 days ago)

Dear Vishal,
I hope you are doing well, I am a senior computer science student and I was amazed by your Neonatal Seizure Detection project as it is going to be very beneficial for my graduation thesis which also related to Neonatal Seizure Detection and i will surely cite your work and effort, so would you please lend me some help?

my concern is about that you entered the filtered data in filtered_babydf8sec.csv in the filtering.ipynb, and then you used filtered_babydf1sec.csv a in the features_final.ipynb which is another file.
if I am mistaken is there a step i missed?

Vishal Nagarajan
to me
Wed, Dec 7, 12:19 AM (10 days ago)

Dear Hady,

Thank you for contacting me regarding my research. Your concern is right. Due to an inadvertent data loss that my team and I faced, filtered_babydf1sec.csv was lost in the process as well. The window lengths that we used are thus 1, 2, 4, 8, and 16 seconds. This means that all operations are analogous to filtered_babydf8sec.csv. Just changing the name, and window length accordingly for a file will make the code work for any file. Hope this clears your concern!

Best,
Vishal Nagarajan

12 References

References

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