3. Methodology

3.1.Introduction

Many industries like nuclear power, aviation, healthcare, transportation & mining are critical to the global economy, but they provide high-risk occupations. Therefore, the safety and health of workers are often at risk due to the nature of the work. To improve safety and productivity, it is crucial to ensure that workers have the cognitive capabilities necessary to perform their tasks with high reliability. This research aims to address this challenge by developing a method which can assess human cognitive capability necessary to perform the specific upcoming cognitive operation. The proposed approach is expected to help the supervisors in managing the situation safely and efficiently. By understanding the cognitive demands of specific tasks, the respective industry can develop better training programmes, equipment designs and risk assessment strategies that can enhance workers' cognitive abilities and reduce the risk of accidents and injuries. This research has the potential to make a significant contribution to the safety-critical industries by improving safety and productivity as well as ensuring that workers can perform their tasks with confidence and competence.

Structure of this chapter (roadmap): The second section discusses the research design. It details and justifies all the key design choices in a logical and intuitive fashion. Section 3 presents the limitations of the study design. Finally, section 4 provides the summary.

3.2. The Research Design

3.2.1. Research Philosophy:

Based on information processing perspective on human performance, cognition primarily depends on individual attention resources and working memory capacity. So, for better cognitive performance in any task, the attention resources and working memory capacity should match with the task demands.

Based on the literature review, it can be concluded that physiological measures, like EEG from prefrontal cortex (Figure 3.1), have features that unintentionally reveal an individual's attentional and working memory status. These features from EEG can better represent the cognitive status and can be related to the cognitive performance in the task. On the other hand, cognitive performance in a task is directly assessed by the observable response time for each behaviour as well as response accuracy.

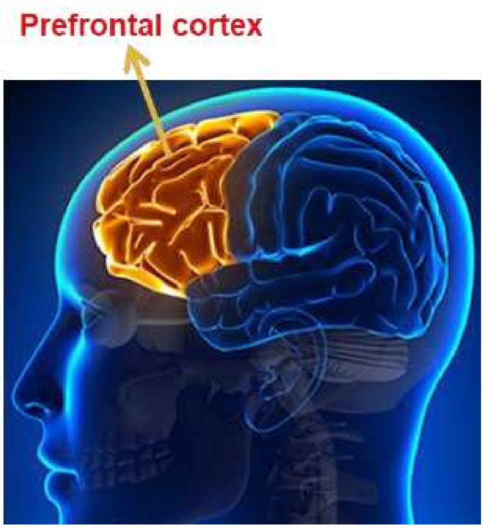

Figure 3.1. Prefrontal cortex of human brain

Primary focus of this research is to develop a predictive model of cognitive or human performance in the upcoming task. So, ethically responsible experimental methods have been designed to gather data that support model development. Proposed methods contain two experimental sessions. The first session was a 5-minute idle session [76] where the researcher recorded brainwaves from the participants. The second session involved recording response time and response accuracy by the participants during a task.

Previous studies have reported that the overall cognitive performance decreases throughout the day. So, even if the researchers can make a model from the EEG data collected while attending a task, it will serve the purpose of the research, but it is not possible to record EEG without noise while performing any task other than in an idle position. Therefore, one may take recordings prior to attending a task or after completing the task. As the cognitive capacity drains with time, the recordings after the task completion might falsely underestimate the cognitive capacity for completing the task and indicate the leftover cognitive capacity of the individual. Recordings prior to assigning a task might falsely overestimate the cognitive capacity for completing the task and the collected data may represent excess capacity than the required capacity to complete the task. The latter is a better option as it has some buffer capacity for better performance and easy to implement in field settings.

The researcher carefully analysed this large volume of gathered data using suitable and advanced analysis techniques to extract features that can represent cognitive status. Based on these features, a model was constructed for predicting cognitive performance.

According to researcher, research philosophy involves the responsible use of data and commitment of upholding the highest ethical standards besides maintaining the privacy and confidentiality of individuals that participate in this research. By approaching this work with integrity, respect and a deep appreciation for the complexity of human cognition, a positive and lasting impact can be made.

3.2.2. Research Type:

Inspired by neuroscience and cognitive psychology, quantitative methods were followed to measure the features of cognitive state and cognitive performance in the task. In neuroscience, researchers mainly use brain imaging techniques, such as EEG, to gather data on neural activity associated with cognitive processes. Cognitive psychologists, on the other hand, use controlled experimental methods, such as reaction time tasks or working memory tests, to gather quantitative data on observable cognitive outcomes. These data can then be analysed using various analytical approaches, such as machine learning algorithms, to identify patterns or relationships between brain activity and cognitive performance.

The chosen methods and approaches are scientifically rigorous and ethically responsible. In addition, they are carefully tailored to the specific needs and goals of the research. Adopted quantitative methods allow the use of standardised instruments and procedures, ensuring the consistency in data collection and analysis.

Followed research methodology helps in collecting objectively measurable data suitable for statistical analysis and hypothesis testing. In addition, it allows for large sample of data, increasing the reliability and generalisation of the findings.

3.2.3. Research Strategy:

To improve safety and productivity in any industrial settings, this research aims to find a way of assessing the present human cognitive capability necessary to perform the upcoming task with reliable performance.

An endeavour will be made in this study to answer the following research questions:

- What are the metrics that can better represent human performance?

- What is the suitable methodology for assessing human performance in industrial settings?
- What is the best predictive model of human performance in the upcoming task?

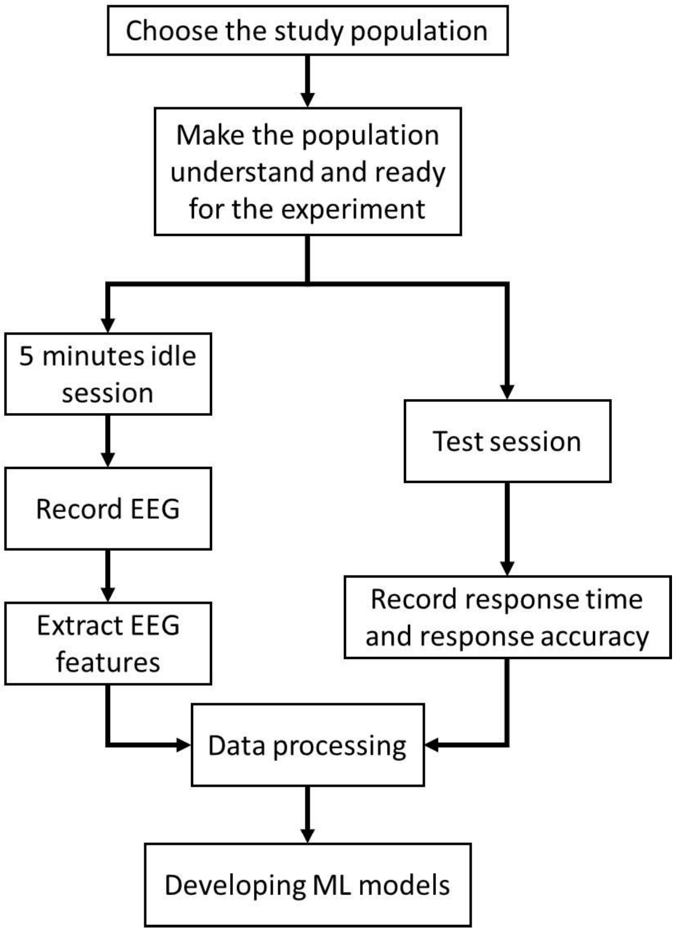

Figure 3.2. Research Strategy

Based on the research questions, the researcher formulated a detailed and systematic plan of action as shown in Figure 3.2. In the first step, the study population (a specific working group of individuals) was chosen, followed by making the participants understand the experimental procedure besides making them ready for the activity. During the experiment, individuals' brain electrical activity was recorded using EEG recorder for 5 minutes in the idle session. They were then allowed to attend the test (this is similar to a training test in simulators). In the test session, the cognitive performance metrics (response time and response accuracy) of attempts made were recorded. Finally, after extracting the features from EEG, the data was processed to build a machine learning model. With the developed model, it is possible to predict the upcoming task performance only with 5 minutes EEG recording.

3.2.4. Time Horizon:

Based on this research aim, it was decided to collect the data from the same individuals at multiple random points in time of the day. This design helped in developing models that predict cognitive performance irrespective of time of the day and may be useful for evaluating cognitive levels effectively.

3.3. Data Collection Method:

In this research, an effort was made to achieve the research objective by building a model based on the EEG features as input variables and cognitive performance as the output variable. For this, the experiment started with a 5-minute idle session where brainwaves of the participants were recorded. Later, the participants were made to attend a cognitive test session. Working memory and attention in this cognitive test were evaluated, which form the key components of the information processing theory [77].

All the participants were trained with the cognitive tests by making them attend the tests once a day from a week prior to the actual experiment with an intent to make sure that the participants have reached their in-built capability level for that specific test. On the day of the experiment, it is easy to judge whether the participant is up to his capability level at that specific time or not.

3.3.1. Research Instrument

EEG headset:

In this study, the OpenBCI Ultracortex Mark IV EEG headset we used for EEG recording. It is a versatile and user-friendly tool for researchers and developers working in the field of EEG. Its customisable design, ease of use and lightweight comfort make it a popular choice for a wide range of applications.

One of the key advantages of the Ultracortex Mark IV is its customisable design. Users can choose the number and location of electrodes based on their specific research or application needs. This flexibility makes it ideal for a wide range of experiments. Additionally, the Ultracortex Mark IV is compatible with a variety of EEG software, which further expands its capabilities.

Another advantage of the Ultracortex Mark IV is its ease of use. The device comes with software that enables users to quickly set up and start collecting EEG data. The software also includes a range of features for signal processing, analysis and visualisation, making it a powerful tool for data analysis.

Finally, the OpenBCI community is active and supportive, providing users with a wealth of resources and tutorials to help them get started with the device and troubleshoot any issues they may encounter. This community support further enhances the device's usability and ensures that users can get the most out of their Ultracortex Mark IV EEG headset.

The validity and reliability of the OpenBCI Ultracortex Mark IV EEG headset depend on several factors, including the study design, data analysis methods and electrode placement. However, there are several studies that have assessed the validity and reliability of EEG recordings using similar devices and there is evidence to suggest that it can produce valid and reliable EEG recordings when used appropriately. [78]–[82].

Lumosity software:

To administer cognitive test in second session, Lumosity software was used. It is a mobile application that offers users a variety of cognitive training exercises designed to improve brain function and enhance mental performance. The app offers a range of activities that target specific cognitive skills, such as memory, attention, flexibility, speed and problem-solving. It has been used by millions of people around the world. The app's creators claim that its exercises are based on scientific research and are validated through rigorous testing.

Lumosity has been used in several research studies as a tool for collecting data on cognitive performance. The app's built-in activities provide researchers with a standardised and controlled way to measure specific cognitive skills in a large number of participants. It has been found that performance on these activities was significantly associated with task performance [83], [84].

The Lumosity software has faced scrutiny due to doubts about the scientific validity of its claims regarding cognitive enhancement. Some studies have questioned the robustness of evidence supporting Lumosity's benefits, emphasising the need for more rigorous research methodologies and independent validation. Critics argue that improvements within Lumosity's games may not translate to broader cognitive skills. In this study, Lumosity has been used as a cognitive assessment tool not to endorse or challenge claims of cognitive enhancement. It has been employed as a standardised tool to assess cognitive abilities, treating it akin to a cognitive assessment battery. By focusing on measuring baseline cognitive performance, this study’s approach contributes to a broader understanding of cognitive assessments without presupposing specific benefits from Lumosity's training regimen.

While Lumosity can be a useful tool for collecting data on cognitive performance, the app's activities are designed for general cognitive training rather than specific research purposes. Therefore, it is necessary to supplement Lumosity data with additional cognitive assessments to ensure the validity and reliability of the results. So, metrics like response time for each attempt in the activities were record and response accuracy from the activity results was evaluated.

3.3.2. Designing and customisation of EEG recording instrument

EEG headset:

The Ultracortex Mark IV is an open-source 3D printed headset intended to work with the open BCI's system. It is capable of reading brain activity EEG from 35 node locations. The Mark IV frame uses dry electrodes, allowing fixing it to the scalp without using any conductive paste. When installed correctly, it only takes 10 seconds to put it on and start reading data. For this study, "OPENBCI ALL-IN-ONE BIOSENSING R&D BUNDLE" has been used. It contains 3D printed frame, electrodes (flat units and spiky units), the wires (ribbon cables), other non 3D printed parts (ear clips, comfort units and screws) and biosensing board (cyton) as shown in Figure 3.3, Figure 3.4 and Figure 3.5.

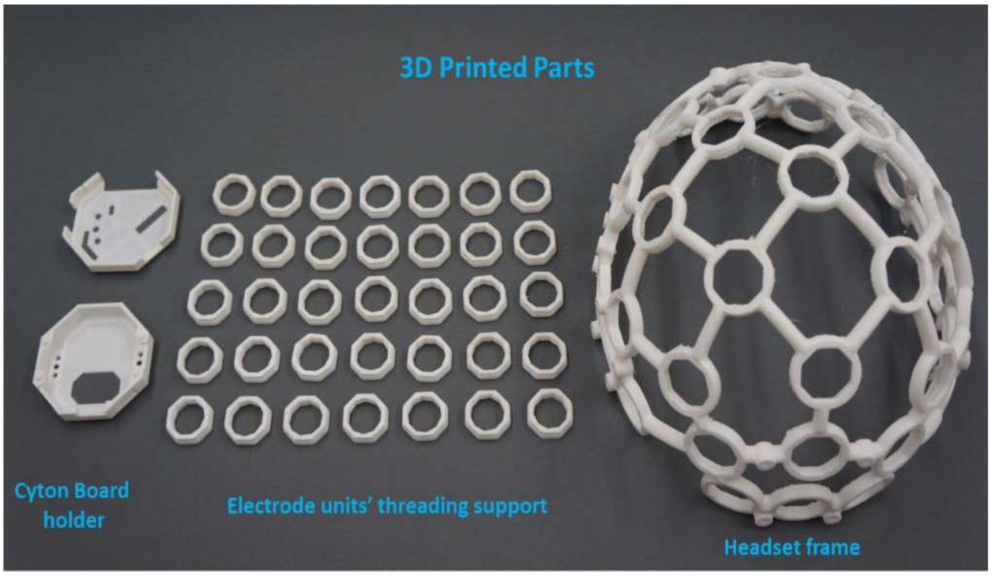

Figure 3.3. 3D printed parts of The Ultracortex Mark IV

Figure 3.4. Electrodes, the wires and other non 3D printed parts of the Ultracortex Mark IV

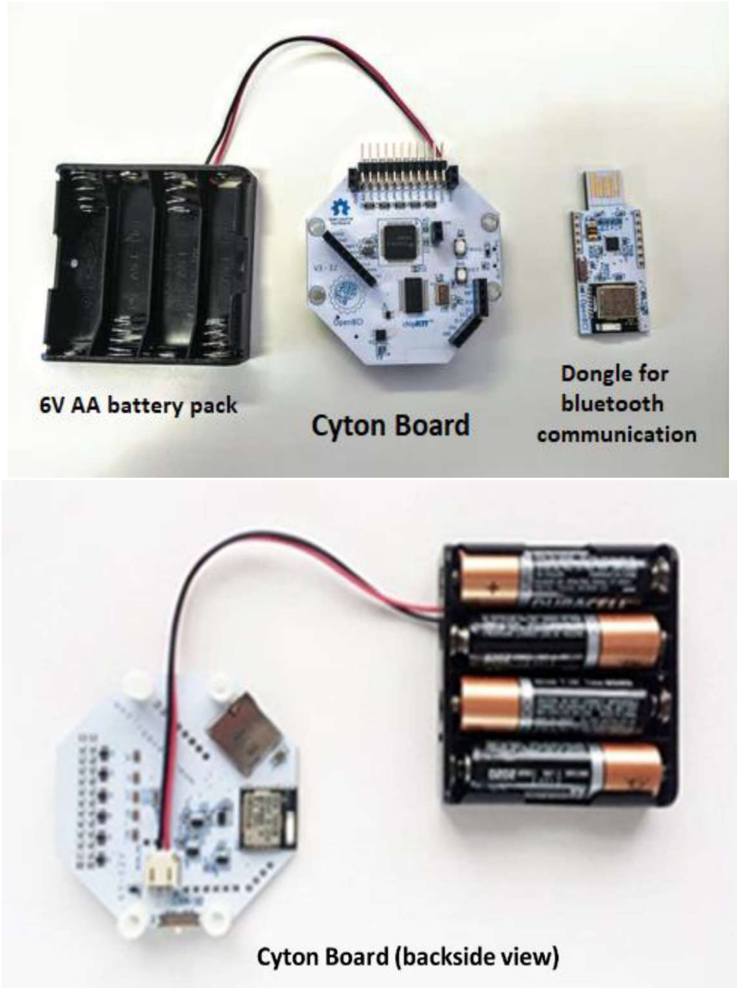

Figure 3.5. Cyton Board of the Ultracortex Mark IV and its Bluetooth Dongle

Assembling the headset for data collection:

For the first time use, it is necessary to build the working headset by assembling the necessary parts suitable for the study. Super glue was applied for fixing 3D printed electrode units' threading supports to the headset frame at 35 node locations, followed by fitting the cyton board holder to the back of headset frame using the screws (Figure 3.6).

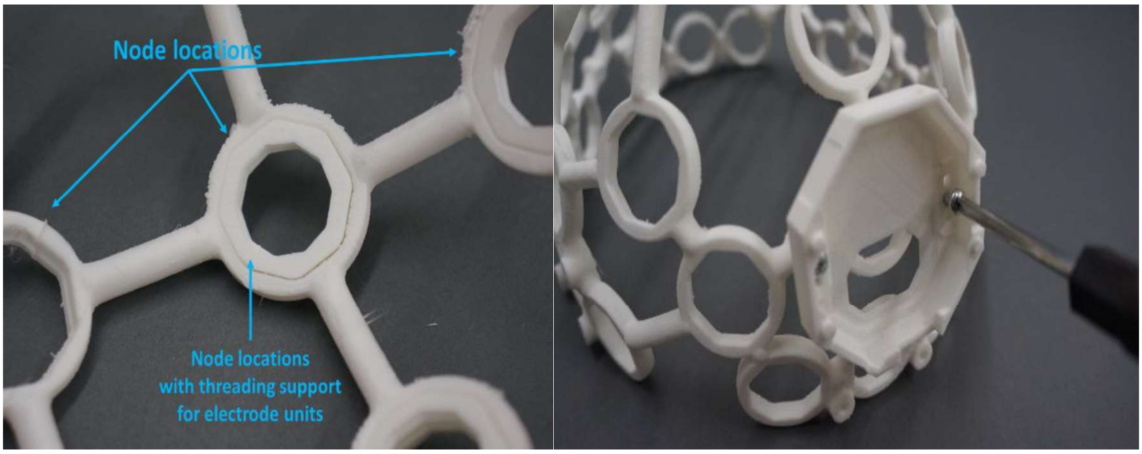

Figure 3.6. Assembling Ultracortex Mark IV: Fixing 3D printed parts together

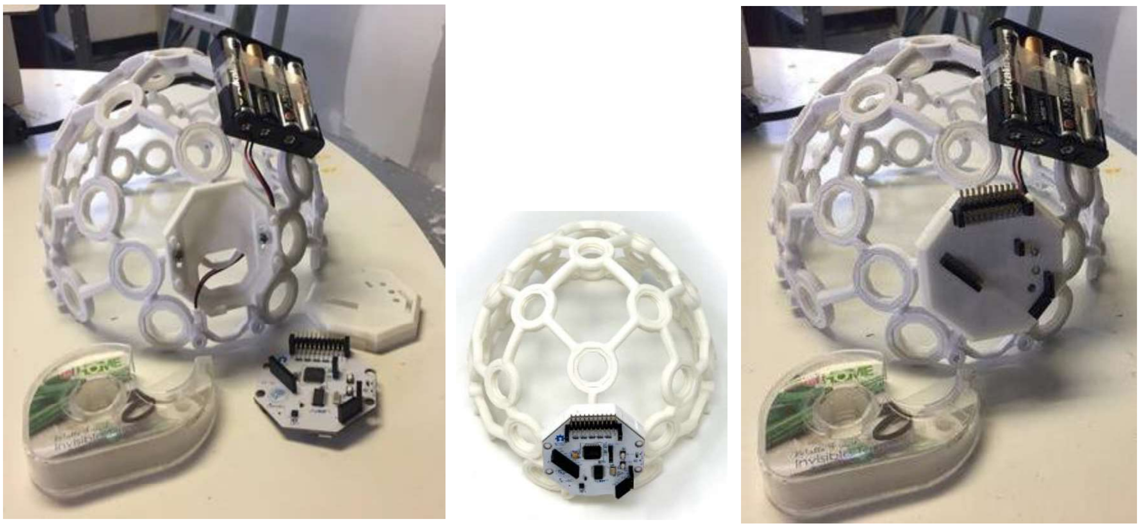

Figure 3.7. Fixing cyton board and pasting battery pack

The next step involved putting the comfort units in place for distributing weight of headset. In this study, the headset weight was mainly focused at the battery pack and cyton board as shown in Figure 3.7. So, the comfort units were kept around the cyton board with batteries as shown in the Figure 3.9 and Figure 3.10.

The Mark IV node locations are based on 10-20 system which is an internationally accepted standard for electrode placement in the context of EEG research. This study has also followed the 10-20 system for electrode placement. For gathering brain electrical activity from prefrontal cortex, electrodes were placed at Fp1, Fpz and Fp2 locations as shown in Figure 3.8. For this, three flat units were put in Fp1, Fpz and Fp2 node locations.

Afterwards, the flat units were connected with the cyton board using ribbon cables as shown in Figure 3.9.

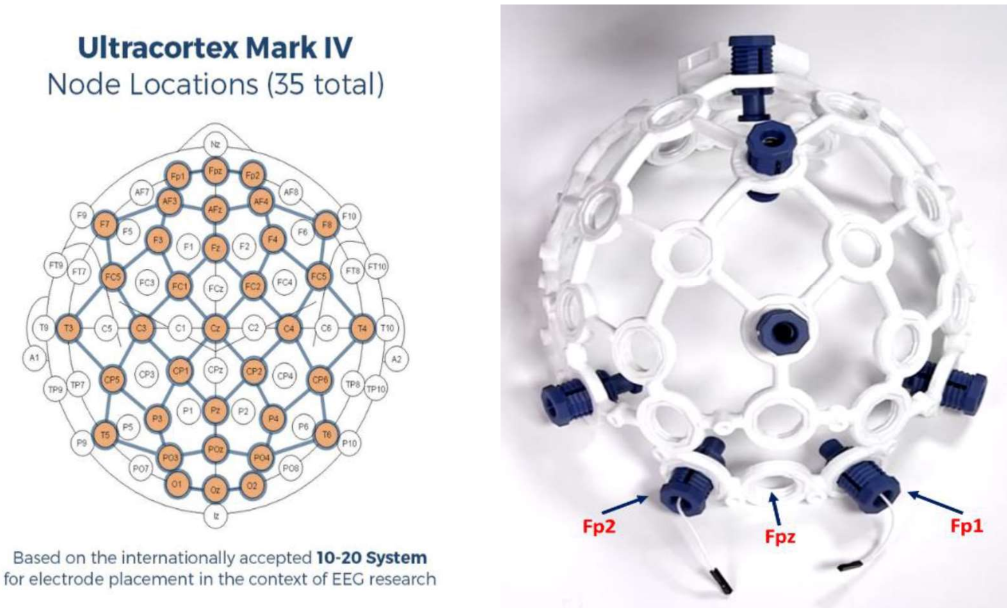

Figure 3.8. Assembling Ultracortex Mark IV: Placing electrodes at Fp2, Fpz and Fp1 based on 10-20 system

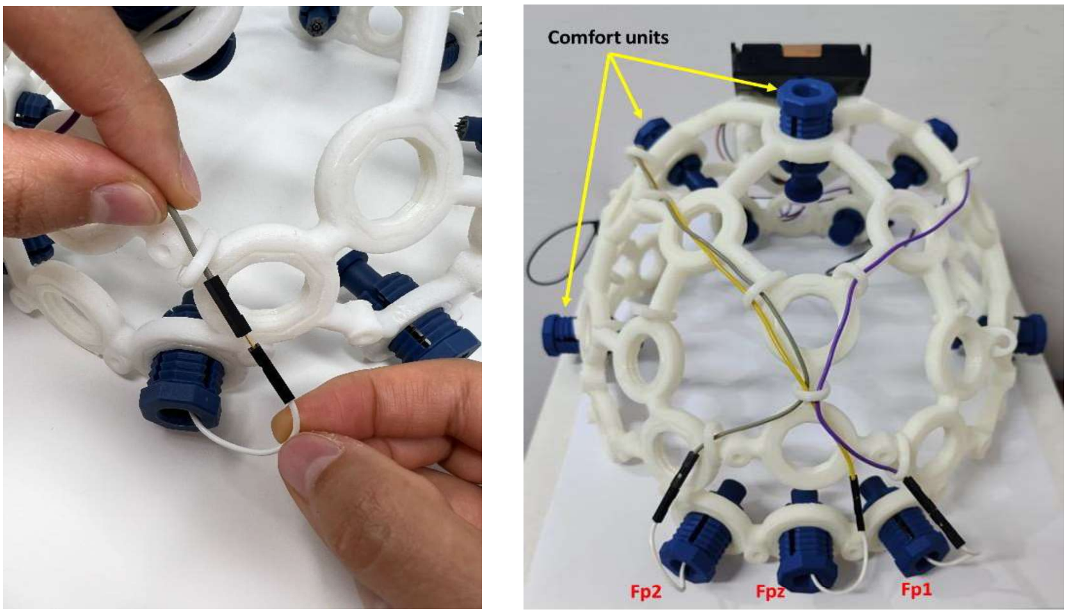

Figure 3.9. Assembling Ultracortex Mark IV: Connecting electrode units to cyton board using ribbon cables and positioning comfort units

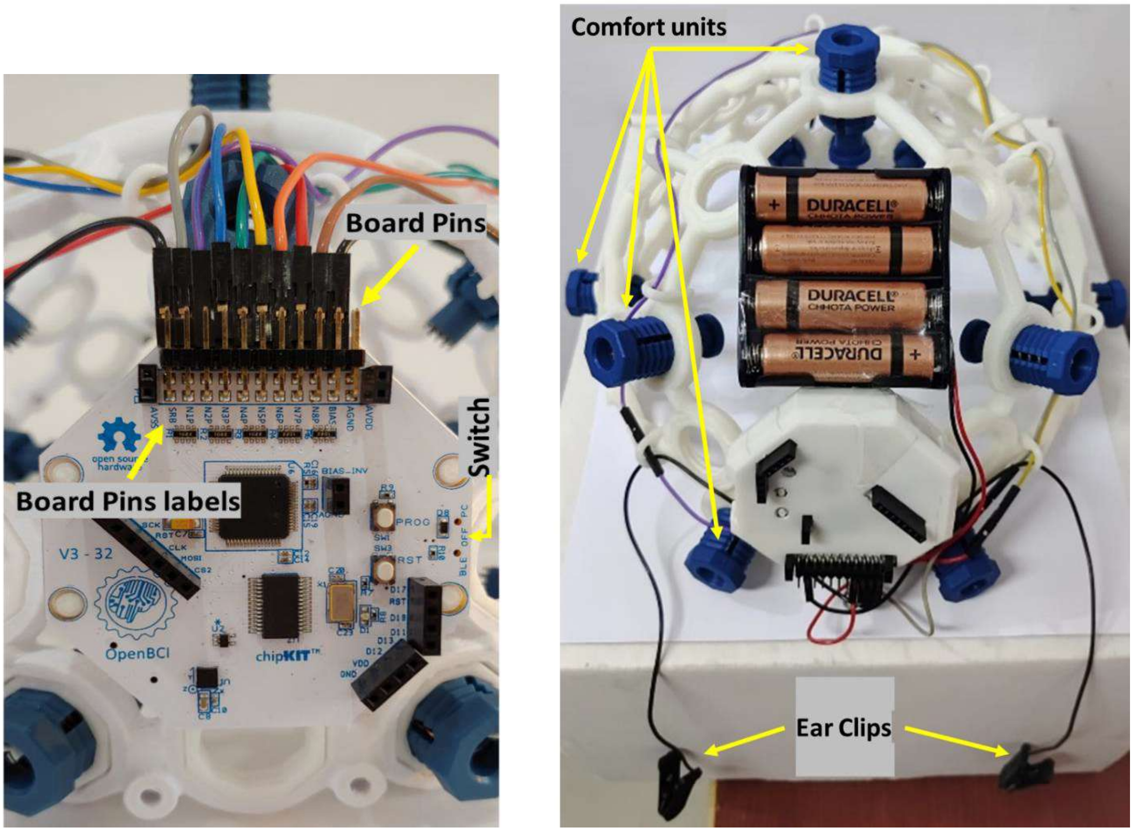

Figure 3.10. Connecting the electrode and ear clip cables to the cyton board pins

Cyton Board Overview: The OpenBCI Cyton Board is an Arduino-compatible, 8-channel neural interface with a 32-bit processor. At its core, the OpenBCI Cyton Board implements the PIC32MX250F128B microcontroller, providing it large local memory and fast processing. The board comes pre-flashed with the chipKIT™ bootloader and the latest OpenBCI firmware. Data is sampled at 250Hz on each of the eight channels. The OpenBCI Cyton Board can be used to sample brain activity (EEG), muscle activity (EMG) and heart activity (ECG). The board communicates wirelessly to a computer via the OpenBCI USB dongle using RFDuino radio modules. It can also communicate wirelessly to any mobile device or tablet compatible with Bluetooth Low Energy (BLE). The board and dongle come pre-loaded with the latest firmware, making OpenBCI accessible to researchers and developers with little to no hardware experience.

To start using cyton board, the battery is required to be plugged into the board on the backside. For this, the battery pack was pasted using duct tape immediately above the cyton board holder as shown in the Figure 3.7, followed by connecting the cyton board with battery pack and fitting it into the board holder securely. Now, the board pins were connected with the ribbon cables from the flat electrode units and ear clips by following the information in Table 3.1 as shown in the Figure 3.10. After connecting electrodes with cyton, Mark IV is ready to use (Figure 3.11).

Table 3.1. Cyton Bord pin connections with Electrodes

Electrode	**Cyton Board Pin**
Left Ear Clip	Bottom SRB pin (SRB2)
FP1	Bottom N1P pin
FPZ	Bottom N3P pin
FP2	Bottom N2P pin
Right Ear Clip	Bottom BIAS pin

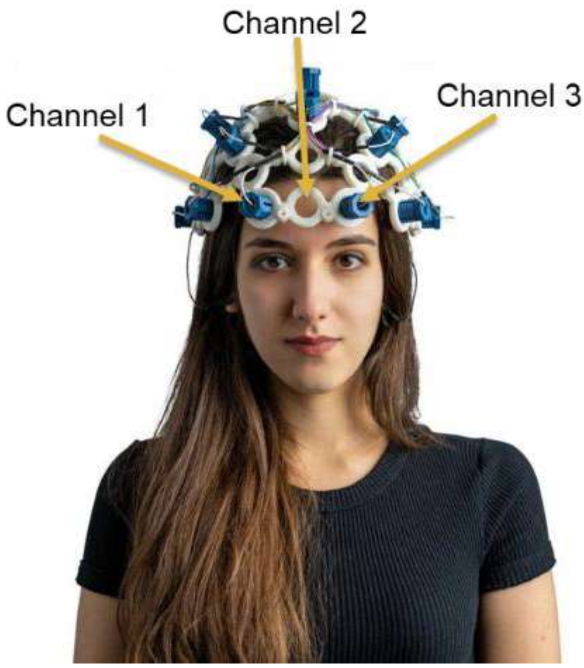

Figure 3.11. Assembled Ultracortex Mark IV

Adjusting the Ultracortex for the head:

The Ultracortex Mark IV was put onto participant's head and the electrode units were gradually tightened until the electrodes are snugly (but comfortably) against his/her scalp. The electrodes and comfort units get tightened in clockwise direction and loosen in counter clockwise direction. One should be cautious enough not to strain the electrode wires while twisting the electrode units as wires may separate from the electrode themselves. Finally, one need to clip the ear clips to both ears. Now, the Ultracortex is assembled and comfortably adjusted to participant's head size and shape as shown in Figure 3.11 and is ready for recording scientifically-validated brain waves (physiological data) by setting the switch on cyton board to PC option.

Hardware/Driver Setup for OpenBCI Graphical User Interface (GUI) (Software):

For working with OpenBCI software and Cyton board, one needs to install the latest FTDI driver (executable setup) on his/her operating system which is available at the site: https://ftdichip.com/drivers/vcp-drivers/. One can download the OpenBCI GUI from here https://openbci.com/downloads. After downloading the standalone OpenBCI GUI, it is easy to connect to cyton board through the supplied USB dongle. The dongle has a switch as shown in Figure 3.12 which should be set to GPIO_6 and then connected to the computer where the drivers and software are installed. The blue light on dongle and cyton board indicates that they have established communication.

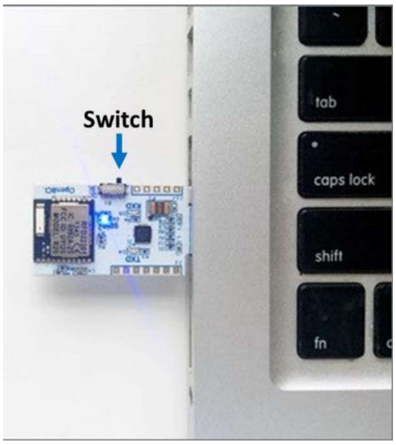

Figure 3.12. USB dongle to establish connection between cyton and computer

Software setup:

The OpenBCI GUI standalone setup folder has many files, but OpenBCI_GUI.exe file was used. Right clicking the mouse pointer on OpenBCI_GUI.exe file and choosing “Run as administrator” will display the software interface screen as shown in Figure 3.13.

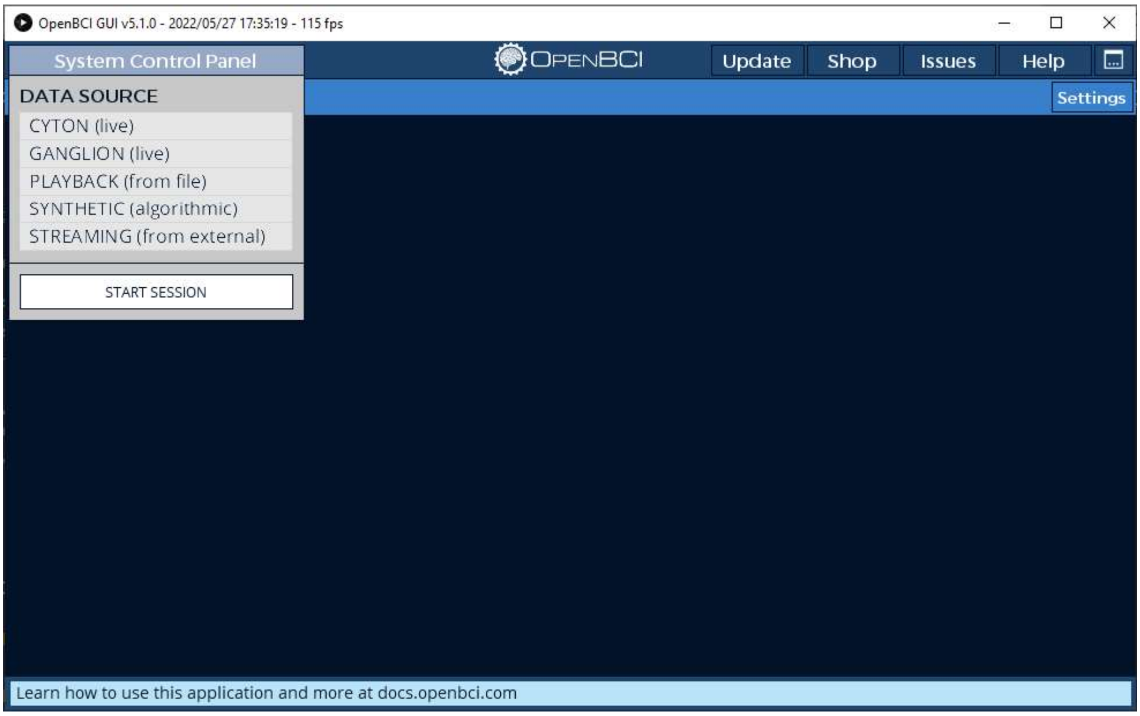

Figure 3.13. Software interface of Ultracortex Mark IV

Click CYTON (live) and then click Serial (from Dongle) and AUTO-CONNECT (other options are by default selected) as shown in Figure 3.14.

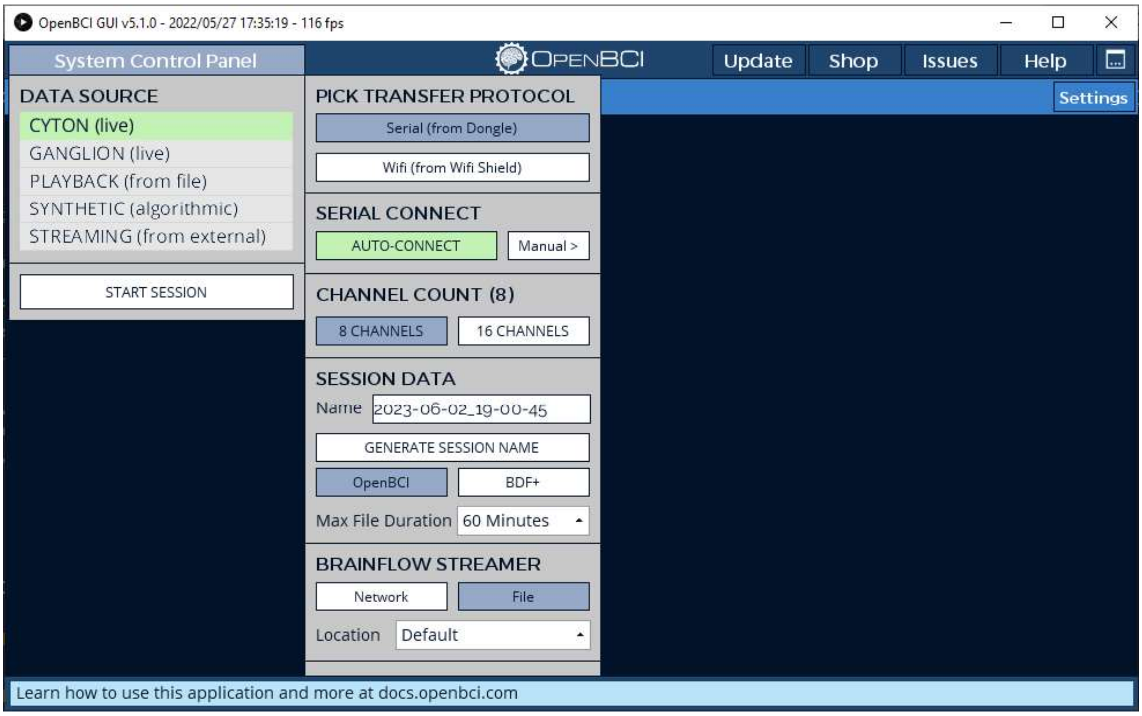

Figure 3.14. Software interface of Ultracortex Mark IV with multiple options

Now, the GUI shows starting session and the following interface appears as shown in Figure 3.15.

Figure 3.15. Software interface after starting the session of Ultracortex Mark IV

After starting the session and having the headset properly adjusted to participant's head, the Start Data Stream (green button) option was chosen to start recording EEG data on the computer as shown in Figure 3.15.

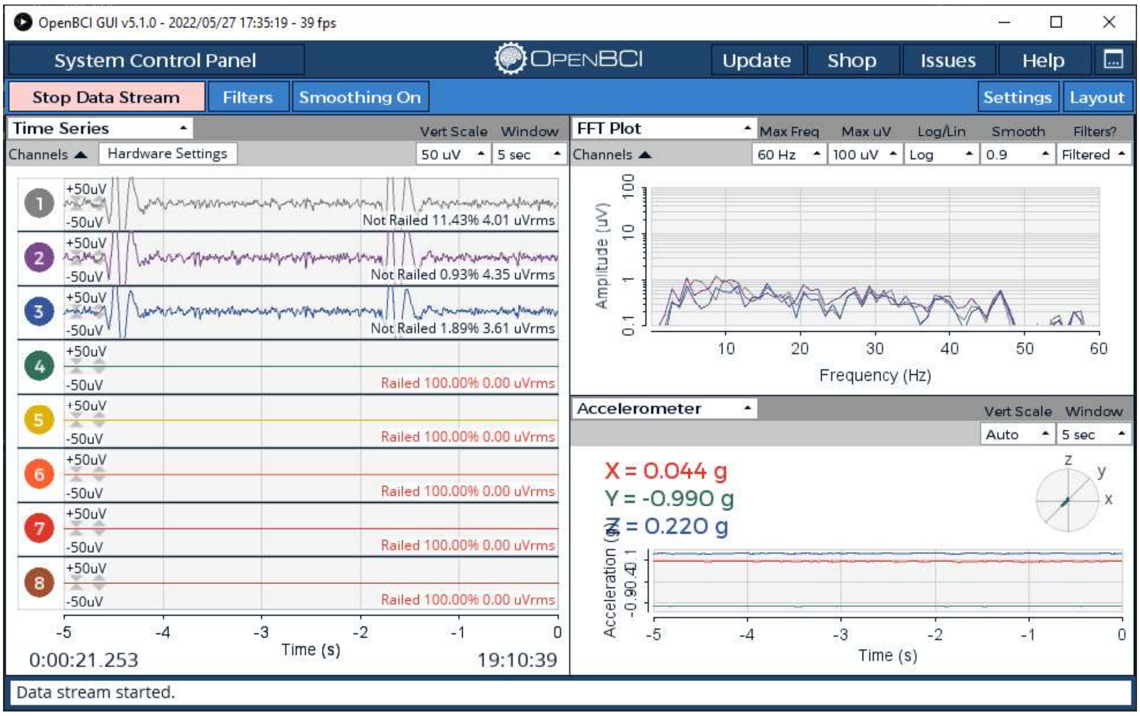

Figure 3.16. Software interface of Ultracortex Mark IV after selecting Start Data Stream option

After completion of recording EEG, Stop Data Stream was clicked to stop recording (Figure 3.16). In the Microsoft Windows operating system, the recorded data will be stored in the folder C:\Users\USER_NAME\Documents\OpenBCI_GUI\Recordings. The recordings are txt files and are directly converted to csv by changing the file name extension from txt to csv. After opening the csv file, the recorded data appears as shown in Table 3.2. A sample is also given in Appendix 1.

Table 3.2. Recorded EEG Data format of Ultracortex Mark IV

Column	Name	Description	Appearance in GUI
1	Sample Index	The index of the sample per second (0-250)	-
2	EXG Channel 0	EEG/EMG/ECG channel connected to N1P pins	Channel 1
3	EXG Channel 1	EEG/EMG/ECG channel connected to N2P pins	Channel 2
4	EXG Channel 2	EEG/EMG/ECG channel connected to N3P pins	Channel 3
….	….	….	….

Lumosity software

Lumosity software can be installed on android mobile phone from the Google Play Store. The Play Store name for the application is “Lumosity: Brain Training”. After installing the application, it asks to provide some basic personal information. Once the preliminary setup is completed, under the Activity tab, “Memory Serves” activity was chosen from Memory category and “Trouble Brewing” activity from Attention category. These activities were chosen for this study because Memory Serves is helpful in assessing Working Memory and Trouble Brewing is helpful in assessing Divided Attention.

3.3.3. Ethics Statement for data collection

The procedure and the purpose of conducting the study were explained to the participants a week before commencing the experiment, ensuring that the participants were well accustomed to the test and have reached their inbuilt capability level by attending the test at least once a day. The participants were assured that the final experiment would not cause any harm nor it would have any negative consequences. Written consent for participating in the experiment was obtained from all the interested participants. The study received approval from the Institute Evaluation committee where the work is carried out.

3.3.4. Experimental Setup

The experiment was carried out in a controlled environment to avoid sudden changes in temperature, noise or illumination levels. The preparedness of the participants was judged by their confirmation that they were capable to complete the task and self-motivated (without any incentive for their participation). It was ascertained that the participants didn't have any caffeine or nicotine in their systems. The participants were tested individually using Lumosity application installed on their personal android phones. Figure 3.17 shows a pictorial representation of the experimental setup.

Figure 3.17. Experimental Setup (Session A and Session B)

The experiment consisted of two sessions: session A was a 5-minute idle period and session B was a 5-minute test of cognitive ability. In session A, Ultracortex Mark IV EEG headset was used to record the subjects' brains' electrical activity. In Session B, the participants took a cognitive ability test with the help of Lumosity software. This software is a cognitive training application marketed to enhance working memory, divided attention and other cognitive processes [84].

Extra precautions were taken during the test to ensure that EEG records were unaffected by any external noise. As head and body movements can cause noise in the EEG during session A, participants were encouraged to sit comfortably, remain as motionless as possible and make as few head movements as possible. In order to limit background electrical noise, the EEG headset was placed on each subject's head and the amplifier was located one metre away from the computer and other electronic devices in the room. The participants were under observation to ensure that they weren't falling asleep or closing their eyes throughout the entire session.

3.3.5. EEG Recording

Electroencephalogram (EEG) studies the electrical activity of the brain produced by large segments of neurons firing in tandem. Fluctuations in the voltage of ionic currents produced by neurons are recorded through electrodes [85]. Electrodes are the physical sensors or transducers that are placed on the scalp to perform the analogue recording. They are connected to amplifiers, which not only amplify, but also filter the EEG activity. EEG data is represented by channels for each electrode, with voltages represented on the x-axis and time represented on the y-axis (Figure 3.19). EEG activity is quite small and is measured in microvolts.

EEG uses the principle of differential amplification or recording voltage differences between different points using a pair of electrodes that compares one active exploring electrode site with another neighbouring or distant reference electrode. Only through measuring differences in electrical potential, discernible EEG waveforms are generated.

In this study, EEG was recorded for 10 students with an average age of 27 ± 5 years, twice a day for 15 days. EEG was recorded using the OpenBCI helmet and was stored on the computer using OpenBCI GUI software. The placement of three electrodes on the frontal lobe (Fp1, Fpz and Fp2) followed the 10-20 system. Each channel of the EEG headset recorded at a sampling rate of 250 Hz. Using RFDuino radio modules, the helmet communicated wirelessly with a computer using the OpenBCI USB dongle. Being the electrodes nearest to the eyes, they recorded electromyographic (EMG) signals along with EEG. These recordings were then stored as a txt file on the computer's local drive. A sample of raw EEG recording is given in Appendix 1.

The EEG signal is comprised of various frequency bands, each associated with different brain states and functions. The standard EEG frequency bands are Delta (0.1 - 4 Hz), Theta (4 - 8 Hz), Alpha (8 - 13 Hz), Beta (13 - 30 Hz) and Gamma (30+ Hz).

3.4. Data Analysis and Model Development

As explained in the previous sections about the methodology, the experiment was performed in two sessions. In session A, EEG recordings were carried out, whereas response time and response accuracy were recorded in session B. After removing the first 5 seconds of noise from EEG data, advanced analytical tools like brainstorm and BLINK were used to extract EEG features. All these features were then used to develop predictive model of cognitive performance. The detail flow of the whole process is given in Figure 3.18.

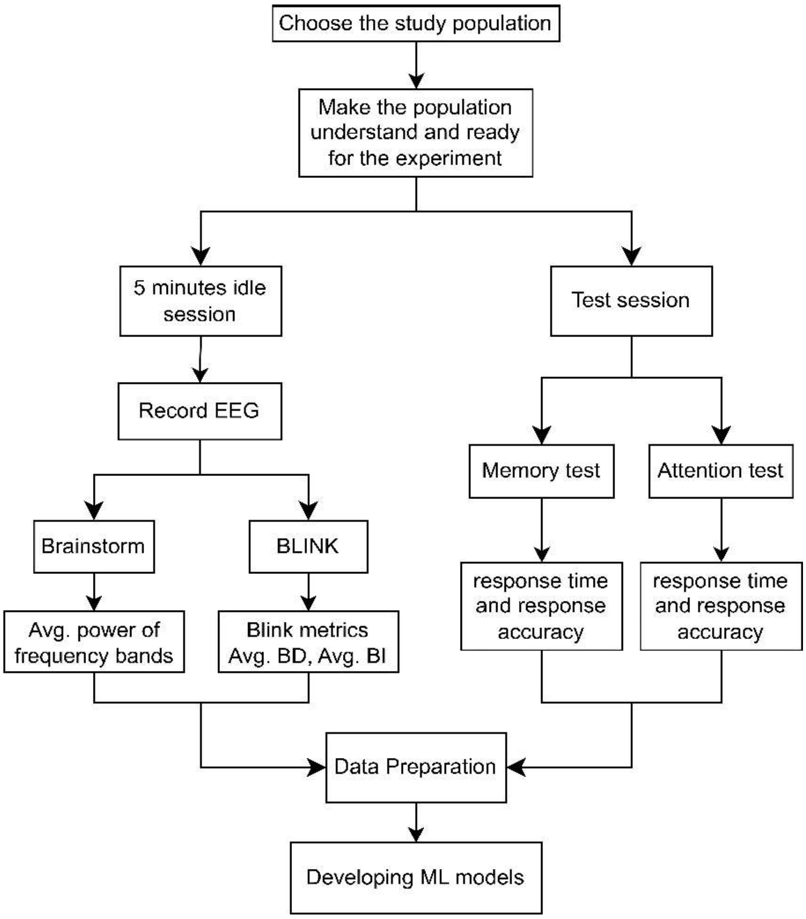

Figure 3.18. Methodological flow of predictive model development

3.4.1. Data Preparation

Brainstorm:

To extract EEG features, Brainstorm was used. Brainstorm is a software application designed for EEG analysis, which has become an important tool for researchers in the field of neuroscience. It was developed by a team of researchers at the Functional Brain Mapping Laboratory at the University of Rennes in France and is an open-source software that is widely used by researchers around the globe. It provides a comprehensive set of tools for analysing and visualising EEG data, making it a powerful and versatile tool for researchers. Its user-friendly interface helps analyse EEG without having much expertise in EEG analysis. In addition, the validity of Brainstorm has been demonstrated in numerous studies, where it has been shown to produce results that are comparable to other established EEG analysis tools [86], [87].

For using brainstorm application, the application files were first added to the path in MATLAB, followed by giving "brainstorm.m" command in the MATLAB window that opened up brainstorm interface. Using the interface, the raw EEG data files were added to the application. For extracting the features out of raw EEG, the below process was followed and a MATLAB code (Appendix 3) was written.

EEG recordings (Figure 3.19) were first band-passed from 0.1 Hz to 49 Hz to remove unnecessary frequency bands. Then the signal of artifacts (i.e., eyeblinks) and effects of external noise sources (i.e., electromagnetic fields from electrical devices) were cleaned by applying signal-space projection. Signal space projection is used for transforming a large collection of signals into a smaller collection of signals with the primary goal of denoising or reducing the dimensionality of the original signals. Later, the power spectral density function was used to determine the power distribution within a signal across a range of frequency bands (delta, theta, alpha, beta and gamma). A sample of such power distribution is given in Figure 3.20. Finally, the average power of various frequency bands (AvgDelta, AvgTheta, AvgAlpha, AvgBeta, and AvgGamma) was evaluated and the power values of different frequency bands across different electrodes/channels were averaged. The Brainstorm output sample is given in Appendix 4.

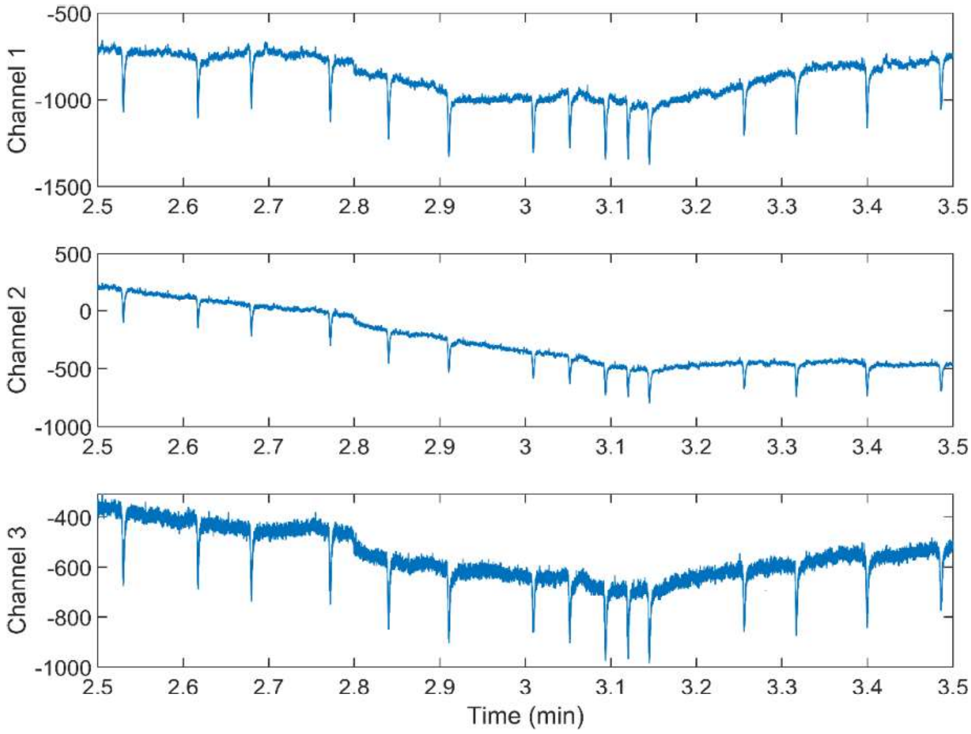

Figure 3.19. Raw EEG data from Fp1, Fpz and Fp2

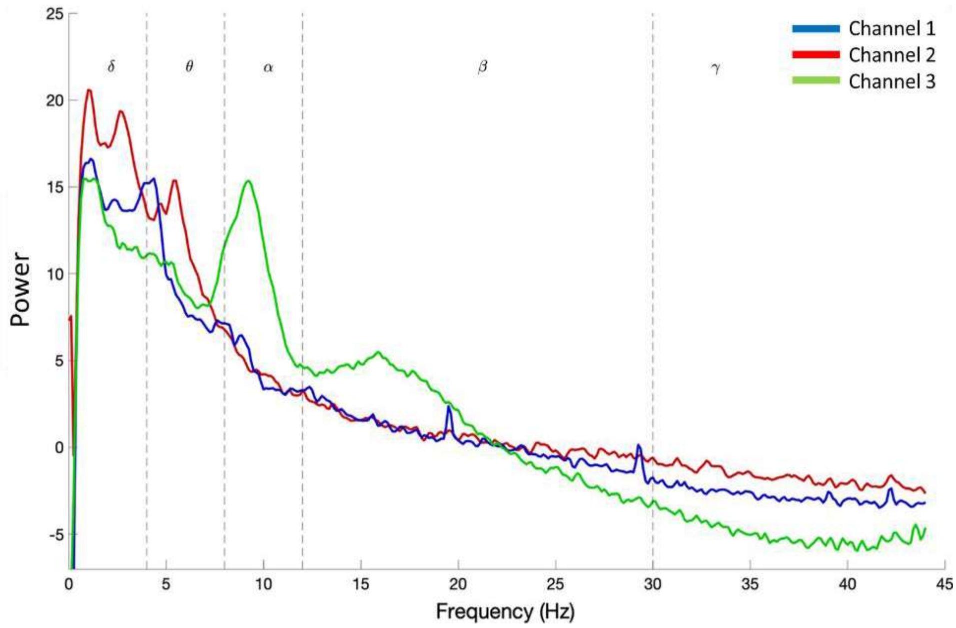

Figure 3.20. EEG power spectral density plot

BLINK:

Generally, blinks are treated as artifacts and noise while analysing EEG signals. They carry important information about mental processes. From the raw EEG recordings with eye-blink waveforms, blink metrics were captured using BLINK python software (Appendix 5). BLINK algorithm assumed that the eye-blink patterns are consistent for a single user for a short period. It performed data pre-processing and found local minima & stable points in EEG signal shown in Figure 3.21. BLINK then extracted a template eye-blink signal (or fingerprint) from the found local minima & stable points. Afterwards, BLINK computed the correlation of template with all the eye-blink waveforms in the EEG signal. Based on the correlation threshold comparison (i.e., time domain and voltage domain), the waveforms were classified as eye-blink or noise. Finally, precise time stamps for minima and stable points of all blinks were obtained as output (Figure 3.22). A sample of BLINK output is given in Appendix 6.

From the three outputs (i.e., 2 stable points and 1 minima), it is easy to compute blink metrics like blink duration (BD) and blink interval (BI). Blink duration is the amount of time an eyelid takes from the beginning of its closure and subsequently to its full opening (or time between stable points). BI is the time gap between each blink (or between each minima point).

Finally, BD (Avg.BD) and BI (Avg.BI) were averaged for the subjects' eye-blinks across the entire session A. A typical eye-blink waveform is shown in Figure 3.22 below.

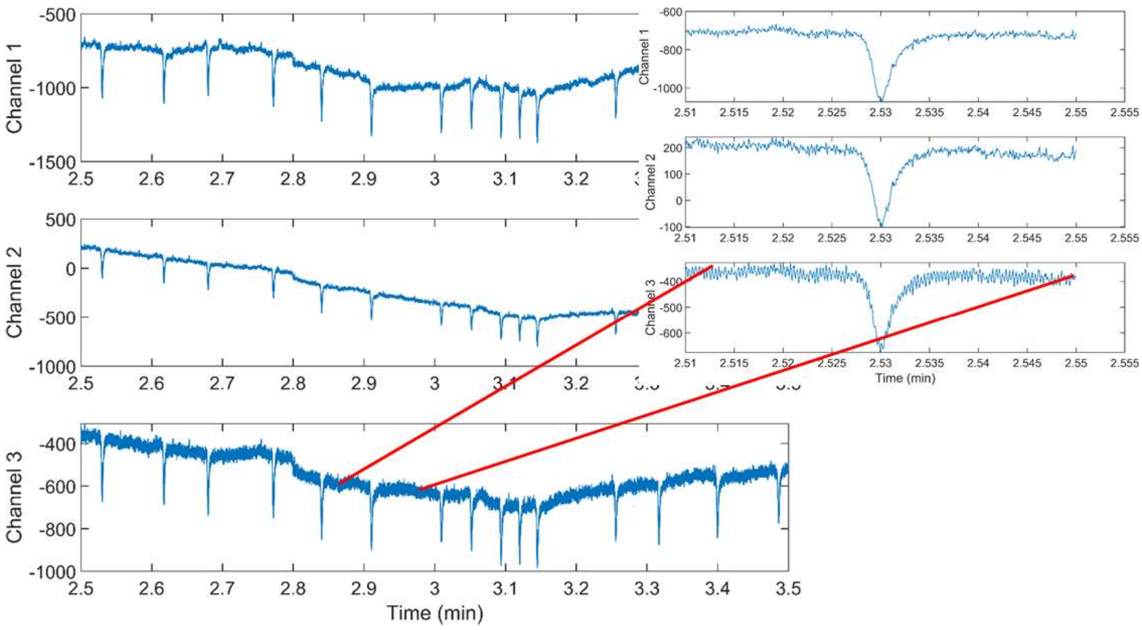

Figure 3.21. Local minima & stable points in EEG signal

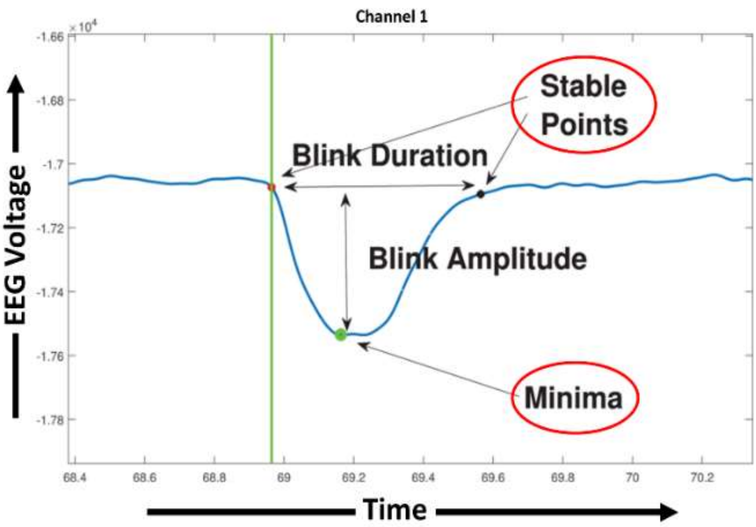

Figure 3.22. A typical eye-blink waveform in EEG signal recordings

Lumosity:

Figure 3.23. Right and left images indicate two views of the task in the attention test

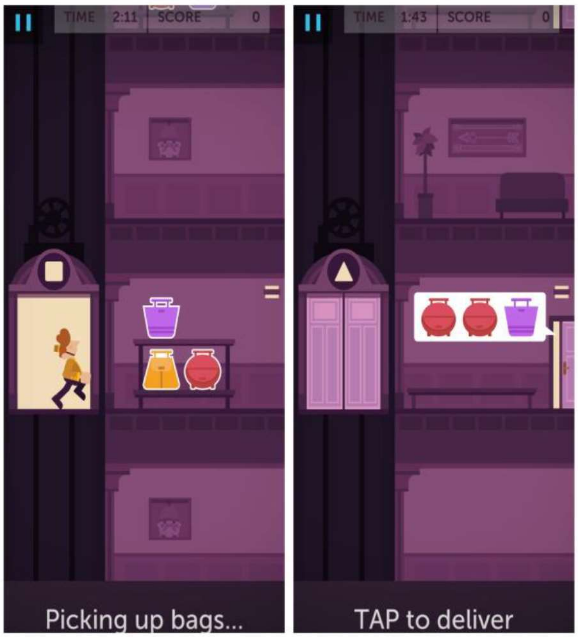

Figure 3.24. Right and left images indicate the stages in the working memory test

In Session B, participants completed two activities that tested memory capacity and attention capacity. As shown in Figure 3.23, the first two images are the two views of the task in the attention activity and the latter two images are different stages of the memory activity as shown in Figure 3.24. In the attention activity, there were different screens or focus points for orders received and a coffee vending machine. As a process, the participant will receive orders for coffee with different flavours and he/she prepare them on the given machine. If he/she delivers the ordered coffee, then it is a success. It is a failure if he/she makes coffee with a flavour that does not match the ordered flavour or if the coffee overflows from the cup. The activity duration is 120 seconds and the complexity, like the number of coffee flavours and coffee vending points, increases with the increasing level of the activity.

In the memory activity, a bellboy goes on picking up different kinds of bags on different floors in the hotel. The participant's task is to remember the number of different bags the bellboy picks. Later, on some of the floors, the guest will request a certain bag or bags. Then the participant should recall whether he has such a bag or bags and immediately tap the mobile screen to deliver them. If the player taps the screen to deliver and the guest requirement matches exactly what the player previously picked from other floors, then it is a success. It is a failure if the player taps to deliver and does not have what the guest requested. The activity duration is nearly 150 seconds and the complexities, like the number of bags picked and the lift's speed, increases with the increasing level of the activity. Finally, the success rate was found for each participant in both activities (memory success rate (MSR) and attention success rate (ASR)) using the Equation 3.1. In session B, the number of successful and failed attempts and time taken to complete the task were recorded. A sample of these recordings is given in Appendix 2.

$$\text{Success Rate} = (\text{number of successes}) / (\text{number of successes} + \text{number of failures}) \qquad \text{Equation 3.1}$$

3.4.2. Data Analysis

For this study, machine learning was preferred over traditional statistics thanks to its ability to provide highly accurate predictions. Traditional statistics primarily focus on inferring relationships between variables, while machine learning goes beyond that by leveraging data to construct models as well as to make predictions. Statistical models heavily rely on specific assumptions. If these assumptions are flawed, the results might be unreliable and the model may be misleading. In contrast, machine learning extracts valuable insights directly from the data itself, without relying on intricate mathematical models. By training algorithms with real examples, machine learning algorithms learn how to effectively map input data to desired outputs, enabling them to tackle complex real-world problems that traditional statistical approaches may struggle to handle.

Machine learning algorithms need data in a particular form: a number of observations, where each observation consists of several features. For building a predictive model, these features are the predictor variables: the inputs that the model uses to determine the output. Features can be any measurements that help distinguish the different observations. In this study, the raw data was transformed into a set of features using the knowledge about the physical system behind the EEG signals. Using brainstorm, average power of frequency bands (delta, theta, alpha, beta and gamma) was extracted. Using blink software, Avg blink duration and Avg blink interval were extracted. In addition, from the two cognitive tests, along with accuracy in the test, reaction time for each attempt was extracted. All these variable values are given in Appendix 7.

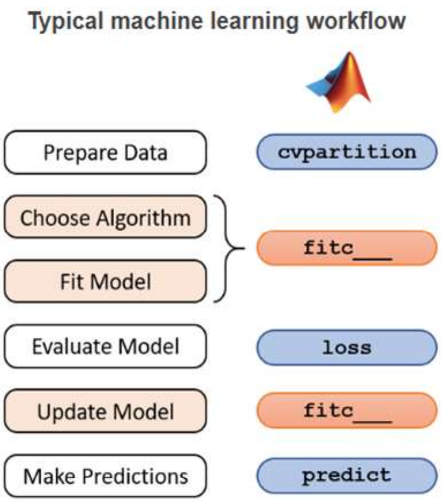

Figure 3.25. Typical machine learning workflow

Data Preparation:

As mentioned above, ten predictor variables, namely Subject ID, reaction time for each attempt in memory activity & attention activity, Avg blink duration, Avg blink interval, Avg delta, Avg theta, Avg alpha, Avg beta, Avg gamma and two response variables (MSR, ASR), were estimated.

In MATLAB, the data was imported and the whole dataset was classified into two categories. Category-I includes the MSR or ASR values equal to '1' and all other values come under category-II. The typical machine learning workflow given in Figure 3.25 was followed. A moving mean of 5 data points was used to fill missing values, then outliers were identified and replaced with linear interpolation of neighbouring, non-outlier values. Afterwards, the data was normalised or the range of data was rescaled to [0, 1]. Finally, a machine learning algorithm was chosen to develop a predictive model for classification.

A classification model divides the feature space into different regions, each labelled with one of the desired output categories. To determine this division, a machine learning method was used, which is like a recipe for creating the model from the training data. There are various machine learning methods that work well in different situations and there is no single best method for all cases. To do practical machine learning, it's often best to simply try out different methods and see which one works best for the specific problem. For this study, four methods were tried which include nearest neighbour, decision tree, support vector machines and neural networks.

Nearest Neighbour Classification:

It was assumed that the categories tried to predict were nicely clustered in the space of predictor variables. In this classification, a simple, most straightforward and effective way to classify a new observation is to look for the closest known observation and assign the new observation to the same category as its nearest neighbour. This is a basic idea behind k-nearest neighbours (kNN) classification (Figure 3.26).

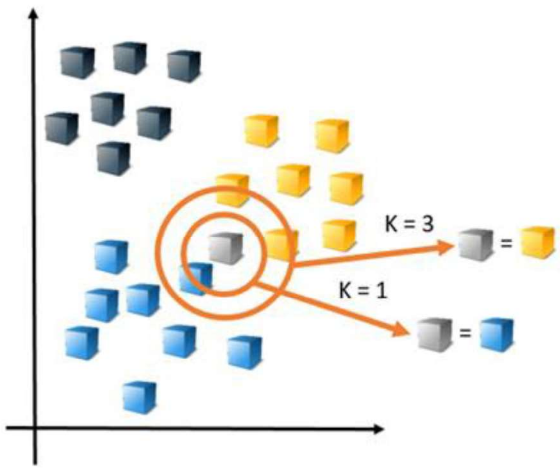

Figure 3.26. K-Nearest Neighbours (kNN) Classification Model

This approach is obviously very sensitive to the known data. In reality, the categories are not cleanly separated. If the nearest neighbour happens to be an outlier, the new observation is likely to be misclassified. A simple way to avoid this problem is to look at more neighbours and use the majority class of the k nearest neighbours to make the classification. When using this method, no assumptions are required to be made about the underlying distribution of the data. For this study, the optimal model was achieved using k as 4.

Decision Trees:

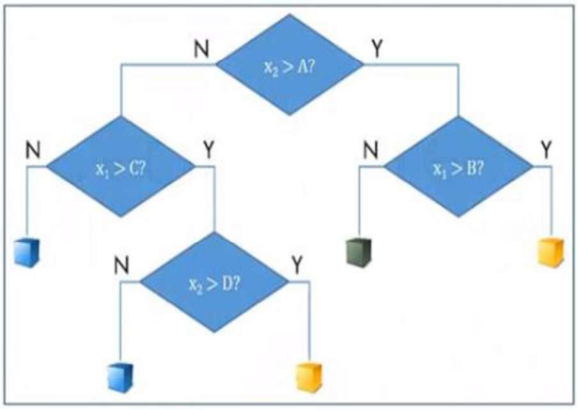

Figure 3.27. Decision Tree Classification Model

K-nearest neighbours (kNN) are distance-based classification models. Thus, all predictors are required to be numeric or all predictors are required to be categorical. Sometimes data sets contain both numeric and categorical predictors, i.e., mixed predictors. In such cases, kNN model cannot be used with all data. Like kNN models, decision tree models do not make any assumptions about the data and they do allow a mixture of numeric and categorical predictors given that they treat predictors independently.

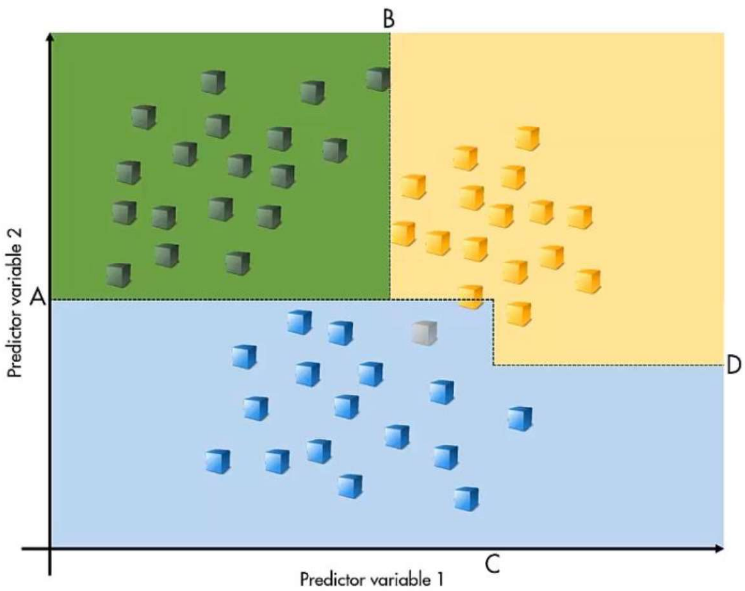

Figure 3.28. Decision Tree Classification

Binary decision trees (Figure 3.27) classify observations by creating a sequence of yes(Y)/no(N) question. Given the training data, the decision tree is built by considering all the possible splits in each variable. Using a given criterion for how good a potential split is, the best possible split is chosen. Then the process repeats at the next level of the tree. This continues until all the branches terminate, which happens when no further splits on that branch can improve the criterion value. The end result is a classifier that divides the predictor space into a collection of rectangular regions (Figure 3.28). Once a tree classifier is trained, making predictions is extremely quick because it requires nothing more than a handful of binary decisions. As always, realistic data will have noise. Theoretically, a sufficiently complex tree could fit an arbitrarily complex boundary between points. However, this generally means that the model is overfitting the data. Sometimes trees are pruned, i.e., number of splits is reduced, for creating a simpler model that may have a higher loss but better generalisation to new data.

Support Vector Machines:

A simple way to classify observations into two classes is to draw a linear boundary between them. However, even if the data is perfectly separable, there are many possible linear boundaries that could be drawn. One of the approaches for this kind of problem would be to put the boundary as far as possible from any of the observations. This is the basic idea behind support vector machine classification. A Support Vector Machine (SVM) algorithm classifies data by finding the “best” hyperplane that separates all data points as shown in Figure 3.29.

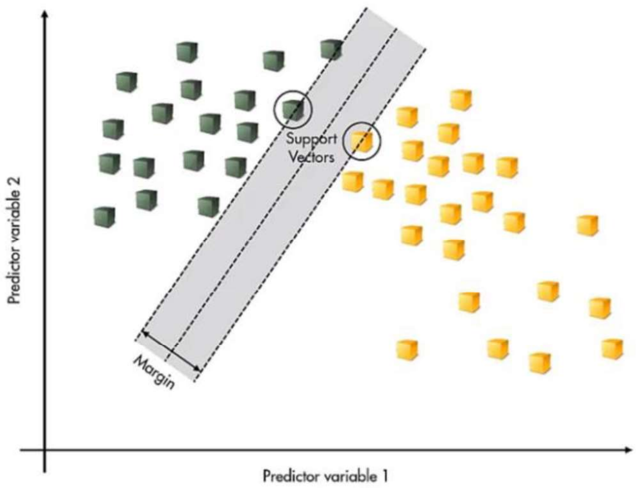

Figure 3.29. Support Vector Machine Classification Model-I

If the data is actually linearly separable, it results in a simple optimisation problem. The coefficients of the linear boundary should be chosen to maximise the margin, i.e. the distance between the boundary and the nearest observations, subject to the constraint that all observations must be on the correct side of the boundary. Note that in the end, the optimal solution is determined only by the observations nearest to the boundary. These observations are referred to as the support vectors.

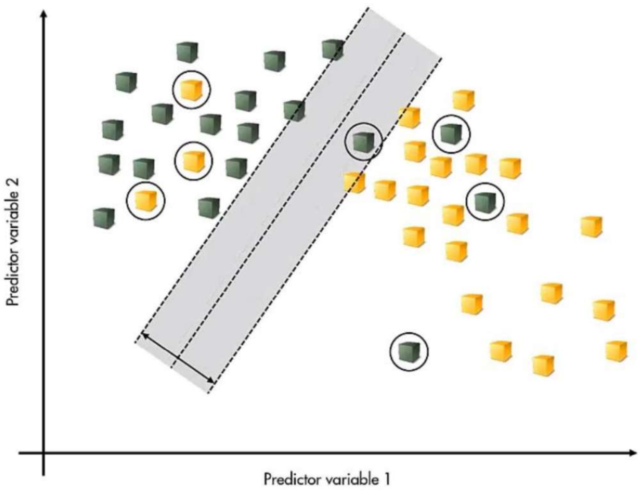

Figure 3.30. Support Vector Machine Classification Model-II

However, the noisy data may not be linearly separable, i.e. there is no linear boundary that can correctly classify every observation. In this case, the optimisation problem can be modified to maximise the margin, but with a penalty term for misclassified observations. Observations are correctly classified only if they lie on the correct side of the margin. So, the penalty term prevents a solution that cheats by having a huge margin. The SVM solution is the one that gives the best possible separation between the classes, i.e. the widest margin without unnecessary misclassifications (Figure 3.30). Note that the SVM formulation works only for binary classification problems. Multi-class problems are solved by combining multiple binary classifiers.

Artificial Neural Network:

Certain machine learning tasks are very easy for humans, at least at a small scale, but traditionally very hard for computers. Artificial Neural networks try to mimic key characteristics of the human brain with a computer model. The human brain is a massive natural neural network. A huge number of cells, known as neurons, are interconnected by electrical pathways. Brain activity involves the transmission of impulses between neurons. For learning to happen, the brain needs to adjust the strength of these neural connections. Artificial intelligence simulates this framework by arranging interconnected neurons into what's called an artificial neural network. One type of artificial neural network is a feedforward network, which is useful for predictive supervised learning problems where the goal is to map a given set of inputs to a given set of outputs.

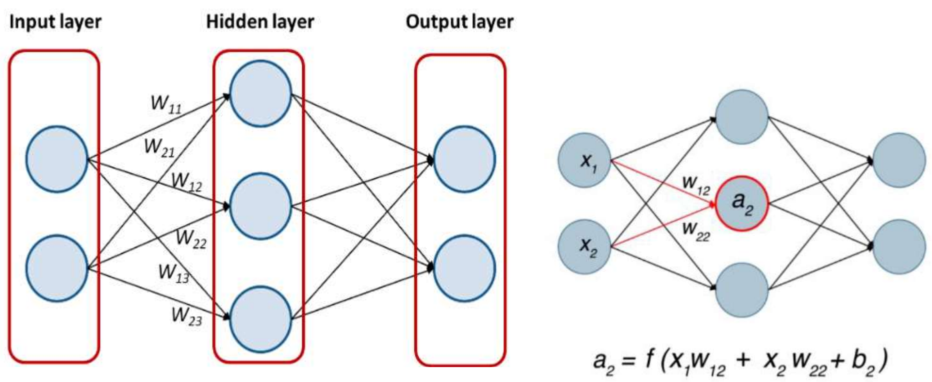

Figure 3.31. Feedforward Neural Network Model

The neurons in a feedforward neural network are arranged in discrete layers as shown in Figure 3.31 left: an input layer, some number of hidden layers and an output layer. For classification problems, the network has one input neuron for each predictor variable and one output neuron for each response class. Information is passed or fed forward from one layer to the next. Each neuron is connected to every neuron in the layer before it. The strength of the connection between any two neurons is given by a numeric weight value.

The value passed to a neuron is calculated by taking all the values of the neurons in the previous layer, multiplying them by the corresponding weights and summing the results. This sum, plus an extra offset known as the bias, is passed as the input to a function known as the transfer function for that layer. The output from this function is the value passed to the neuron (Figure 3.31 right). This process is repeated for all the neurons in a layer and then again for the next layer. Typically, the transfer functions for the last layer map's values to the range 0 to 1. The value of each output neuron is the degree to which the network predicts that the observation comes from that corresponding response class. With many iterations, these networks further learn to recognise patterns by adjusting the connections between the neurons through trial and error. Therefore, the weights, biases and transfer functions determine how inputs are transformed into outputs.

This method does not make any assumptions about the data. However, it requires the data to be normalised. For this study, an optimal model using 5 neurons in hidden layer was achieved.

The whole MATLAB Code is given in Appendix 8.

3.5. The Methodological Limitations

While conducting the study, several methodological limitations were encountered. It is important for these limitations to be acknowledged, as they may influence the interpretation and generalization of the findings. The limitations include: sample size, experiment duration, limited test battery, and limited machine learning models.

Justification and Mitigation:

These methodological limitations were justified and managed to the best possible degree considering the available resources and research scope. The justification for these limitations lies in the need to balance the feasibility of the study with the desired research objectives. Mitigation strategies were employed to minimise the impact of these limitations:

1. Sample Size Justification: While the sample size was relatively small, efforts were made to ensure the selection of participants from diverse backgrounds to enhance the representation of the target population as much as possible. Additionally, the participants' characteristics and demographics were carefully documented and reported to provide transparency as well as to facilitate future comparison and replication.

2. Experiment Design: The limited duration of the experiment sessions was a trade-off to ensure participant engagement and compliance. To mitigate this limitation, the experimental tasks were carefully designed and standardised to elicit reliable and measurable cognitive responses within the given timeframe. The use of well-established cognitive tests from Lumosity also helped in ensuring the validity and relevance of the measurements.

3. Test Battery Selection: While the test battery was limited to memory and attention tests from Lumosity, these cognitive functions were specifically chosen as they play a crucial role in various safety-critical industries. The study acknowledges that future research should include simulator cognitive assessments to capture a wider range of cognitive processes.

4. Machine Learning Model Selection: The choice of machine learning models was based on the available literature and common algorithms used in similar studies. While other models or ensemble techniques could have been explored, the selected models (KNN, SVM, Decision Trees and Neural Networks) were deemed suitable for the classification task at hand. Model performance and comparison were carefully evaluated and reported to provide transparency and reproducibility.

Value of the Study:

Despite these limitations, the study still provides valuable insights and contributions to the field. It offers a systematic approach to evaluating cognitive processes and performance in safety-critical industries using EEG signals and cognitive tests. The findings contribute to the understanding of cognitive workload and fatigue management as well as the development of an objective assessment tool. The study's results, including the identification of the KNN algorithm as the most effective for classification, provide practical guidance for organisations seeking to improve human performance and reduce errors. The study's value lies in its incremental contribution to the existing literature and its potential to inform future research and practical applications in the field of cognitive performance optimisation.

3.6. Concluding Summary

In conclusion, this study focused on developing a model to predict cognitive performance by utilising EEG data and cognitive task performance measures. Grounded in the information processing perspective, the pivotal role of attention resources and working memory capacity in cognitive functioning was recognised. To achieve the objectives of the study, a methodology consisting of two sessions was implemented. The first session involved a 5-minute idle period for EEG recording, while the second session entailed performing cognitive tasks to measure response time and accuracy.

By carefully analysing the gathered data using advanced analysis techniques, relevant features from the EEG data were extracted to serve as indicators of cognitive status. These features formed the foundation for constructing a predictive model for cognitive performance. Throughout the research process, the highest ethical standards and prioritised participant privacy and confidentiality were upheld. The methodology adhered to responsible data use, aligning with the commitment to maintaining integrity and respect for the individuals involved in the study. By focusing on the interplay between cognitive processes and performance, this study contributes to the broader understanding of cognitive performance optimisation.