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# BCI Data Repository Generation and Processing

**COLLEGE OF**
**ELECTRICAL AND MECHANICAL ENGINEERING**
**NATIONAL UNIVERSITY OF SCIENCES AND TECHNOLOGY**
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**2024**

COLLEGE OF ELECTRICAL AND MECHANICAL ENGINEERING

# DE-42 MTS
# PROJECT REPORT

## BCI Data Repository Generation and Processing

Submitted to the Department of Mechatronics Engineering
in partial fulfillment of the requirements
for the degree of
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**in**
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# ABSTRACT

The scope of this project encompasses the identification and resolution of the technical issues within the EEG equipment available at NCRA, the design of protocols for data acquisition across various brain regions, the EEG data acquisition and repository generation and the analysis of the acquired EEG data through preprocessing and machine learning algorithms. Initially, the training for use of EEG equipment was acquired and multiple sessions were conducted in CMH to learn the EEG data acquisition technique. Meanwhile, efforts were made to contact the equipment OEM to provide after-sales service so that issues can be resolved. The software was updated and features including the selection of up to 128 channels for data acquisition, option to check for the connectivity status for EEG cap and the option to check the connectivity status of each channel respectively were introduced. All issues within EEG software were resolved. The EEG caps were verified via short-circuit test and there were no issues found within the connectivity of the electrodes. The ground zero test was conducted for verification of the master/amplifier box. The results showed that amplifier IC was malfunctioning and the data for channels Fp1, Fp2, C3 and C4 was erroneous. These channels also had an impact on the data of other channels as the data for other channels was accurate to some extent but erroneous too. These results were verified by the OEM R&D. Meanwhile, the data was collected according to the desired protocol within optimum environmental conditions and testing parameters and an EEG data repository was generated. After the data acquisition, the data was preprocessed and analyzed. For preprocessing, the data was filtered using bandpass filter of 0.5-30 Hz and notch filter of 50 Hz. After filtering the EEG data, the Fast Fourier Transform (FFT) was done to analyze the frequency domain response of the EEG data and statistical analysis was done to analyze the time domain response of the EEG data. After these steps, the filtered and preprocessed EEG data was analyzed using machine learning algorithms including Support Vector Machine (SVM), Linear Discriminant Analysis (LDA) and Random Forest (RF) algorithms and the results were found for unlabeled data. From this analysis, it was concluded that the channels Fp1, Fp2, C3 and C4 showed a different and erroneous behavior. However, the response for other channels was accurate to some extent but still erroneous due to the interference and impact of these channels. From all these observations, we can conclude that the data can be acquired using this equipment, but it would be erroneous for other channels due to the impact of data of these channels. It is proposed that in order to get accurate data and continue research using the equipment available in NCRA, the amplifier IC within amplifier box needs to be either repaired or replaced.

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# LIST OF SYMBOLS

**Acronyms**

BCI Brain Computer Interface

EEG Electroencephalogram

fNIRS Functional Near-Infrared Spectroscopy

ML Machine Learning

FFT Fast Fourier Transform

SVM Support Vector Machine

LDA Linear Discriminant Analysis

RF Random Forest

TF True Positive

TN True Negative

FP False Positive

FN False Negative

# Chapter 1- INTRODUCTION

Electroencephalography (EEG) has emerged as a pivotal neuroimaging method for capturing brain electrical activity, providing valuable insights into brain function and disorders. This literature review examines the evolution of EEG technology, focusing on the advancements in preprocessing techniques and equipment management. The review delves into the significant improvements made in EEG data preprocessing, including the development of standardized data classifications and specialized filters tailored to diverse demographics. Additionally, the study explores the consistent nature of EEG equipment while highlighting minor modifications over the years.

Drawing from previous research studies, this review meticulously analyzes the diverse methods employed in EEG preprocessing, their advantages, and disadvantages. Furthermore, it addresses the challenges associated with EEG data analysis and emphasizes the need for precision and reliability in EEG measurements. The findings shed light on the crucial facets of EEG research, guiding future studies and applications in both clinical and research domains.

An extensively used neuroimaging method for capturing brain electrical activity is called electroencephalography, or EEG. In other words, the collection of data recorded from the brain, mostly in microelectrons, used to produce a signal for further exploring the brain and competing with any disease that might be related to it is the basic preview of the field of EEG. It is an important technique that offers insights into brain function and disorders in both clinical and research spaces.

The evolution of EEG technology in the past years has allowed the human mind to be explored in its most clinically unreachable regions and point out most medical irregularities before its danger zone. In research, it has enabled the connection between the human and the computers to lessen with the design of gadgets which operate relative to the instructions given by the brain. To guarantee the precision and dependability of EEG measurements, proper preprocessing of the EEG data and efficient equipment management are essential.

The equipment used in EEG has been maintained as a constant technique with minor modifications over the years. On the other hand, the preprocessing od the data has improved majorly over the years with the development of standard classifications of the data according to its use and its filters have been researched with respect to different regions with different ages, sex and ethnicities which may or may not possess any similarities with the recording done for the same tasks or different tasks.

Usually, the data of the patient is moved through some basic filters such as the notch filter which makes the data more readable and concise in its own method and according to the equipment used for recording it. Using data from earlier studies, this literature review seeks to address important facets of

EEG preprocessing and equipment management. Also, the review sheds light on the various classifications of EEG and the differences on work done on it over the past few years while providing the assortment of methods used in it with the advantages and disadvantages prior to and after the entablement of the user with corresponding data with all its features and information.

### 1.1. Classification

Electroencephalography (EEG) data can be broadly classified into two main types based on the method used to record the data: invasive and non-invasive method.

#### 1.1.1. Invasive Method

The invasive EEG recording method involves the surgical insertion of electrodes directly onto the patient's skull. These electrodes are meticulously placed and connected to a computer through wires, allowing the data to be collected with minimal errors in the form of artifacts.

One of the key advantages of this method is the high precision achieved due to the electrodes' deep connection, resulting in superior spatial resolution and amplitude of recorded brain signals [1].

Despite its clinical significance, the complexity of the procedure lies in the insertion process and the maintenance of correct electrode placement for accurate data collection. Intrusive recordings offer exceptional opportunities for highly accurate electrophysiological studies, providing detailed insights into human brain function concerning both space and time.

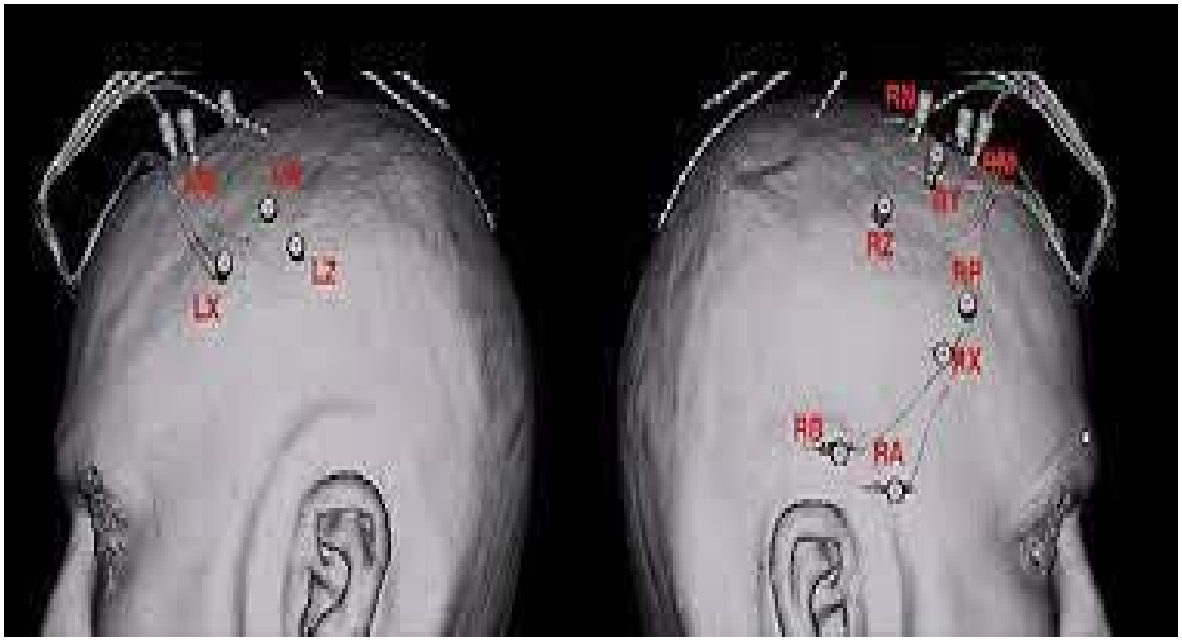


Figure 1.1: Invasive EEG

### 1.1.2. Non-Invasive

In contrast, non-invasive EEG recording techniques eliminate the need for surgery. Data collection in this method is swift, as no surgical procedures are involved. However, the method is susceptible to artifacts caused by external signals or friction from the patient's head. Despite these challenges, non-invasive EEG methods are widely used due to their ease of application and ability to fulfill minimal data quality requirements.

It is important to note that for deeper data extraction, invasive methods are preferred, as they significantly reduce the margin of error compared to non-invasive methods. The reduced susceptibility to artifact contamination remains a key advantage of invasive EEG recordings, making them essential for various advanced neurophysiological studies [2][3][4].

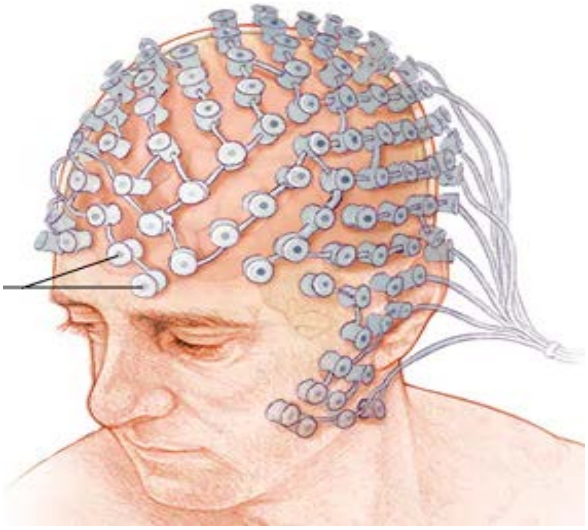

Figure 1.2: Non-Invasive EEG

The figure above shows how the electrodes are used for non-invasive EEG recording technique. For this technique, the electrodes are placed on the scalp according to the 10-20 measurement system which would be discussed in later section. The number of electrodes for which data can be acquired is also referred to as number of channels. The maximum number of channels for any EEG equipment until now is 256 channels for which the data can be acquired. Hence, non-invasive EEG method is an ideal choice for medical and research purposes.

# Chapter 2- LITERATURE REVIEW

## 2.1. Historical Developments

The field of encephalography, spanning over a century, has undergone remarkable advancements. In 1875, English physician Richard Caton discovered electrical currents in the brain by studying EEG data from exposed rabbit and monkey brains. Hans Berger, a German neurologist, amplified brain electrical activity using radio equipment on a person's scalp in 1924, laying the foundation for electroencephalography applications. He introduced the term "electroencephalogram" and observed variations in brain activity during different states such as sleep, anesthesia, and neurological conditions like epilepsy. In 1934, Adrian and Matthews confirmed the existence of human brain waves, discovering periodic fluctuations at frequencies of 10 to 12 Hz, known as "alpha rhythm." Mobile EEG technology has been employed in various cognitive processes, including spatial cognition, attention, memory, speech processing, motor processing, sports, urban behaviors, emotion recognition, neurofeedback, motor rehabilitation, and epilepsy diagnosis [5][6].

## 2.2. EEG Equipment

### 2.2.1. Multi-Channel Headsets

The EEG headsets are available in a variety of formations and channels. The number of channels present on the cap is dependent on the objective of the cap and the area of expertise for its use. The referencing of the data from the channels varies from application to application as the then provided data might be set as the standard protocol for use in the corresponding area.

The headsets are available in formations of 12, 24, 36, 48 and up to 256 number of channels, maybe used for recording data from different parts of the brain. The current headset available in the NCRA is of 24 channels which are divided into two sections being the ones for the right side of the brain and the other being for the left side of the brain.

### 2.2.2. Electrode Caps

To maintain electrodes precisely in place on the scalp, EEG electrode caps are utilized. To accommodate diverse head shapes and research demands, they are available in a range of sizes and electrode combinations. EEG electrodes are applied to the scalp either with conductive paste or gel or through the electrode cap. Ag/AgCl (silver/silver chloride) electrodes are among the various types of electrodes that are utilized.

### 2.2.3. Amplifiers

The feeble electrical impulses that the electrodes capture is amplified and processed by EEG amplifiers.

They also eliminate interference and noise. Amplifiers can operate independently or as a component of a larger EEG system.

### 2.2.4. Electrode Gel/Paste

To improve the electrical connection between the electrodes and the scalp, conductive gel or paste is applied. It improves signal quality by lowering impedance.

### 2.2.5. Reference and Ground Electrodes

To create a reference for the EEG measurements, these electrodes are utilized as grounding and reference points.

### 2.2.6. Cleaning supplies

Tools for keeping caps, electrodes, and other accessories clean to preserve signal quality and hygienic conditions.

### 2.2.7. Signal Processing Software

EEG data collection, analysis, and visualization are done with specialized software. For bespoke analysis, popular software packages include MATLAB, BrainVision, Analyzer and EEGLAB.

### 2.2.8. Storage and Recording Systems

Computers or EEG recorders are commonly used for recording and storing data. Storage devices with a large capacity are employed to store the copious amounts of EEG data produced throughout a session.

## 2.3. Different Systems

### 2.3.1. G. Tec

G. Tec is renowned for producing top-notch EEG systems that are applied in both medical and research settings. For research-grade brain-computer interface and neurofeedback studies, they provide both clinical EEG devices and systems fit for scientific uses.

Figure 2.1: G-Tec System EEG Equipment

### 2.3.2. Brain Vision

EEG solutions are available from BrainVision for both research and clinical applications. For processing EEG data, they offer a variety of electrode caps, EEG amplifiers, and analysis software. Its main applications lie in the use of amplifiers of recorded usable data.


Figure 2.2: BrainVision EEG Equipment

### 2.3.3. Emotiv

Emotiv manufactures a variety of EEG headsets intended for a range of uses, such as brain-computer interface (BCI) development, gaming, and research. Emotiv headsets are frequently used for brain-signal-based computer or device control as well as cognitive neuroscience research.


Figure 2.3: Emotiv EEG Equipment

### 2.3.4. NeuroSky

EEG headsets from NeuroSky are available. these headsets are frequently seen in consumer goods like games and apps for meditation. They are intended to offer perceptions into the states of relaxation, concentration, and meditation.


Figure 2.4: NeuroSky (Headet & Sensor Module) EEG Equipment

### 2.3.5. NCC Medical

The EEG equipment from NCC Medical is offered primarily for the purpose of monitoring EEG of patients. It is a Chinese based company. The equipment is present NCRA and it is being used for research projects at CEME NUST, Islamabad. The data for current project is collected by using the equipment shown below:


Figure 2.5: NCC Medical EEG Equipment

## 2.4. Development of Protocols

### 2.4.1. Associated research on BCI user education

View an extensive review on BCI user training [7] for more information. A lot of research was done to improve BCI performance and usability through user training by addressing user skills, learning, and contextual states, or states that relate to the context or task at hand, like confidence to complete the task, feeling in control, sense of agency, workload, attention, understanding, and motivation. In this case, the current BCI user training is scheduled according to when it is offered, that is, prior to, during, or following the user-BCI contact [8]. It is evident from the time division of user training suggested for a systematic review of related work that the following goals should be considered when creating a user training protocol to increase performance:

- Long before the encounter, develop user skills, primarily by giving the user several sessions of training prior to their engagement with a BCI. During such training, BCI performance predictors—that is, human characteristics that correlate with or forecast performance—are frequently researched. For example, mental object rotation [9], muscle relaxation [10], mindful meditation [11], sports, playing an instrument or game [12], and so forth are among the skills that have been studied for SMR paradigms. Additionally, stable predictors like temperament [13], handedness [14], and personality [15] might shed light on customized task and interface

designs. Heart rate variability and gamma oscillations, which measure attention span for SMR, have also been linked to ERP performance [16, 17]. Despite the fact that [18] have questioned the presence of trustworthy indicators. Indeed, trustworthy comparisons may be hampered by the variations in the experimental techniques, particularly in SMR paradigms. And forecasts [19], as well as replication of outcomes.

- Before the interaction or during intermissions, prepare user contextual states by offering different kinds of support, like task objectives and descriptions of BCI features. Users' sense of agency may have enhanced when raw EEG signals were displayed to them [20], and real-time brain activation maps were proposed [21]. Putting individualized tangible items in front of users can improve their performance and sense of control [22]. Event-Related Desynchronization was improved by both imagined and physical motor training prior to the interaction [23]. Additionally, they included first-person demonstrations of the completed work in instructional movies.
- Enhance the interaction between BCI and the user, for example, by adding gamification to the interface to enhance the user experience [24]. or by immersing users in virtual reality (VR) environments [25] (by employing proprioceptive, 'embodied' feedback [26, 27], with multimodal output [28] and game-like context [29]). Specifically, a significant improvement in performance was shown when proprioceptive multimodal input (touch and visual events) was contrasted with non-proprioceptive feedback [30].

### 2.4.2. Proposed Procedure Protocol

#### 2.4.2.1. Conceptual

BCI user training models may include a brief explanatory text, video, or oral presentation that uses well-known and educational word metaphors—such as "your brain is like a muscle that can be trained"—to explain the concepts and underlying mechanisms of BCI [31]. It is important to note that a brain-computer interface (BCI) cannot "read" people's minds. that is, it cannot determine a person's IQ, emotional stability, or overall health, nor can it implant ideas into a person's head. It might also include a simulation of the activity [32] or a video showing someone else accomplishing the work.

#### 2.4.2.2. Procedural

Like Motor/Mental Imagery (MI), procedural BCI models do not have detailed how-to guides for developing mental strategies. But outside of a BCI, we can instruct, explain, and/or even train users. Setting, to be in specific states (cognitive, emotional, and physical [33]), such as high attention [34, 35], taught with mindful meditation, which have demonstrated to be advantageous for BCI

performance. Keep in mind that the type of brain modulation or the goal of the BCI determines the 'optimal' user states. Instructions should be clear, educational, and suggest mental exercises to be performed, such as "squeezing a ball". They should also suggest exercises that may involve complex movements, such as imagined movements involving several bodily parts [36].

Crucially, tactics—that is, behaviors that one is accustomed to or has previously learned—should be suggested [37, 38]. As an aside (and untested in BCI yet), phrases that begin with "do not think of" a specific action ought to be avoided as, according to the ironic process theory, it will lead one's thoughts to focus on that specific action. Rather, the undesirable cognitive techniques ought to be kept relatively vague.

#### 2.4.2.3. Interactive

BCI models were employed to train a valuable skill or state, such as tactile selective attention prior to the motor imagery task [39], or to assess user competence to personalize (adapt) the future task and improve performance [39]. Employed an adaptive P300 BCI game to boost visual attention. it might also be considered when providing basic BCI user training. A designer or experimenter should select and explain one or more models based on the paradigm and goal of the BCI application.

### 2.5. Data Collection Types

#### 2.5.1. Motor Imagery

In order to best achieve the test's objectives, the test subject is shown pictures of any area of the body in a predetermined order throughout the motor imagery test. The test's objective is for the test subject to create a mental image of the body part that represents the image when viewing it. This process creates a brain impulse that the acquisition system can pick up and record [40]. To aid the test subject in identifying the images, the subject's perspective is centered in a cross in the center of the test, and images of the test subjects' extremities appear to the sides (in line with their hands) with a completely blacked out background. Some time is allotted to each occurrence (motor imagery), which offers a framework for response and the recording of brain signals.

#### 2.5.2. Visually Evoked Potential (VEP)

In this test, participants are required to search within photographs of natural landscapes, including forests and rivers, for a little stimulus. For example, the stimulus occurs at an arbitrary point within the image between 8 and 16 seconds following the start of the image. The participant is instructed to remain still during this time, only using his gaze to locate his position on the screen. The image is replaced with a dark screen for 3000 ms after 1000 ms (time: relative to example), and the test is then run five times. The test's duration fluctuates because the stimulus on the screen takes a different amount of

time to display.

### 2.5.3. Steady-State Visual Evoked Potential (SSVEP)

Its purpose is to collect information on brain signal stimuli during a basic focus exercise. With the example of the five-box test, it is explained here. By staring at a set of five boxes on a screen, participants in a basic attention exercise are asked to provide information about the stimulus in their brain signals [40]. Here, our goal is to distinguish between attention-related and non-attention-related inputs. In contrast to ocular exams, the participant must distinguish quickly between many stimuli of different kinds. Throughout the test, participants fix their gaze on a cross that has five boxes (boxes) constantly presented above it. Every test block lasts 76 seconds, and one of the boxes has a green color variation. Throughout the testing intervals, the positioning of this table was random.

## 2.6. Types of Signals

Electrical impulses are how neurons exchange messages. To measure the electric impulse's amplitude, electrodes are applied to the scalp. A typical EG signal has a frequency range of 1 Hz to 100 Hz, with the 100 Hz frequency being quite rare. The amplitude ranges from 10μV to 100μV. In a nutshell, the EEG signal is explained as rhythmic activity divided into frequency bands according to distinct brain functions [41]. The EEG brain signals are generally found in following frequency bands

- The delta (δ) activity ([0.5–4] Hz) is more closely associated with anesthesia and sleep.
- Theta ($\theta$) activity ([4–8] Hz) characterizing the stage of microsleep leading to sleepiness.
- The alpha (α) activity ([8–13] Hz) that is acquired during diminished visual attention and provides information to the temporal cortex and somatosensory cortex.
- The beta (β) activity ([13–30] Hz) that arises from problem-solving or active thinking.

The difference between the types of signals provided above is the difference between the moods and muscle activity strength of the patients. The frequency is an example of how the brain works in different conditions as moods developing and the overall body image are an embodiment of the condition of the brain at that specific time [42]. Hence, if a person exhibits a certain mood or emotional tolerance, the part of the brain activity which is a usual part of the patient's daily life can be known.

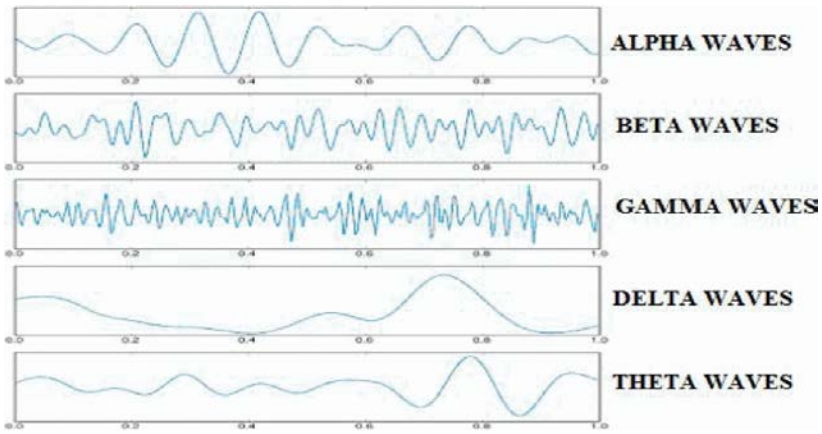

Figure 2.6: Types of EEG Signal (frequency) [42]

## 2.7. 10-20 Technique

The International 10-20 system (Jasper 1958) is widely utilized for the placement of EEG electrodes and for the correlation of sites on the outside of the skull with areas beneath the cortex. The 10-20 system has been used more frequently in recent years to orient coils in transcranial magnetic stimulation (TMS) experiments. TMS is being extensively researched for its potential as a therapy in psychiatry and neurology. It was developed for the purpose of researching non-invasively cortical information processing in cognitive neuroscience [43].

The fundamental challenge in all these applications is to accurately position the Magnetic coil over the targeted cortex area to use the induced electromagnetic field to alter the local neuronal activity. Traditionally, the 10-20 system relies on identifying anatomical features such as the nasion, inion, and Preauricular spots are used, and electrodes are subsequently placed at predetermined distances from these spots in increments of 10% or 20% to account for changes in head size.

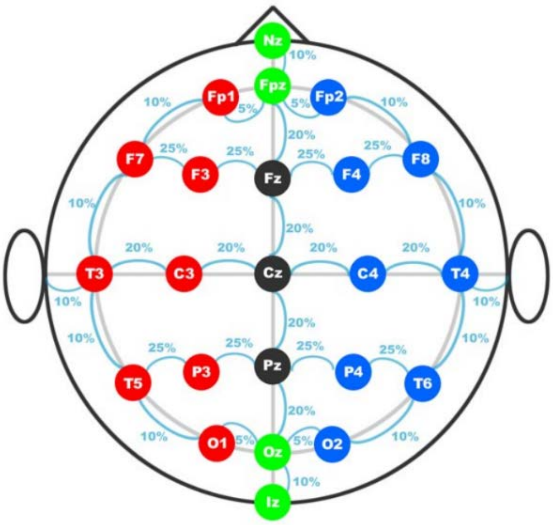

Figure 2.7: 10-20 Measurement System [43]

## 2.8. Artifacts

The existence of artefacts that originate from sources other than the brain and greatly pollute the obtained signals is one of the most frequent issues with EEG recordings. Consequently, during the past 15 years, a lot of study has concentrated on figuring out how to handle these artefacts during the preprocessing phase. Research in this field is still ongoing, though, as no single technique for detecting or removing artefacts is perfect or applicable in all situations. Consequently, during the past 15 years, a lot of study has concentrated on figuring out how to handle these artefacts during the preprocessing phase. Research in this field is still ongoing, though, as no single technique for detecting or removing artefacts is perfect or applicable in all situations [44]. An example of these artifacts is shown in the figure below:

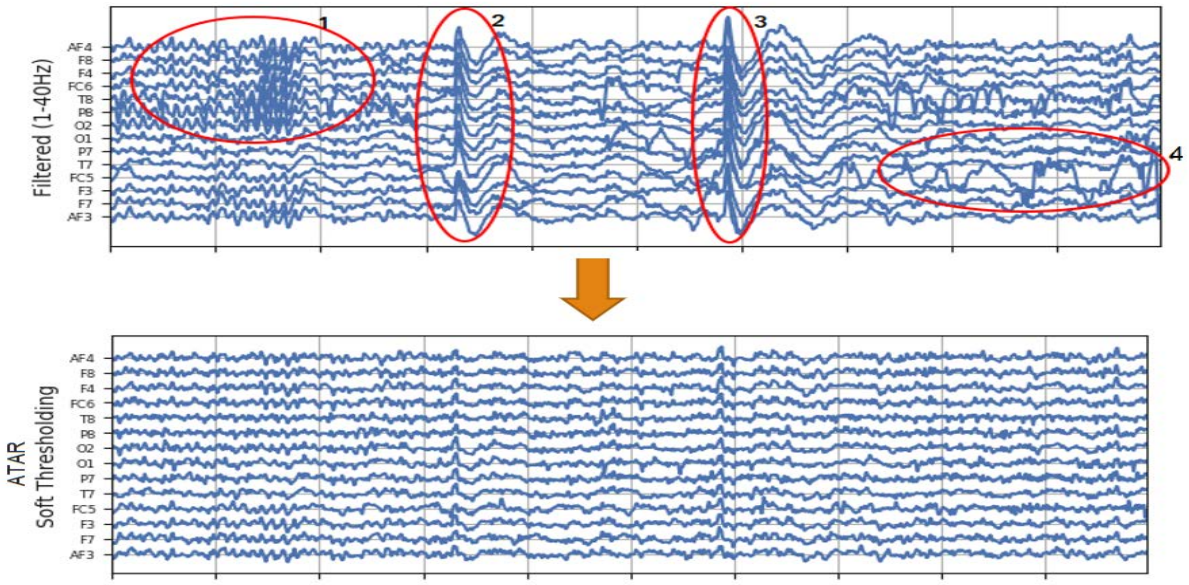


Figure 2.8: Artifacts [44]

These artifacts may be caused by any movements made by the patients or in the surrounding environment or any electrical influence made by surrounding electric devices. The removal of these artifacts is done by using different methods which include using various filters and classifiers which contribute to producing a uniform signal in which the actions made by the patients are recorded and visible in the mannerly and vivid form.

# Chapter 3- EEG Equipment operation

The data acquisition for this project is done using EEG equipment. The equipment used for EEG data acquisition is Type-F Nation 128W EEG by the company NCC Medical. This company is in Shanghai, China. This chapter covers the important aspects of equipment hardware, its dedicated software, and some key considerations regarding data acquisition procedure.

## 3.1. EEG Hardware

As mentioned earlier, the hardware used for EEG data acquisition is Type-F Nation 7128W EEG by the company NCC Medical. The most important and basic components for any EEG equipment are master box, EEG Cap or cup electrodes and the EEG software. The EEG software will be explained in later sections. The EEG equipment also has some accessories along with the basic components which are listed below:

1. Master Box with 128 channels Type-F Amplifier
2. EEG Controller
3. Photic Stimulator
4. EEG Cap
5. Laptop
6. TX/RX Cable
7. USB Cable
8. Syringe/Electrode Gel/Cup electrode Cover.
9. EEG Equipment Trolley

The EEG equipment is shown in the figure below:

Figure 3.1: EEG Equipment

The master box, its supporting controller and the EEG caps or cup electrodes are explained in the subsequent sections.

### 3.1.1. Master box and amplifier

The master box is the core component within any EEG equipment. The master box for this equipment has a Type-F amplifier. The purpose of an amplifier within master box of any EEG equipment is to amplify, accommodate and convert the analogue electrical signals from the electrodes to digital signals so that they can be processed by the computer to give information about EEG. The table below covers some technical specifications of the Type-F Amplifier:

Table 3.1: Specifications of EEG Equipment

| **Parameters `** | **Specifications** |
|---|---|
| Calibration Voltage | 100Uv |
| Sensitivity | 100uV/cm |
| Time Constant | 0.1s, 0.2s, 0.3s (error ≤ ± 20%) |
| Noise level | ≤ 0.5μVRMS |
| Amplitude-frequency characteristics | 1Hz-30Hz, error of +5% ~ -30% |
| Input impedance | >5MΩ |
| Polarization Voltage Tolerance | ± 300mV with ±5% |
| Common mode rejection ratio | ≥100 dB |

The master box is generally connected with the computer via EEG controller and the EEG cap. An important point to remember is that the amplifier within the master box has a rechargeable battery. So, while conducting the EEG experiment, the master box must be disconnected from the power supply to

avoid unnecessary interference.


Figure 3.2: Master Box

### 3.1.2. Controller

The controller works as a processor and communication system between amplifier, electrodes, and other peripheral devices. In other words, it acts as a bridge between brain and computer interface for this equipment. The controller is powered by a 19V DC power supply, and it has a power and reset button.


Figure 3.3: Controller

### 3.1.3. Electrode Cap

The EEG signals are acquired from the brain via an electrode cap which has multiple electrodes on it. The number of electrodes is also referred to as number of channels. This equipment can be configured with 24, 32, 36, 64 and 128 channels EEG caps. The electrodes of EEG caps are sensitive and require electrode gel for connection with the scalp prior to the EEG experiment. The EEG cap is shown in the following figure:

Figure 3.4: Electrode Cap

There are some important precautions and procedures that must be considered while choosing and using the electrode cap. These are mentioned below:

1. Make sure that the electrode cap size and head circumference is compatible according to 10-20 electrode placement system.
2. Make sure the subject has a short haircut (little to no hair) to make sure the electrodes are connected to the scalp and dealing with the hair is easy.
3. Make sure that the electrodes caps are in good condition as they tend or develop a green pigment on them if not cleaned properly after a session of recording. Also, given the differences in power, make sure they are functioning fine electrically.
4. Make sure that the gel provided is in a usable condition. Fear not using plenty of it to make the proper contact as it is readily available.
5. Provided there are different protocols of each recording session, make sure the subject is aware of the standard protocol and is at ease with the environment and the time slot taken is up to the conditions of mental peace required while recording EEG signals.
6. Make sure that the cap fitted is of the size of the subject as the placement of electrodes is in a precise placing with little error margin.
7. Make sure that the connector of the electrode cap is connected to the master box rightfully and the indication of it is shown on the software of NCC medical.
8. Here are some visual representations of how the electrode cap is connected in real life situation

using the available equipment.

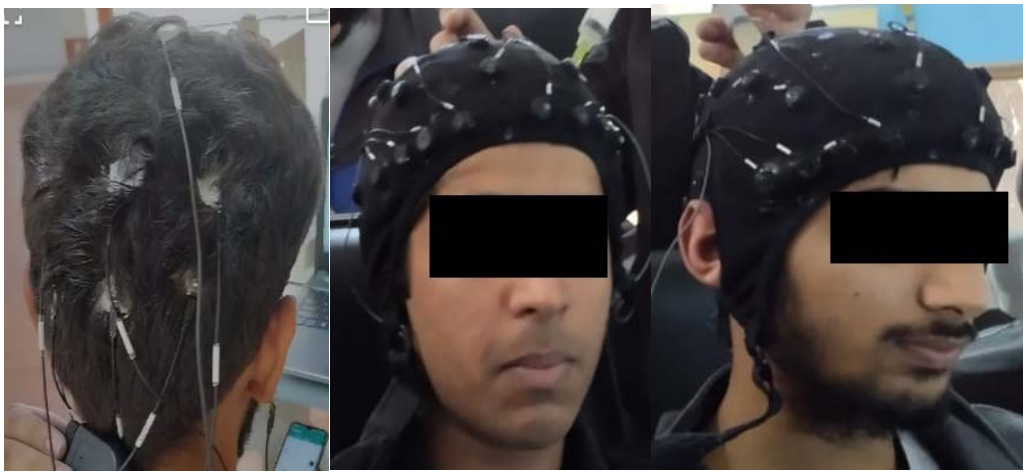

Figure 3.5: Connected Electrode Caps on Subjects

### 3.2. EEG Software

The software is provided by equipment's OEM i.e. NCC Medical which is in Shanghai, China. The software's name is EngNCERP. The software offers a variety of options for EEG acquisition, visualization, and analysis. The software can be configured with up to 128 channels. This improves both acquisition and quality of the EEG data. One important thing to remember is that EEG software and its file type is different for different OEMs. File type for this EEG software is NED. The main user panel and monitoring/recording panel will be discussed in subsequent sections:

#### 3.2.1. User Panel

The GUI of main user panel is shown below:

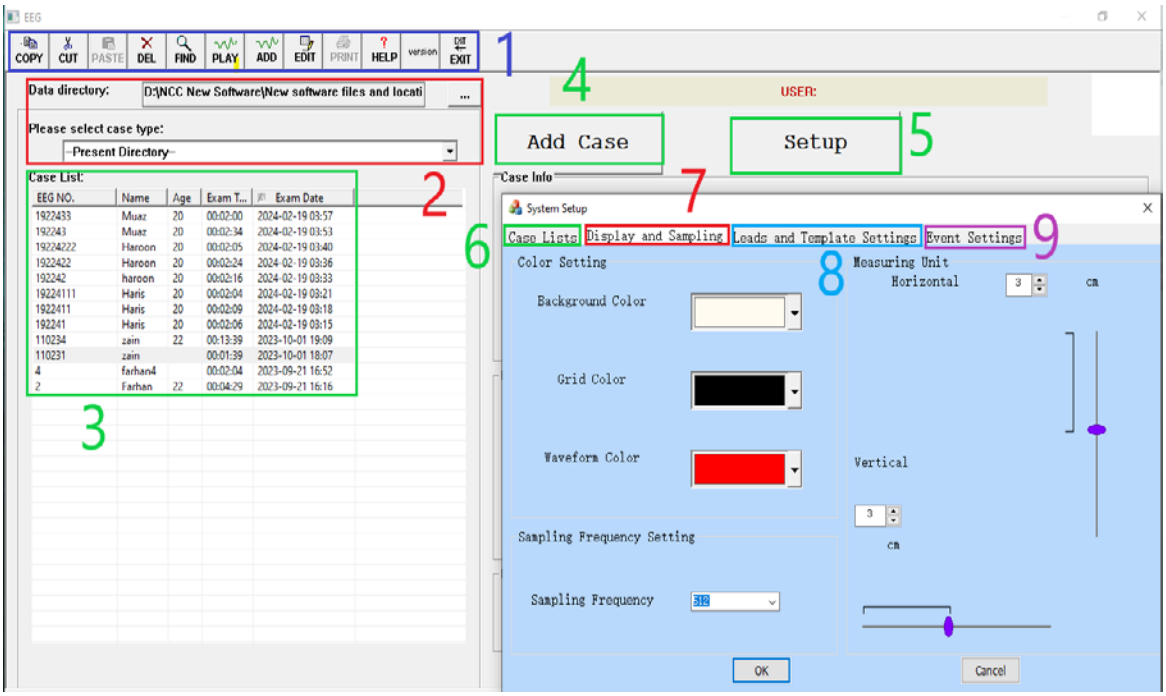


Figure 3.6: EEG Software Layout

The basic features are outlined and numbered in the above figure. These are explained in the following sections.

### 3.2.1.1. Top Menu

The top menu labelled as “1” contains some basic options for data file. These are listed below:

- Copy: It is used to copy the NED file from data repository.
- Cut: It is used to cut the NED file from data repository.
- Paste: It is used to paste the NED file in data repository.
- Delete: It is used to delete the NED file from data repository.
- Find: It is used to search for any existing NED file within data repository.
- Play: It is used to play the NED file, which can be selected from data repository, to view EEG signals.
- Add: It is used to add a new case in data repository.
- Edit: It is used to edit the case/experiment information for any NED file in data repository.
- Print: It is used to print the report of EEG signals/waves of selected NED file from data repository.
- Help: It is used to provide technical support to assist the equipment operator.
- Version: It shows the version of the EEG software.

### 3.2.1.2. Data Directory

The Data directory which is labelled as “2” contains the path/location to extract data files. For every experiment, this directory must be set before the test so that files can be saved to the predefined location. The following path is generally used for this equipment:

Local Disk C:\EngNCERP\eegdata\dat

There is a “case type” option under the data directory which is used to define the case type for the file. This option assists in saving the files categorically in groups which are given below:

- Brain trauma
- Headache
- Brain tumor
- Epilepsy
- Children
- Normal
- Untreated
- Present directory

For academic or research purposes, “present directory” is used.

### 3.2.1.3. Data Repository

The block labelled as “3” is the data repository which shows all experiments that were conducted along with some basic and distinctive details. These details are listed below:

- EEG No.
- Name
- Age
- Exam date
- Exam time (duration)

For EEG experiment, multiples files are created whenever a new case is added. These are listed below:

| | | | |
|---|---|---|---|
| 1) NED | 2) NAT | 3) ENT | 4) MON |
| 5) POWER | 6) PRR | 7) SPT | 8) AEEG |
| 9) APEN | 10) BIS | 11) BSI | 12) BSR |
| 13) EMG | 14) RESE | 15) SAMPEN | 16) SLP |
| 17) SPT | 18) SEF | 19) MF | 20) DTA |

As stated earlier, the main file is the NED file for any EEG experiment that is done using this equipment and its software. If any EEG case file is to be imported and played on another PC/laptop with same EEG software installed on it, importing only NED won't be sufficient. All the files listed above must be imported along with NED file so that the EEG recording can be viewed.

#### 3.2.1.4. Add case

The block labelled as "4" shows the option by which a new case can be added. By adding a new case, EEG experiment can be conducted and recorded. To add a case, following information is required:

- EEG Configuration (number of channels of EEG headset)
- EEG No.
- Subject name
- Subject age
- Subject gender
- Subject contact details
- Subject history (details of any brain injury)
- Bed/ward/Hospital details.
- Medication

Before any EEG experiment, whether it's for medical or research purposes, these details must be filled.

#### 3.2.1.5. Setup

The Setup labelled as "5" contains various settings that can be adjusted prior to the EEG test. The settings available are listed below and will be discussed respectively:

- Case lists
- Display and Sampling
- Leads and Template Settings
- Event Settings

**Case lists:** The Case lists labelled as "6" is used to save information such as case lists or case

information. These are explained below:

- **Case lists:** As discussed earlier, the case type for EEG files must be defined prior to any EEG test. By using this option, we can add or define a new case type based on the type of research conducted so that files can be stored categorically.
- **Case information:** By using this feature, we can add new parameters for case information. This helps to save maximum details about the subject before and after the EEG experiment. Hence, assisting in research.

**Display and Sampling:** The settings in block labelled as "7" help to the change display of the EEG recording screen. We can change grid, background, and waveform color. We can also change the sampling frequency by using this option.

**Leads and Template Settings:** The Leads and Template settings labelled as "8" are used for EEG channels. By using this feature, we can:

- Add custom montage.
- Change the hardware configuration according to the electrode cap channels so that software is compatible.
- Adjust the electrode gain.

**Event Settings:** The Event settings labelled as "9" are used to add instant and long events such as breathing, eyes closed, eyes opened, flash stimulus or markers for any specific movement during EEG experiment.

### 3.2.2. Record/Monitor Panel

The figure below shows the GUI of EEG monitoring and recording panel. The main purpose of this panel is to:

- Monitor the EEG
- Record the EEG
- Analyze and print the EEG results.

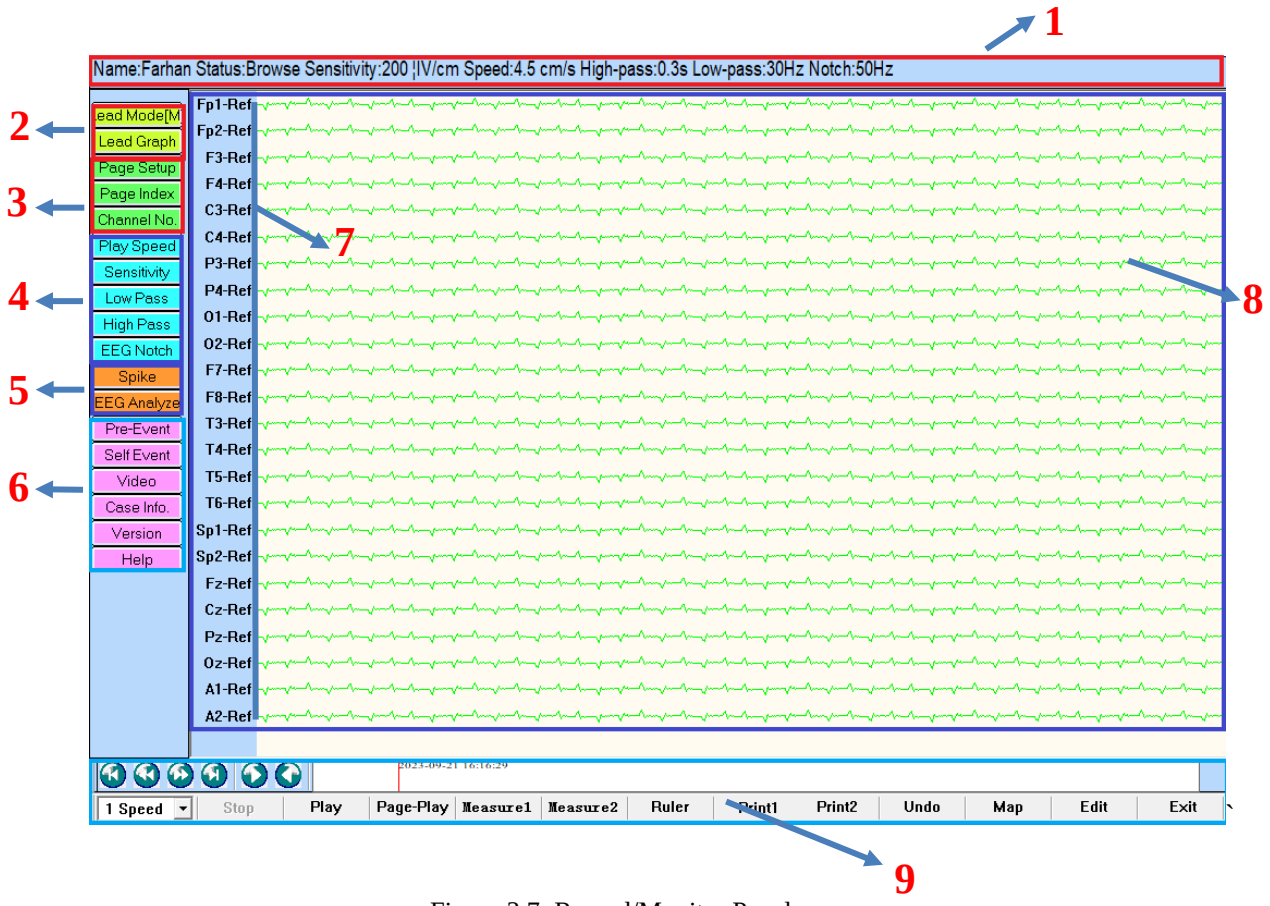


Figure 3.7: Record/Monitor Panel

### 3.2.2.1. Features explanation

The features are both outlined and labelled. The details of these features are given below:

- The top bar shows some specific details regarding the EEG experiment being conducted. These details include the name of subject, sensitivity, speed, bandpass filter, and notch filter.
- The block labelled as “2” gives the option to access a lead graph which shows the electrode placement pattern for electrode cap that is being used for EEG experiment. We can also access different montages for the EEG experiment.
- The block labelled as “3” shows options for accessing and arranging the page. “Page Setup” helps to select how many channels can be displayed per page. By using “Page Index”, we can jump to any page. Using “Channel no.”, we can select which channels to display or hide on a specific page.
- Within block labelled as “4”, there are options for low pass (usually at 30Hz), high pass (usually at 0.3s), and notch filter (usually at 50Hz). We can also adjust the play speed of the EEG data and sensitivity of the electrodes.

- Using the “EEG Analyze” option within block labelled as “5”, we can analyze and plot the EEG data. This feature processes the EEG data and gives details about the subject such as FFT power of the EEG, EMG Index which reflects the amount of myoelectric interference component, Burst Suppression Ratio which reflects the decrease in brain metabolic rate and DTABR (ratio of slow and fast wave) which gives indication of trauma.
- The block labelled as “6” shows options for adding events, defining events during the experiment, and accessing the case information. Options are also available to view the version of the software and access the help.
- The block labelled as “7” shows the channels for which EEG data is collected against time. The channels may vary based on hardware configuration. This equipment can be configured for 24, 32, 36, 64, 128 and 256 channels. Number of channels shown on one page, as discussed earlier, can be changed by using the options provided in the block which is labelled as “3”.
- The block labelled as “8” shows the EEG data being recorded for each channel against time. All wave types i.e. alpha, beta, gamma, and delta can be observed in this section while EEG experiment is being conducted.
- The options in bottom menu are used whenever the EEG data available in the data repository must be reviewed or analyzed. There are options to play the recording, adjust the play speed, measure any specific part of the data to analyze the wave patterns and perform mapping operation on the selected data.

#### 3.2.2.2. Impedance Feature

In EEG equipment, the connectivity status between master box and the EEG cap cable is shown on the software. This information alone is not sufficient because it is also important to ensure the connectivity of each electrode prior to EEG recording. Within the EEG software, there is an “Impedance” feature which is used to ensure the connectivity of each electrode.

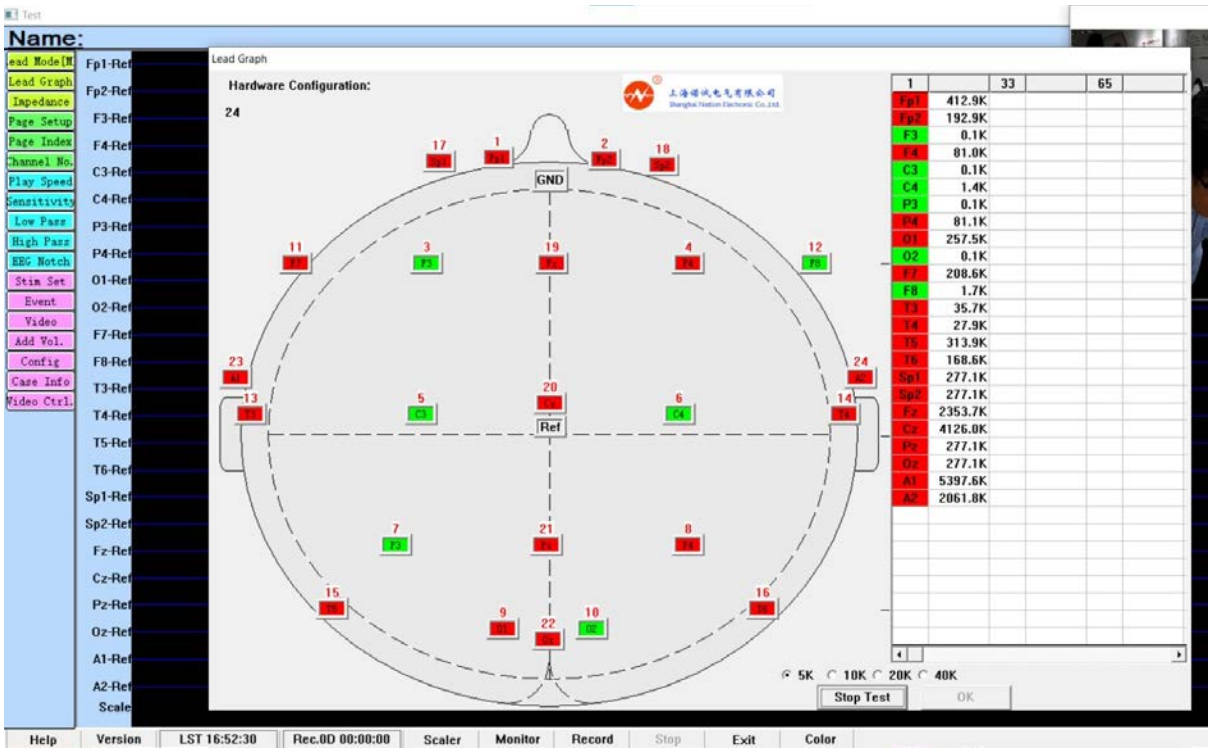

Figure 3.8: Impedance Screen

For this equipment, the maximum allowable impedance for each electrode is 100k. Within this range, the EEG data will be accurate but if it is above 100k, the data will be faulty. To conduct the impedance test, following steps can be followed:

- Ensure that an adequate amount of electrode gel is applied on the scalp to establish connection between the head and the electrodes.
- Ensure that the EEG cap cable is connected to the master box and status is indicated with blue color.
- Add subject information and then click on “Routine EEG”. Before recording or monitoring the EEG data, click “Impedance” which is shown in the menu at top left corner.
- Before starting the impedance test, click on the desired threshold value for impedance. The options available are 5k, 10k, 20k and 40k.
- After selecting the threshold value for impedance, start the test. The electrodes with impedance below threshold value will be shown as green and the electrodes with impedance above threshold value will be shown as red. As mentioned earlier, the data can still be considered as accurate if the impedance for electrode is below 100k.
- If the impedance is above 100K, apply more electrode gel on the scalp to ensure better connectivity between head and electrodes.

### 3.3. Key Considerations for operating the equipment

The Shanghai NCC 128-Channel F-type EEG equipment is a sensitive apparatus. We must follow certain protocols and procedures before starting with any of the prescribed EEG experiments. Without these steps, it is not possible to collect reliable EEG data. Some main procedures and protocols are discussed below:

- The location for EEG experiment should be soundproof.
- The room temperature should be maintained at 20°C ~ 24°C.
- There should be no electrical interference and electrical noise in the experiment location.
- Ensure the connections of master box, EEG controller and EEG cap.
- The master box should be disconnected from the power supply before starting the EEG experiment.
- The electrodes should be cleaned prior to the experiment.
- The experiment subject should wash their head prior to the experiment.
- All sources of radio waves should be kept away from the equipment.
- The electrode gel should be used to establish smooth connection between electrodes and scalp.
- The operator must follow the 10-20 measurement system to place the electrodes accurately on the scalp.
- The protocols for the experiment should be made clear to the subject so that the EEG data can be collected accurately.
- The subject should avoid unnecessary movements as it can cause artifacts in the EEG data.
- The operator should set notch filter, high pass filter and low pass filter to view noise-free data while recording.
- After recording the EEG data, the operator should convert the NED file to EDF file so that it can be used for research purposes.
- After the experiment, the subject can wash their head.
- The operator must clean the electrodes to prevent corrosion caused by thin film formed on electrode surface by electrode gel.

By following these procedures prior to the experiment, we can collect reliable and accurate EEG data.

# Chapter 4 - Functional Near-Infrared Spectroscopy(fNIRS):

The following chapter constitutes the work done in the field of FNIRS during the project as part of the criteria required by a certain PhD student. In the order of data repository technique and processing, the steps remain almost the same whereas the technology is vastly different. FNIRS, as stated in its name, is a relatively new field with its current use mainly in research and not in commercial use due to numerous reasons.

## 4.1. Introduction to fNIRS

Functional near-infrared spectroscopy (fNIRS), a non-invasive brain research technique, measures cerebral hemodynamic to infer neuronal activity. Since its debut, functional neural network recognition (fNIRS) has been extensively employed in neuroscience research, providing insights into the neural underpinnings of cognitive and motor functions as well as therapeutic and anatomical applications. Because of its resilience, safety, and mobility, this technology is widely used for research.

### 4.1.1. Synopsis of fNIRS Technology

When near-infrared light penetrates the skull, brain tissue, and scalp, changes in blood oxygenation related to neuronal activity alter the characteristics of light absorption. By detecting these changes, fNIRS provides a temporal and geographical mapping of brain activity (Boas et al., 2004. Ferrari & Quaresima, 2012). Being non-invasive, radiation-free, and less expensive than other imaging modalities such as fMRI and PET, this approach has several advantages.

Brain-computer interfaces (BCIs) have shown considerable promise in the application of fNIRS. Brain-computer interfaces, or BCIs, open new channels of communication and control for those with severe motor disabilities. Unlike larger systems like fMRI, fNIRS devices are portable and can be used in several contexts, such as the patient's home or during regular activities. Because of its adaptability, fNIRS is especially useful for tracking brain activity over an extended period in realistic settings.

For applications involving youngsters, the elderly, or people with physical limitations who might not be able to accept more intrusive or restrictive technologies, fNIRS's ability to detect even little movements and its non-restrictive physical setup are essential (Coyle et al., 2007).

### 4.1.2. New Applications and Prospects for the Future

The use of fNIRS is spreading outside of traditional neuroscience and into disciplines like social psychology, neurodevelopmental studies, and the assessment of psychiatric disorders. Advances in functional non-invasive remote sensing (fNIRS) technology, such as the creation of wearable systems, are opening the door to ambient brain activity monitoring, which could revolutionize methods for

evaluating cognitive performance and mental health (Ayaz et al., 2013. Pinti et al., 2018). A rapidly developing field of study is the combination of fNIRS with other neuroimaging and neurophysiological methods, such as fMRI and EEG. By utilizing the complimentary qualities of each modality, these multimodal techniques seek to offer a more thorough understanding of brain function, hence improving the application and reliability of brain-computer interfaces (BCIs) (Fazli et al., 2012). To sum up, fNIRS is a unique and effective tool in the cognitive neuroscience and microengineering toolbox. The advancement of neurotechnology and its incorporation into multi-modal imaging frameworks hold great potential to improve our comprehension of the brain and broaden the scope of its applications.

### 4.2. Principles of fNIRS Technology

In this section, we will discuss the fundamentals of physics and optics involved in the fNIRS technology. The key elements of the fNIRS system will also be discussed in this section.

#### 4.2.1. The Fundamentals of fNIRS Technology

A sophisticated imaging method called functional near-infrared spectroscopy (fNIRS) uses near-infrared light to investigate the brain's metabolic processes. To fully appreciate the potential and constraints of fNIRS technology in neuroscientific research and clinical applications, one must have a solid understanding of basic concepts involved within fNIRS technology.

#### 4.2.2. Fundamental Principles of Physics and Optics

Optical spectroscopy is the foundation of fNIRS technology. Since near-infrared light may more easily permeate biological tissues at these wavelengths than visible light, it is commonly utilized between 650 and 900 nm. This light is either absorbed or dispersed by biological tissues.

fNIRS provides a dynamic measure of cerebral blood flow and oxygenation associated with brain activity by monitoring changes in the concentrations of these chromophores through the measurement of differential light absorption. To measure these concentrations, the modified Beer-Lambert Law is frequently used, which connects variations in light absorption to both the concentration of absorbing materials and the pathlength of light through tissue (Strangman et al., 2002).

#### 4.2.3. Elements of fNIRS system

A fNIRS system consists of the following essential parts:

##### 4.2.3.1. Sources of Light

Usually, these are light emitting diodes (LEDs) or lasers that release light with a targeted near-infrared wavelength.

#### 4.2.3.2. Indicators

The light that has entered biological tissue is detected using photodiodes. Since light weakens as it travels through and interacts with tissue, these detectors are sensitive to changes in light intensity.

#### 4.2.3.3. Optodes

These are the scalp sites of contact where light is either detected (by detector optodes) or provided (by source optodes). The regions of the brain being monitored, and the spatial resolution of the measurement are determined by the arrangement and positioning of these optodes.

#### 4.2.3.4. System of Data Acquisition

The signals from the detectors are gathered and processed by this system. It transforms the converts analogue signals into digital format, reduces noise, and calculates variations in light absorption, which allow for the determination of variations in chromophore concentration.

#### 4.2.3.5. Software for Analysis

To evaluate the functional data in connection to brain activity, statistical analysis is performed, signal correction methods are applied, and the raw data is analyzed using specialized software. In this project, the infamous NIRS software is used to collect the data and use it to convert it into usable formats as well as extract its features. Some snapshots have been attached for better understanding of how it works along with the subjects.

##### 4.2.3.5.1. Establishing connection between the optodes

The cap is fitted onto the subject keeping in mind the short haircut requirement as well as the size of the cap for the respective subject is decided so to help in placing the optodes at the perfect positions corresponding to the scalp. As the figure shown below, the indication of the status of connection is shown with color indications of grey(saturated), red(critical), yellow (acceptable) and green(excellent). The conditions displayed are crucial for all optodes to be green so to ensure getting the required quality of data.

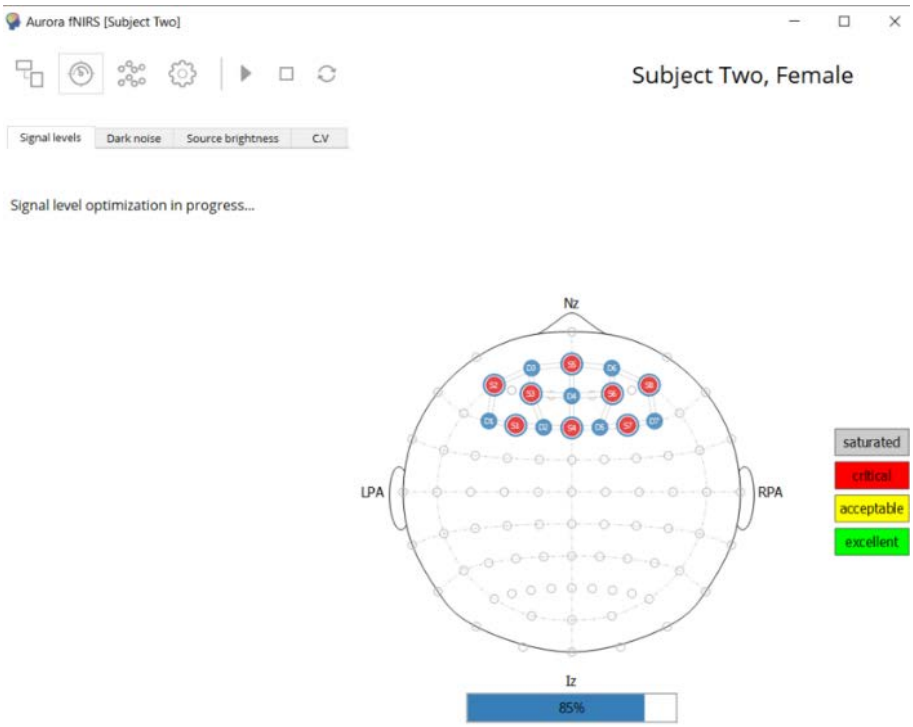


Figure 4.1: Connection Status of Caps

### 4.2.3.5.2. Data collection and monitoring

The collection of data is started by selecting any required conditions or default montage and the authenticated data is recorded. Many features such as event placements etc can be done on the data to further display it in a better presentable format. Usually, the sensitivity is kept at a gradient so to endure oneself if any irregular peaks emerge causing disturbances in the recorded data.

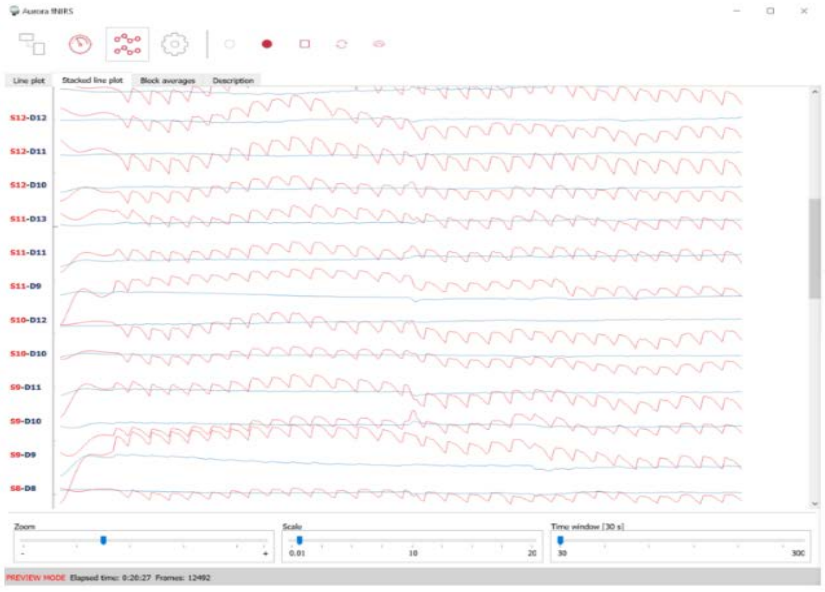

Figure 4.2: Data Recording Graphs

### 4.3. Methodology of fNIRS

Functional Near-Infrared Spectroscopy (fNIRS) involves several important processes in its approach, from experiment setup to data collection and analysis. The standard operating methods and factors to be considered when performing fNIRS research are described in this part. These are essential to guaranteeing the validity and consistency of the results.

#### 4.3.1. Setup for an Experiment

To get high-quality data for fNIRS investigations, the experimental setup is essential. Prior to optode placement, the participant's head is measured and marked to determine the proper positions based on the regions of interest in the brain. The optodes, which comprise light sources as well as detectors, are then firmly fastened to the scalp using a band or cap akin to those used in EEG research. Maintaining adequate scalp contact is crucial to reduce artefacts from movement and surrounding light. Lighting and electromagnetic interference in the experimental setup need to be managed since they can skew the results. Furthermore, educating participants about the process, guaranteeing their comfort, and reducing any movement during data collection are also part of participant preparation.


Figure 4.3: Controller and Amplifier (left) and Converter Box to PC (right)

#### 4.3.2. Data Gathering and Examination

In functional near-infrared spectroscopy (fNIRS), data is collected by tracking the absorption of near-infrared light by brain tissues at various intervals throughout the experiment. Following the acquisition of the raw data, preprocessing is performed to eliminate physiological noise and artefacts, such as those resulting from respiration, heartbeat, and head movements. Preprocessing frequently entails filtering methods and may involve algorithms created especially to manage the nonlinear characteristics of fNIRS signals. After preprocessing, the data are examined to determine relevant brain activity information. The significance of the observed alterations with respect to the experimental circumstances is then ascertained by statistical analysis.

In order to improve the spatial resolution of the results and comprehend complicated patterns of brain activity, advanced analysis techniques such as statistical parametric mapping, time-series analysis, and machine learning approaches may also be used.

The fNIRS process is extensive and demands painstaking attention to detail to guarantee that the data gathered are reliable and understandable. When these procedures are followed correctly, researchers can examine brain health and dysfunction and gain important understanding of different cognitive processes.

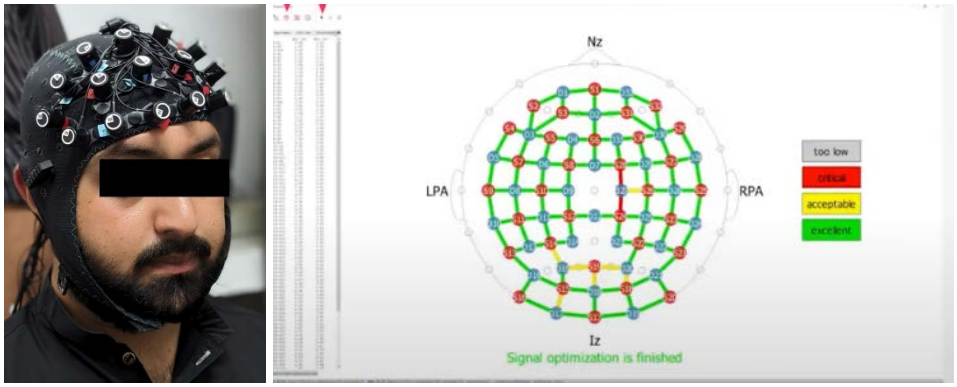


Figure 4.4: Cap connected on Subject (left) and Optode successful connection (right)

### 4.4. Comparative Analysis: fNIRS and EEG

While both Electroencephalography (EEG) and Functional Near-Infrared Spectroscopy (fNIRS) are non-invasive neuroimaging techniques used to analyze brain activity, their approaches, capacities, and uses are very different. This comparative analysis addresses the limitations of fNIRS in comparison to EEG and emphasizes its relative benefits over EEG.

#### 4.4.1. fNIRS benefits over EEG

Because fNIRS uses a different technique to detect brain activity than EEG, it has several advantages over the latter. In contrast to EEG, which records electrical activity, fNIRS analyses hemodynamic responses linked to cerebral activity, offering information about the metabolic activities of the brain. One of fNIRS's primary benefits is that it is less vulnerable to electrical artefacts from external sources or muscle movements, which makes it better suited for motion-based research and naturalistic settings (Scholkmann et al., 2014).

In addition, fNIRS offers a direct measurement of changes in cerebral blood flow and oxygenation, providing additional information to that obtained from the electrical signals detected by EEG. Studying brain areas with a high hemodynamic response can benefit greatly from this. Additionally, fNIRS has the advantage of being relatively simple to set up and doesn't require a lot of preparation or gel

application, which can make participants more comfortable, particularly in long-term studies or with populations like newborns and people with hair on their scalps (Ferrari & Quaresima, 2012).

### 4.4.2. fNIRS's limitations in comparison to EEG

When compared to EEG, fNIRS has drawbacks despite its benefits. FNIRS has a poorer spatial resolution than high-density EEG devices, and it can only monitor cortical regions. it cannot assess activity. In addition, fNIRS offers a direct measurement of changes in cerebral blood flow and oxygenation, providing additional information to that obtained from the electrical signals detected by EEG. Studying brain areas with a high hemodynamic response can benefit greatly from this. Additionally, fNIRS has the advantage of being relatively simple to set up and doesn't require a lot of preparation or gel application, which can make participants more comfortable, particularly in long-term studies or with populations like newborns and people with hair on their scalps (Ferrari & Quaresima, 2012)

When compared to EEG, fNIRS has drawbacks despite its benefits. FNIRS has a poorer spatial resolution than high-density EEG devices, and it can only monitor cortical regions. it cannot assess activity. The precise research topics, the necessary temporal and spatial resolution, and the experimental setup used for the investigation. The robustness of neuroscientific data can be increased, and a more thorough understanding of the underlying brain mechanisms can be obtained by combining fNIRS with EEG and other imaging modalities.

## 4.5. Applications of fNIRS in BCIs

In the area of brain-computer interfaces, functional near-infrared spectroscopy (fNIRS) has shown a great deal of promise, advancing the fields of neurorehabilitation, assistive technologies, and cognitive load assessment. Some important studies regarding the fNIRS applications in BCI are given below:

- Supporting people with movement limitations is one noteworthy use of fNIRS in BCIs. For instance, a study by Coyle, Ward, and Markham (2007) showed how cognitive activities linked to various brain regions can be used to use fNIRS to control a wheelchair. By focusing on activities, participants were able to direct the wheelchair forward and choose preset pathways.
- The use of communication tools for people with severe speech and physical impairments is another important use. A study by Naito et al. (2007) investigated how fNIRS-based BCIs could facilitate communication by letting users choose letters and words that are shown on a screen. in other words, users could 'type' by varying their brain activity.
- The current direction of fNIRS research is towards designs that are easier to use and more portable, opening the technique for use outside of traditional lab settings. The development of

wireless fNIRS devices, which enable real-time brain activity monitoring in a variety of settings and increase the usefulness of fNIRS-BCIs in daily applications, is an example of this trend (Ayaz et al., 2013).

### 4.6. Challenges in fNIRS

Though there are several obstacles preventing Functional Near-Infrared Spectroscopy (fNIRS) from being used more widely and effectively, especially in the field of brain-computer interfaces (BCIs), it remains a promising technique for researching cortical brain function.

#### 4.6.1. Technical Difficulties

The intrinsic restriction on the near-infrared light's penetration depth is one of the main technological difficulties with fNIRS. Because the light from fNIRS sensors can only reach a few centimeters into cerebral tissue, it is not possible to measure deeper brain structures and is limited to cortical regions. The fNIRS signal might get contaminated by extracerebral sources such the scalp, skull, and other tissues that both scatter and absorb infrared light. It may be challenging to distinguish the distinct hemodynamic reactions of the brain due to this contamination, which can dilute the genuine cerebral signal (Gervain et al., 2011). Furthermore, motion artefacts are a major issue since even minute subject motions, like head nods or facial expressions, can cause significant signal interference and make it more difficult to collect and analyze the provided data.

#### 4.6.2. Analysis of the Findings

The interpretation of fNIRS data is not without its difficulties. Because fNIRS analyses changes in blood volume and oxygenation rather than direct electrical activity, the signals it generates are based on indirect estimates of neural activity. This aspect leads to a temporal lag between the neuronal events and their vascular manifestations, complicating the temporal correlation between stimuli and responses (Strangman-et-al.,2002). Moreover, fNIRS's spatial resolution is still constrained when compared to other neuroimaging methods like fMRI, although being better than EEG. This constraint may make it difficult to identify the precise brain regions that are activated, especially when researching adjacent functional areas. In conclusion, while fNIRS has many benefits for non-invasively tracking brain activity, its accuracy and usefulness in research and clinical settings must be carefully balanced against these technical and interpretive issues. Sustained technological progress and methodological refinements are imperative to surmount these challenges and augment the dependability of fNIRS as an apparatus for brain-computer interface.

### 4.7. Innovations and Advances in fNIRS Technology

Enhancing system portability, optimizing signal processing techniques, and incorporating multimodal data are the main directions of fNIRS for BCIs. One notable development is the creation of wearable fNIRS systems, which enable more realistic monitoring of brain activity outside of the lab in everyday situations (Piper et al., 2014). Applications such as ambulatory health monitoring and adaptive interfaces that react in real-time to the mental states of users depend on this trend.
To increase spatial and temporal resolution and lessen sensitivity to outside noise and physiological artefacts, fNIRS in BCIs may see more development in the future. Hybrid BCI systems, which integrate fNIRS with other modalities like EEG or eye-tracking to take use of each method's advantages, are also gaining popularity. These kinds of systems could provide more reliable and precise user intent detections, increasing the possibility of sophisticated BCI applications (Fazli et al., 2012).
With the potential to change how people interact with technology and improve the quality of life for those with disabilities, fNIRS is likely to remain a useful tool in the development of creative and useful BCI applications. This is supported by both ongoing research and technological advancements.

### 4.8: Conclusion

The possibilities and uses of Functional Near-Infrared Spectroscopy (fNIRS) in the context of Brain-Computer Interfaces (BCIs) have been examined in this chapter. By measuring hemodynamic reactions to near-infrared light, fNIRS technology measures brain activity and provides information on changes in cerebral blood flow and oxygenation. The fundamental ideas behind fNIRS, such as its optical characteristics and system elements, lay the groundwork for its incorporation into BCIs. Among the noteworthy applications that were covered are hybrid systems that integrate fNIRS with other neuroimaging modalities, cognitive load monitoring, and motor control interfaces.

The benefits of fNIRS, such as its resilience to electrical noise and lack of need for direct scalp contact, were brought to light by the comparison study with Electroencephalography (EEG). These attributes make fNIRS suitable for specific patient populations and environments. However, difficulties include probing restrictions and a lesser temporal resolution than EEG.

It is highlighted that subcortical brain regions are involved, which now limits its applicability to cortical research primarily. Prospects for fNIRS's influence on the development of BCIs seem bright. Further developments in machine learning models, signal processing algorithms, and sensor technologies are improving the usability and effectiveness of fNIRS-based systems. Especially noteworthy is the advancement of wearable and portable fNIRS technology, which makes real-time brain monitoring possible in a range of contexts outside of conventional laboratory settings. Neurorehabilitation,

adaptive technology, and personalized treatment may all benefit greatly from this. Combining fNIRS with other monitoring technologies, including eye tracking and EEG, provides a multimodal way to see and interact with brain activity. It is anticipated that these hybrid systems will increase the precision and dependability of BCIs, enabling more intricate and subtle communication between people and technology. The potential for fNIRS to enable innovative BCI applications that integrate real-time feedback and adaptive learning processes will probably increase as computational techniques advance, ushering in a revolutionary change in the way cognitive and neurological health is maintained and improved through technology. The work done on discovering this relatively infant technology provides insights into a newer and extensive research facility. As the operation of the device provided by Air University has been a privilege to join hands with, the increment in the knowledge and practical expertise is grateful. In summary, even if fNIRS has drawbacks, incorporating it into BCI research and development has a significant chance of influencing upcoming advancements in neurotechnology. To fully realize the potential of fNIRS in improving human-computer interaction, more study and technology advancement are essential.

# Chapter 5: Equipment Solutions and Data Processing

This chapter is divided into two parts; methods adopted for sorting out technical issues of BCI equipment and solution of processed data. All issues identified within the equipment and solutions will be discussed in this chapter. The data acquisition protocol followed, and the results of processed data will also be discussed in this chapter.

## 5.1. Issues identified within equipment and solutions

During initial EEG experiments, the EEG data was found faulty, and the quality was low. Whenever the FFT for datasets was taken, there were only noise peaks in the graphs and preprocessed data showed poor or no results. From this initial processing, it was concluded that there were some issues with the equipment. The same conclusions were also made by Research Assistants at National Centre for Robotics and Automation and researchers at Neurosciences department in AIR university.

For further information about the EEG equipment and solution for its technical issues, the equipment OEM was contacted through official channels to provide after-sale service for the equipment. Within any EEG equipment, there are three main parts as shown below:

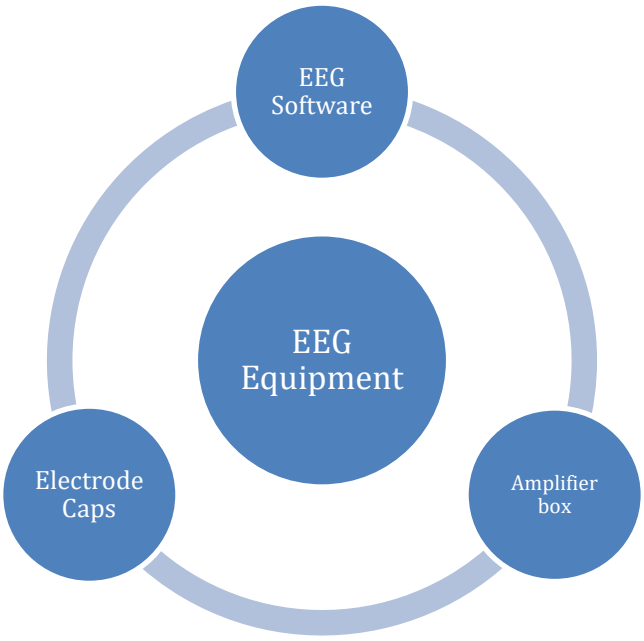


Figure 5.1: Components within EEG Equipment

These are interdependent. The collection of EEG data will not be possible even if one is missing prior to the testing. The most effective approach to detect the technical issues was to check all these components one by one so tests were conducted for electrode caps and amplifier box while updates

were installed for EEG software. The details are provided in subsequent sections.

### 5.1.1. Short circuit test for Electrodes

The first test was conducted for verification of the electrodes. For this purpose, a short circuit test approach was used. The cable connector has 80 pins with one pin dedicated for each electrode. For the short circuit test, a digital multimeter was used. One probe of digital multimeter was placed in contact with all electrodes respectively and other probe in contact with the cable connector as shown in the figure. For each electrode, the DMM showed a short-circuit with its dedicated pin on the cable connector. This test was conducted for all electrode caps that were available in the equipment accessories. After conducting the tests for all provided EEG caps, it was concluded that there were no issues with the available EEG caps.

### 5.1.2. Updates for EEG Software

The EEG software was outdated as its version was valid till 2005 only. The equipment OEM was contacted to provide the new software. The new software was installed successfully via remote meeting with OEM on AnyDesk software. The new software version is shown in the figure below:


Figure 5.2: Software version

In the old software, there was no option to select more than 32 channels. The OEM was contacted to sort out the issue of channel configuration options. This issue was also resolved, and the software can be configured up to 128 channels. In EEG software, there is an impedance feature which is already discussed in chapter 3. This feature was installed on the software to check for connectivity of each electrode. During the experiments, there was an assumption that this feature might be giving wrong information regarding the connectivity of channels. To clear this doubt, the OEM was contacted to update the impedance feature. Hence, all issues within the software were resolved and it was concluded that there is no issue within the software.

### 5.1.3. Master/Amplifier Box

The next step involved the inspection of the amplifier box. A ground zero test was suggested by the OEM in which all electrodes are connected to each other (short-circuited), and the wave is observed

on EEG software. The waveform for all channels must be a straight line. For further verification, the electrode for each corresponding channel is disconnected from other electrodes and a random waveform will be shown on the EEG software for that channel. This shows that the channel and its corresponding electrode give reliable data. This process is done for all channels respectively.

To perform this test, all electrodes were connected to each other via metal conductor. This is shown in the figure below:

Figure 5.3: Setup for ground zero test

With EEG equipment set and all electrodes connected, the waveform was monitored for all channels respectively on the EEG software. The parameters for monitoring the data were:

- High pass: 0.53Hz
- Low pass: 60Hz
- Notch filter: 50Hz
- Sensitivity: 100 uV/cm

These are shown in the figure below:

Figure 5.4: Parameters used for ground zero test.

The figure below shows the waveform generated during ground zero test when all electrodes were connected:

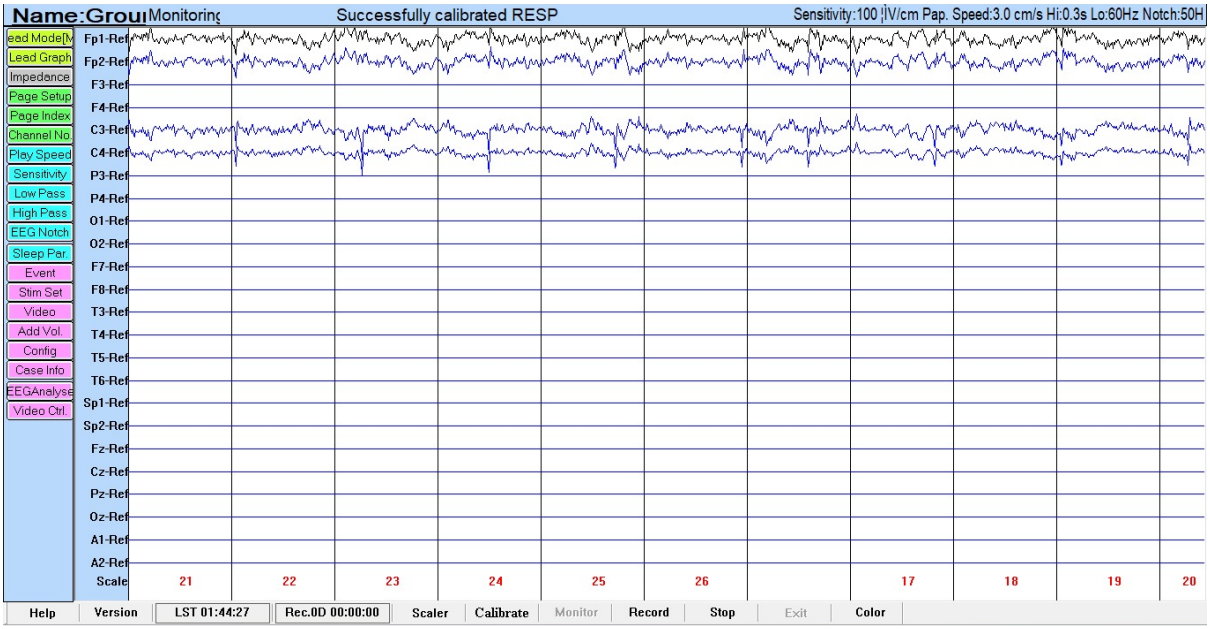

Figure 5.5: Waveforms for all channels while connected to common metal conductor.

As discussed earlier, the next step was to check for each channel by disconnecting its corresponding electrode and observing the wave pattern. As a result of disconnecting the electrodes one by one, it was observed that a waveform was generated for all channels respectively when their corresponding electrode was disconnected.

During the ground zero test, the wave pattern for channels Fp1, Fp2, C3 and C4 showed different behavior. Logically, all waves had to be straight but abnormalities in wave patterns for channels Fp1, Fp2, C3 and C4 were detected when all electrodes were connected as shown in figure. When the corresponding electrodes for channels Fp1, Fp2, C3 and C4 were disconnected respectively, the waveform was still the same. It was also observed that whenever any of these channels was disconnected, it had an impact on the waveforms of other channels i.e. other channels did not have straight line and showed a random, low amplitude waveform. The impedance feature was also utilized for further verification. Logically, the impedance had to be the same for all channels. However, the channels Fp1, Fp2, C3 and C4 had a very high impedance value. The impedance test conducted showed following results:

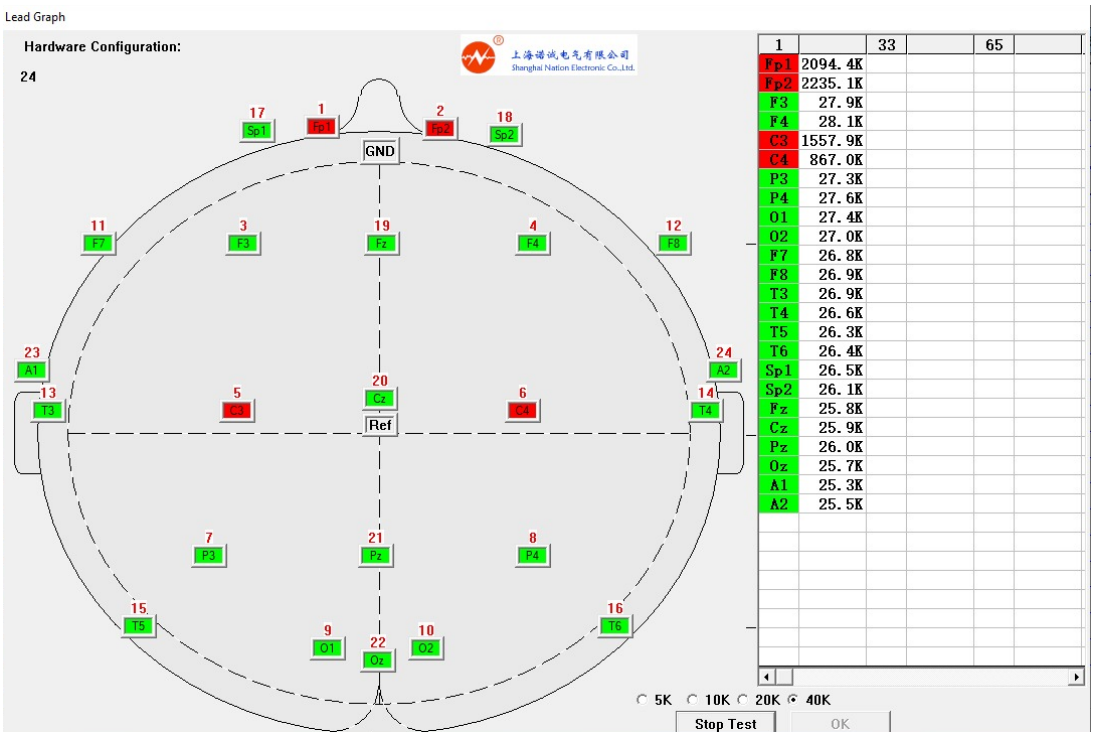


Figure 5.6: Impedance behavior for Fp1, Fp2, C3 and C4 while ground is connected.

The ground electrode was disconnected to check for any impact on all channels. Logically all channels should have a high impedance value. However, the channels Fp1, Fp2, C3 and C4 had a very low impedance value. These values are like the impedance values whenever any EEG experiment is conducted. The impedance results while ground is disconnected is shown on the next page:

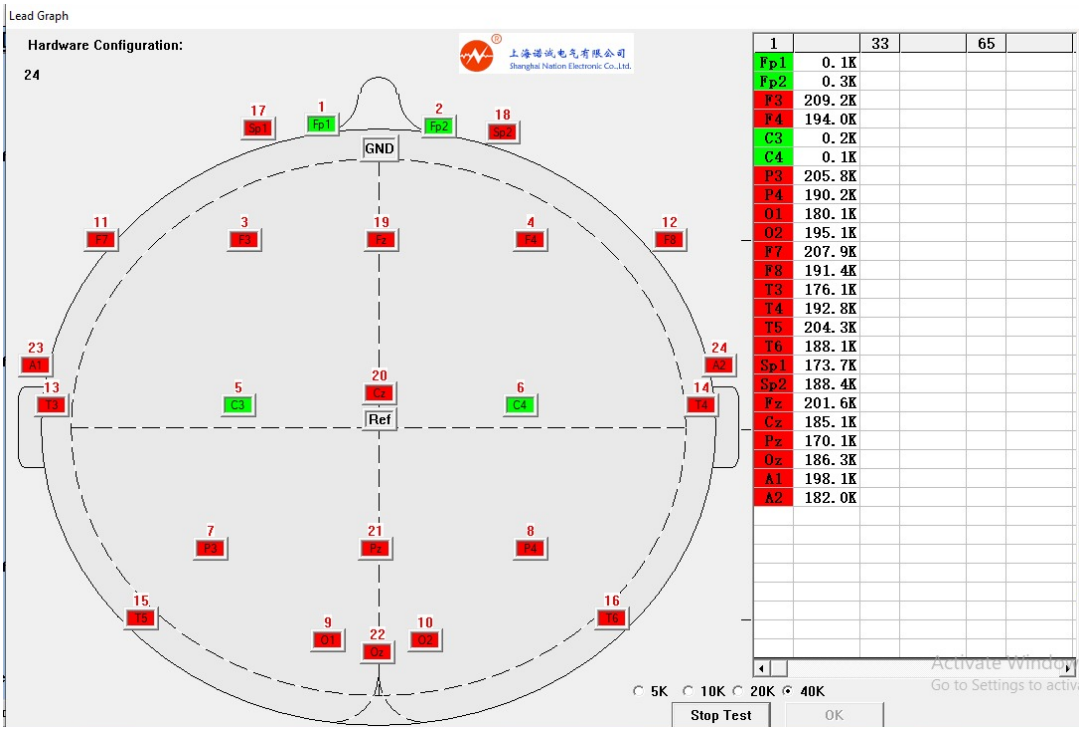

Figure 5.7: Impedance behavior for Fp1, Fp2, C3 and C4 while ground is disconnected.

From these observations, it was concluded that there is an issue within master box and a high probability that the amplifier is malfunctioning. There is also a possibility that the amplifier IC pins dedicated for the channels Fp1, Fp2, C3 and C4 are not able to detect and amplify the signals for these channels and greatly impact the signals for other channels. Finally, we can conclude that there is no problem with the EEG caps and software compatibility.

## 5.2. Data Acquisition, Processing and Analysis

After resolving the maximum issues possible within the EEG equipment, the EEG data was collected for determining the brain cognitive activity within the prefrontal region and processing was done to determine the efficiency. The details of the EEG experiment and its protocol will be discussed in this section. This section also provides the results of preprocessed EEG data and afterwards the efficiency of the EEG data using machine learning models.

Before moving on to the data analysis, we will briefly discuss the testing paradigm and the protocol design for brain data acquisition. The protocol refers to the steps or series of events that should be followed by the test subject during the brain data acquisition process. The protocol must be made clear to the test subjects so that accurate brain data acquisition is possible. The data acquisition was conducted for the prefrontal region. The protocol followed for EEG data that has been analyzed is given below:

- Rest
- Pre-massage Test
- Massage
- Post-massage test
- Rest

The channels used for data acquisition were Fp1, Fp2, F3, F4, F7, F8, Sp1, Sp2 and Fz. These channels are also highlighted in figures.

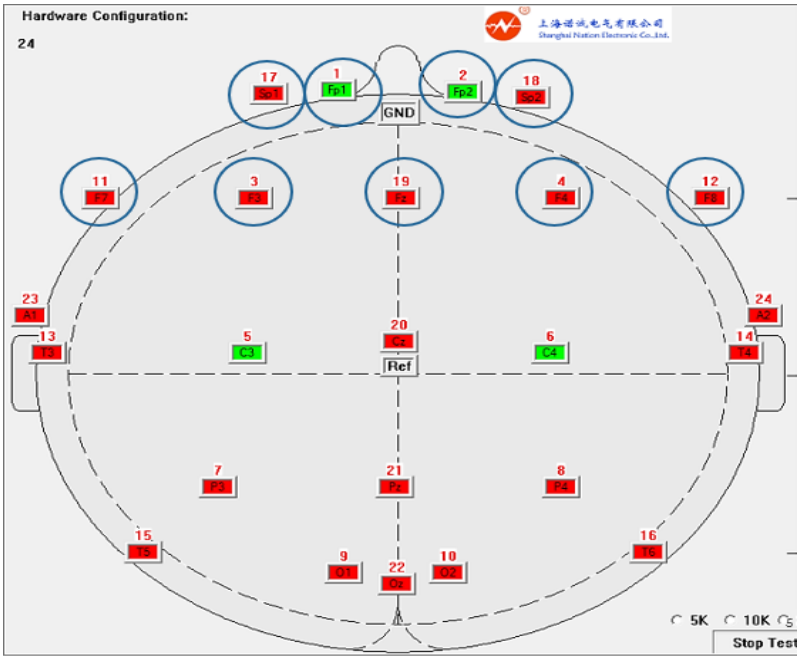


Figure 5.8: Channels selected for data acquisition.

Optimum environmental conditions and testing parameters were ensured for the acquisition of EEG data. After the acquisition of EEG data for the desired channels, the next step is the EEG data processing. This is done to extract meaningful insights and features from the data. The steps involved in EEG data processing are shown below:


Figure 5.9: Steps for processing EEG data

### 5.2.1. EEG Data Filtering

The raw EEG data was collected according to the protocol and EEG data files were converted to csv format so that these can be processed and analyzed. For the brain signals, there are four frequency bands that also reflect the active state of the brain:

- Delta (0.5-4 Hz): Typically associated with deep sleep.
- Alpha (8-13 Hz): Related to relaxed, calm, and meditative states.
- Beta (13-30 Hz): Associated with active thinking, focus, and problem-solving.
- Gamma (30-100 Hz): Linked to high-level cognitive processing and consciousness.

The desired frequency bands were alpha and beta. To extract the maximum data, the raw EEG data was filtered using bandpass filter of 0.5-30 Hz. The data from all desired channels was filtered separately for pre massage. This is shown in a series of subsequent figures below:

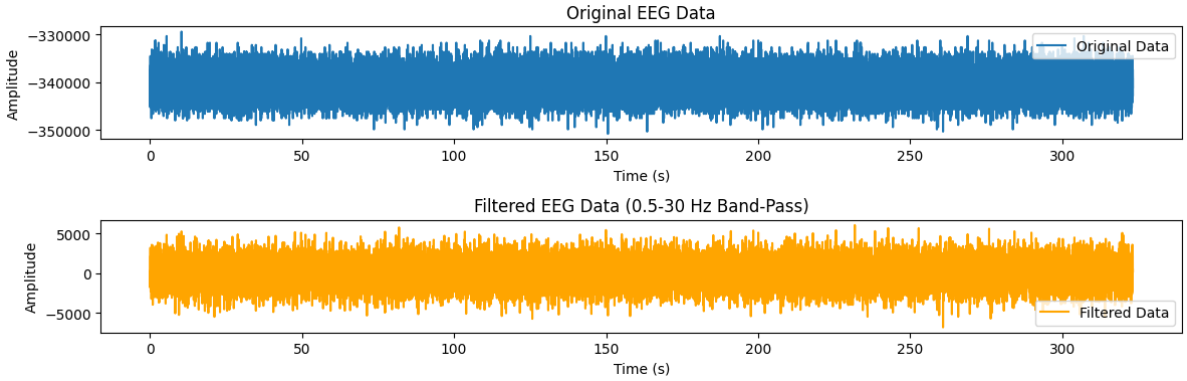


Figure 5.10: Original vs filtered data for Fp1 before massage.

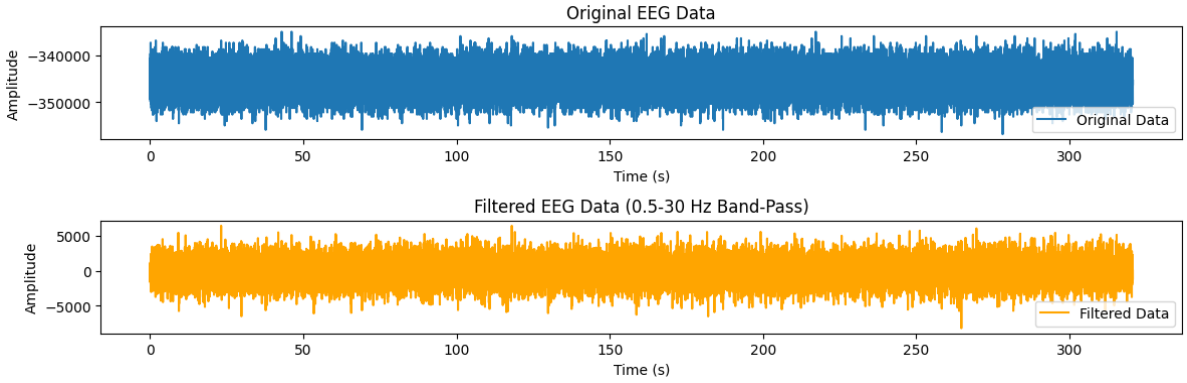


Figure 5.11: Original vs filtered data for Fp2 before massage.

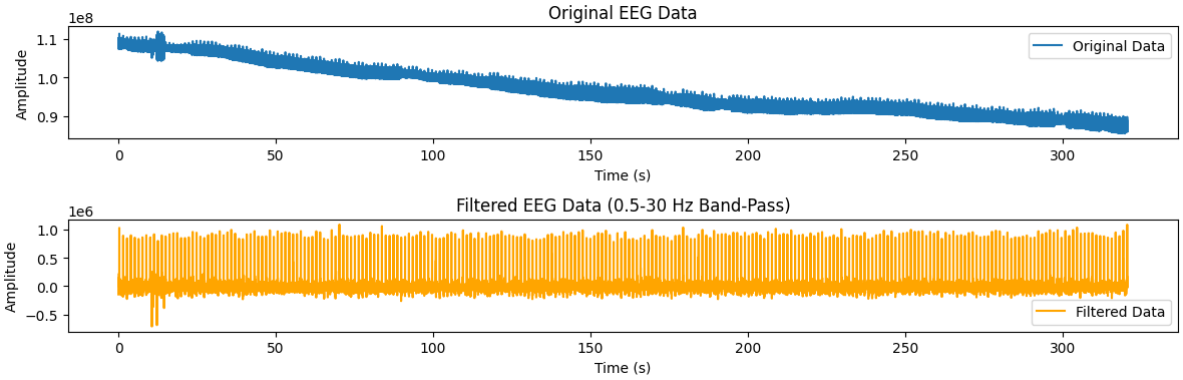


Figure 5.12: Original vs filtered data for F3 before massage.

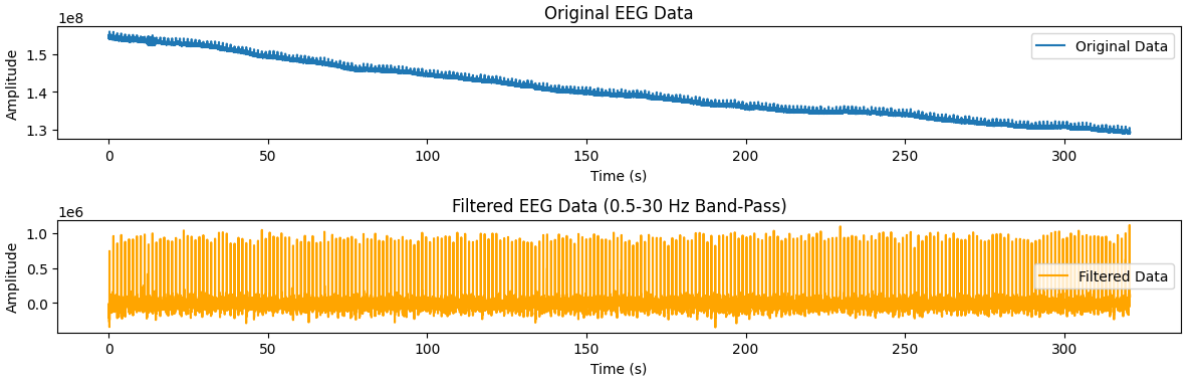


Figure 5.13: Original vs filtered data for F4 before massage.

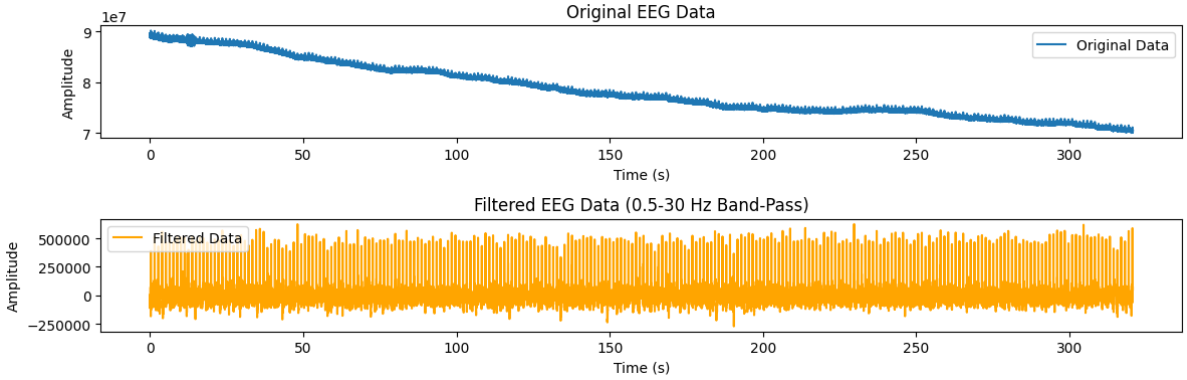


Figure 5.14: Original vs filtered data for F7 before massage.

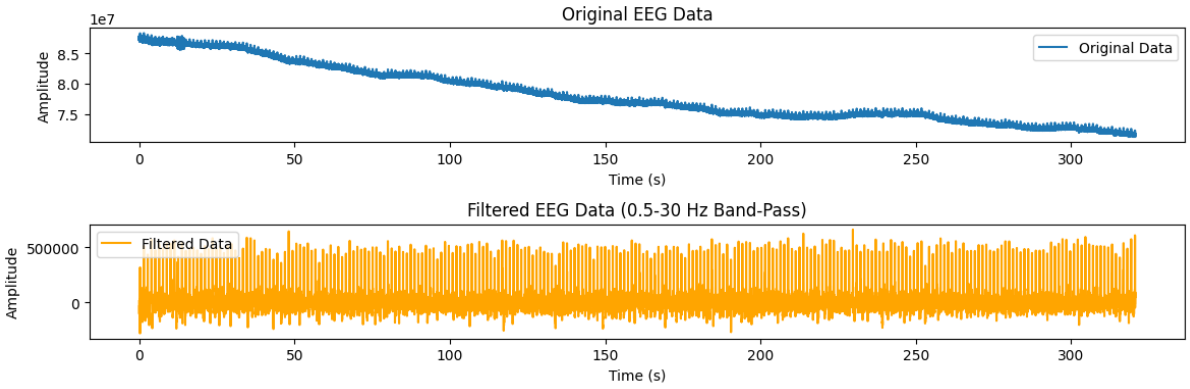


Figure 5.15: Original vs filtered data for F8 before massage.

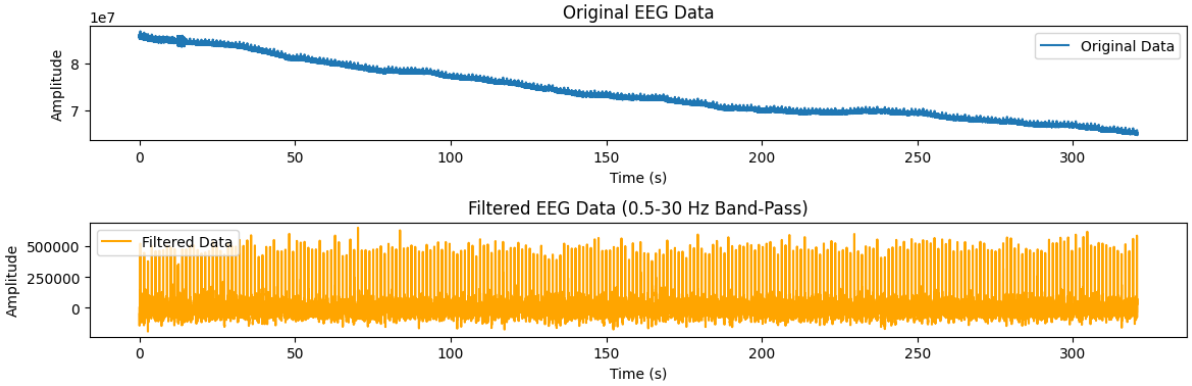


Figure 5.16: Original vs filtered data for Sp1 before massage.

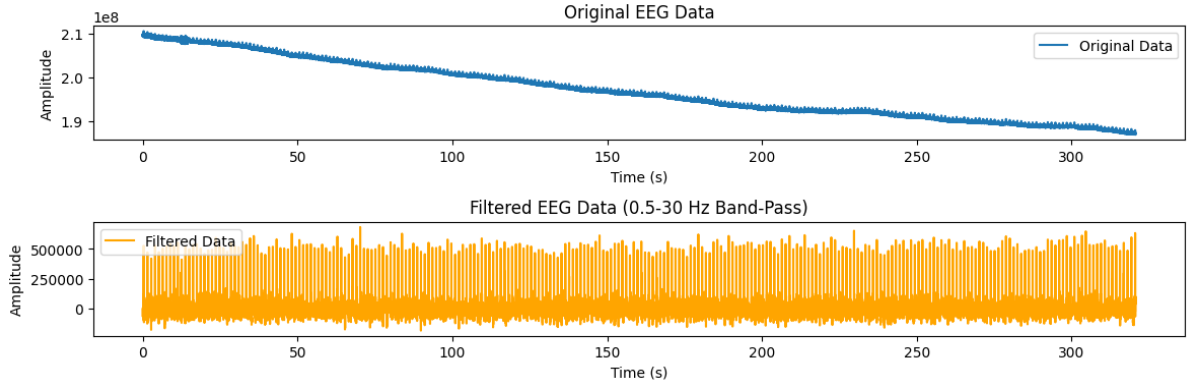


Figure 5.17: Original vs filtered data for Sp2 before massage.

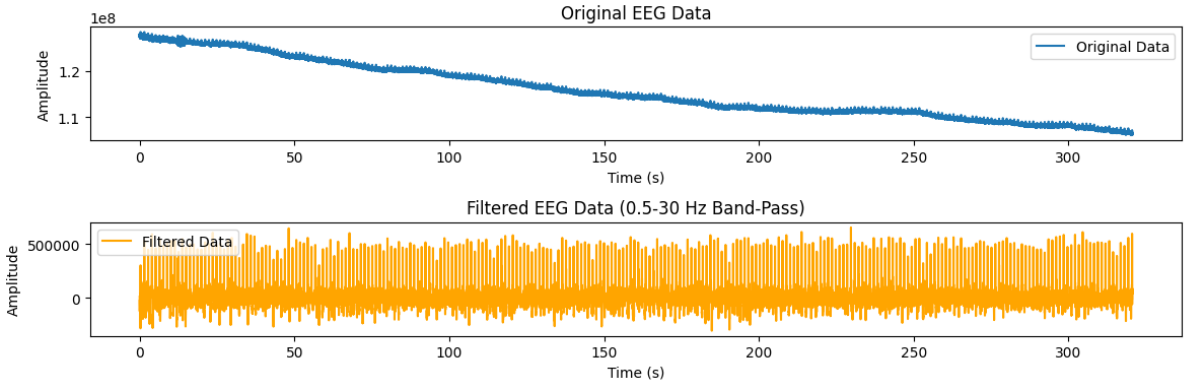


Figure 5.18: Original vs filtered data for Fz before massage.

The data from all desired channels was also filtered separately for post massage test. This is shown in a series of subsequent figures below:

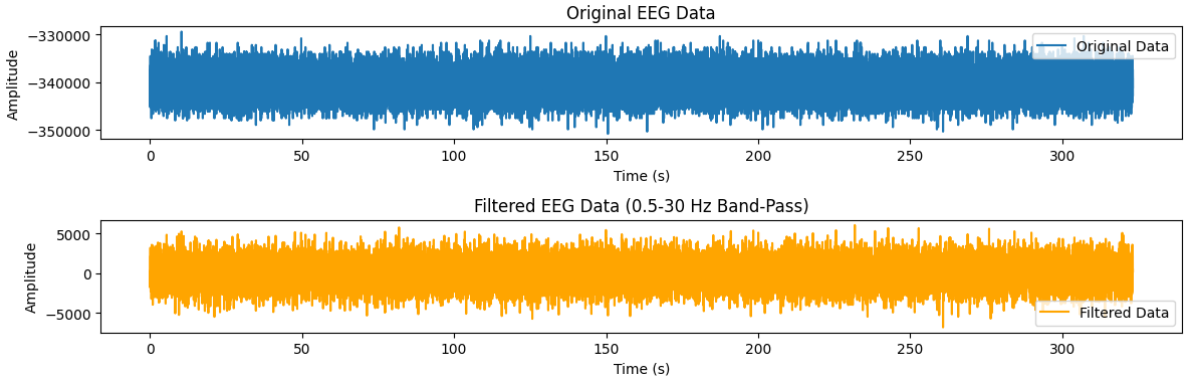


Figure 5.19: Original vs filtered data for Fp1 after massage.

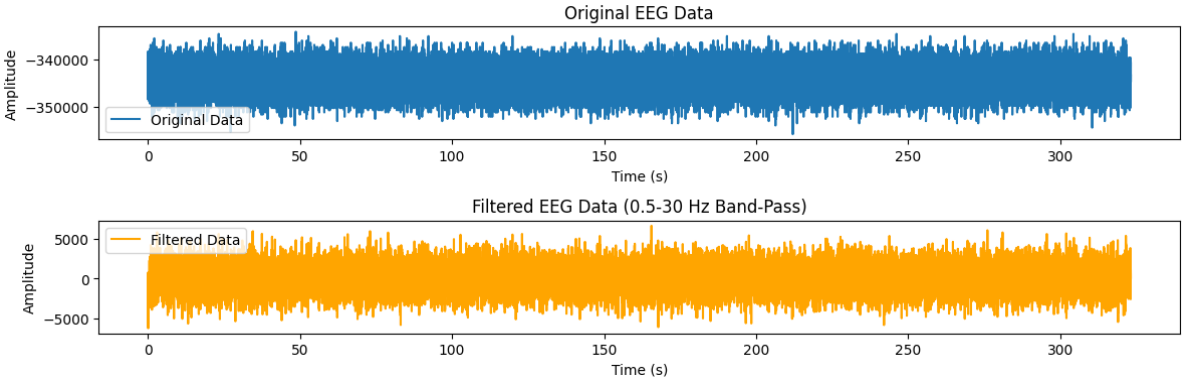


Figure 5.20: Original vs filtered data for Fp2 after massage.

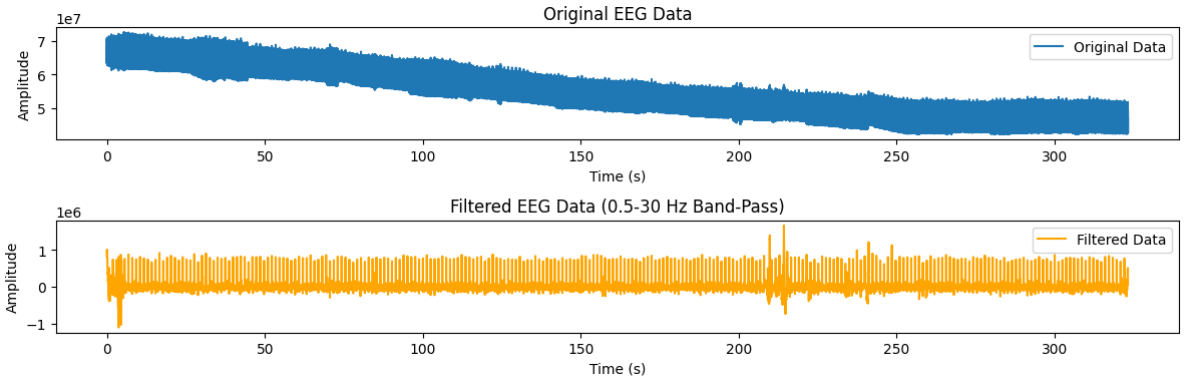


Figure 5.21: Original vs filtered data for F3 after massage.

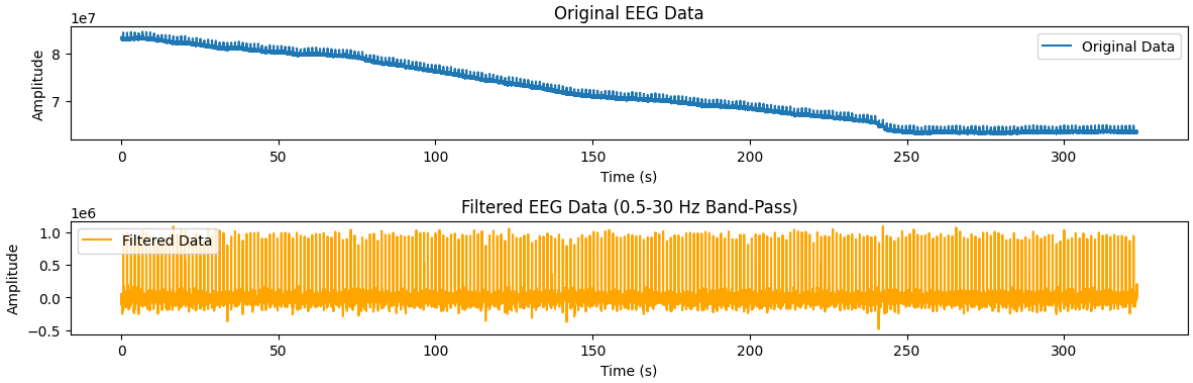


Figure 5.22: Original vs filtered data for F4 after massage.

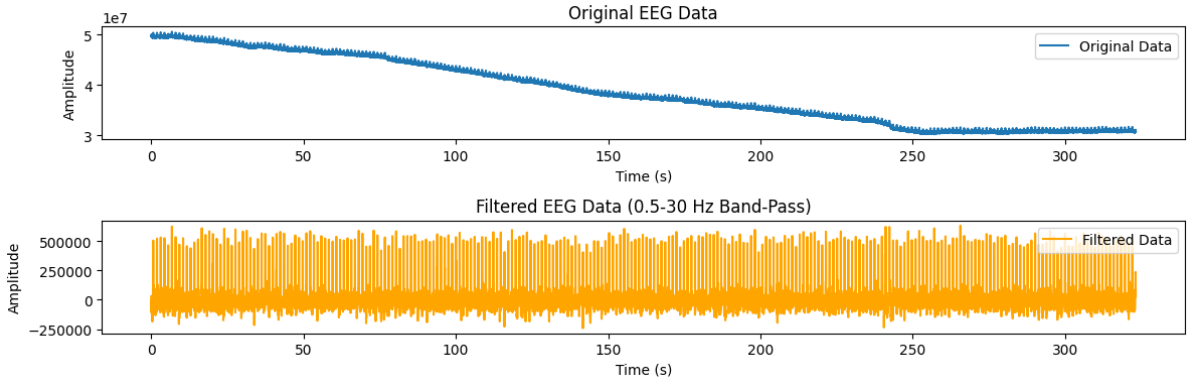


Figure 5.23: Original vs filtered data for F7 after massage.

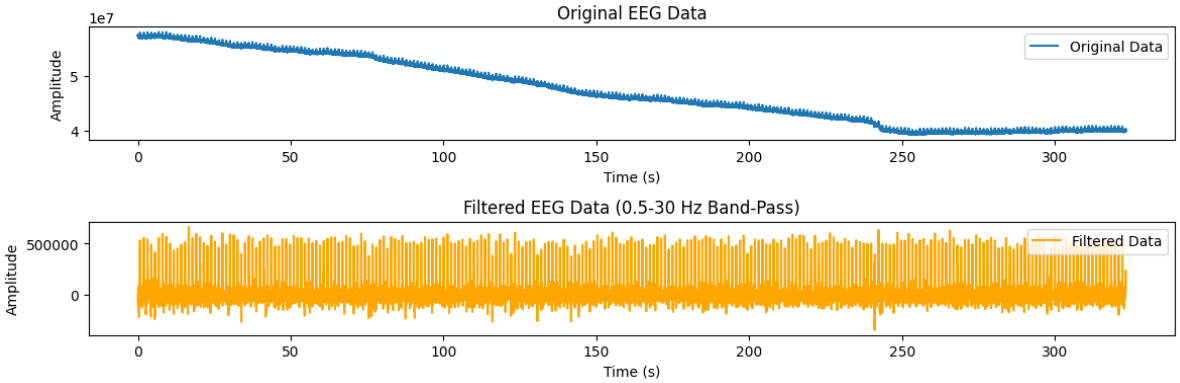


Figure 5.24: Original vs filtered data for F8 after massage.

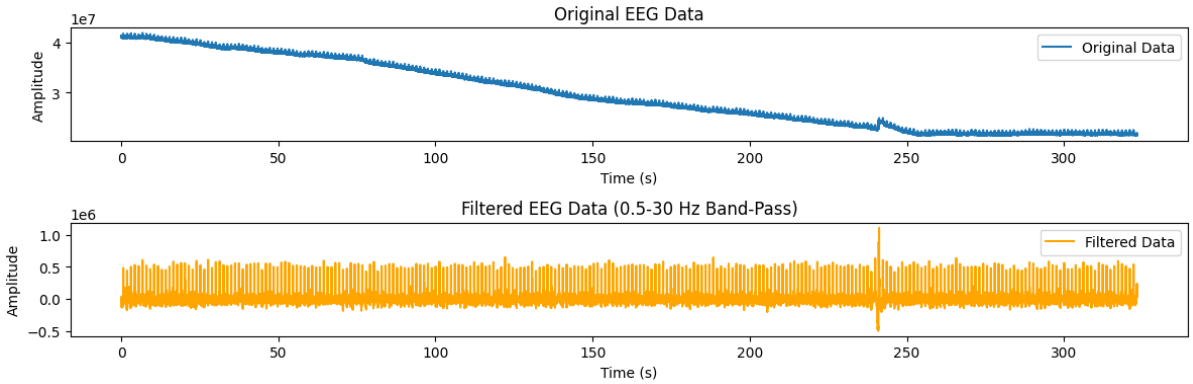


Figure 5.25: Original vs filtered data for Sp1 after massage.

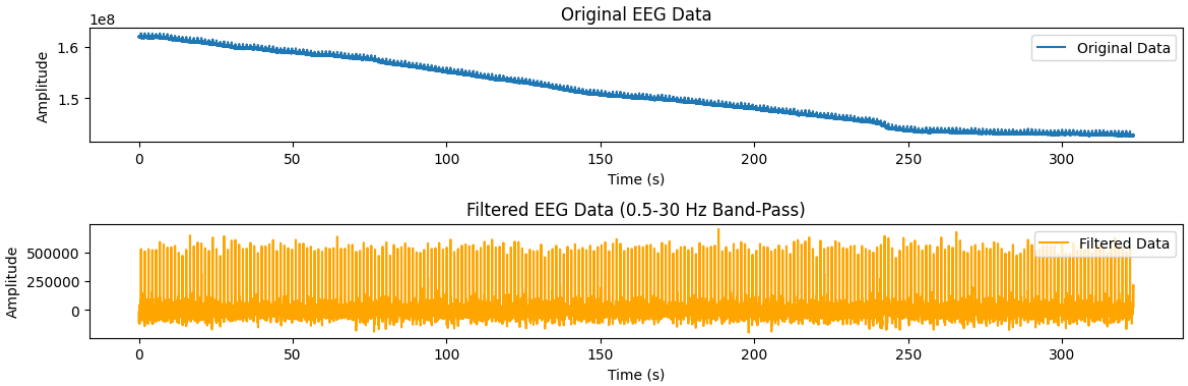


Figure 5.26: Original vs filtered data for Sp2 after massage.

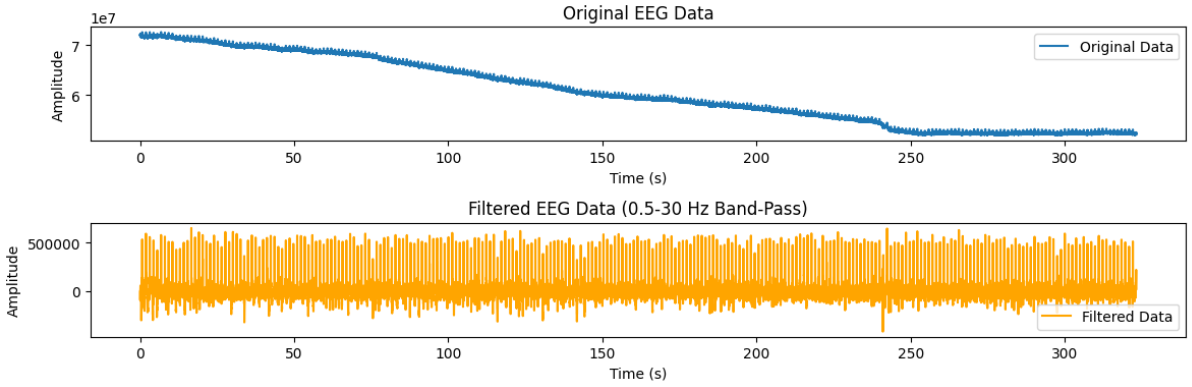


Figure 5.27: Original vs filtered data for Fz after massage.

### 5.2.2. Frequency domain analysis

The frequency domain analysis provides insights about the dominant frequencies and their distribution within the EEG data. It is done by using Fast Fourier Transform (FFT). The FFT converts time-domain EEG signals into frequency domain. This transformation indicates different frequency bands present in the EEG signals. After filtering EEG data, FFT was applied on the EEG data of each channel respectively. The results are shown in a subsequent series of figures below:

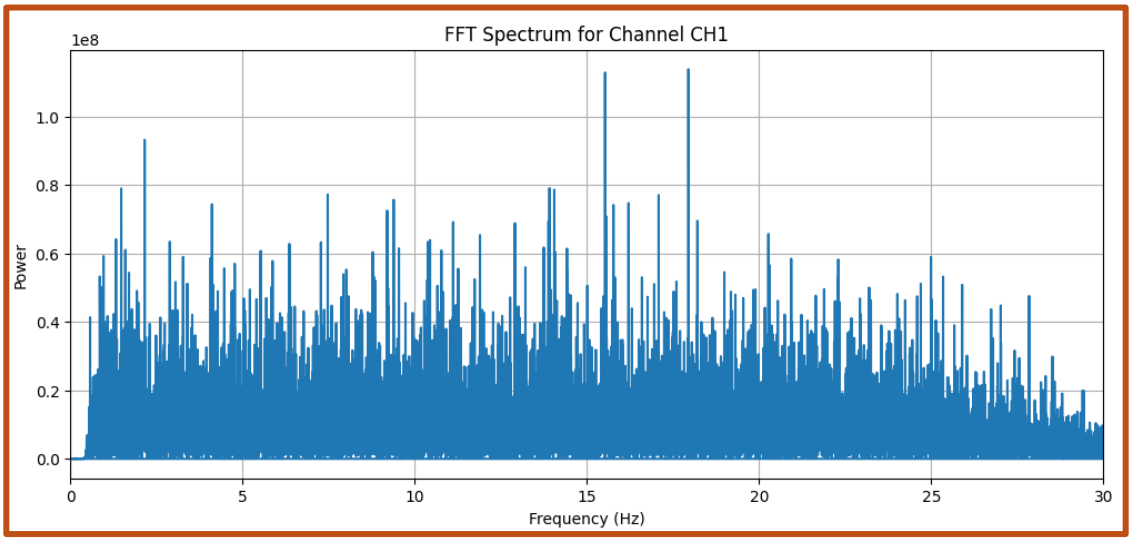


Figure 5.28: FFT for Fp1

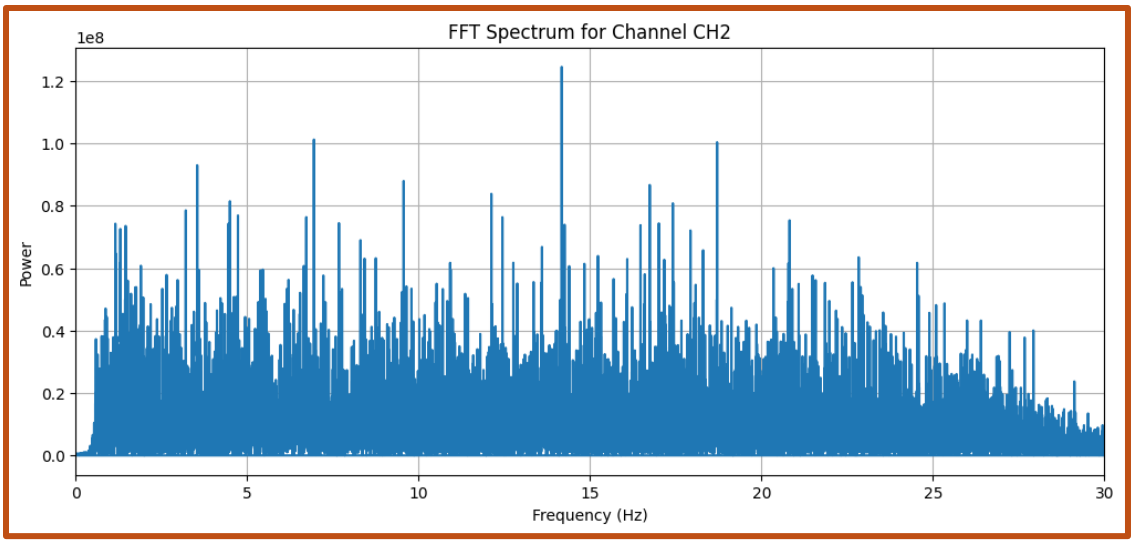


Figure 5.29: FFT for Fp2

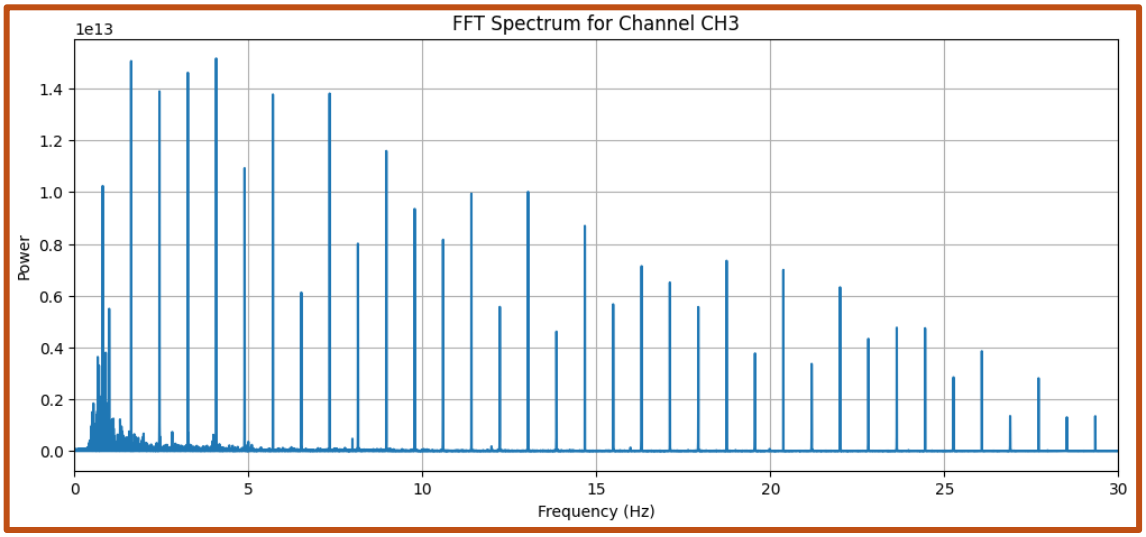


Figure 5.30: FFT for F3

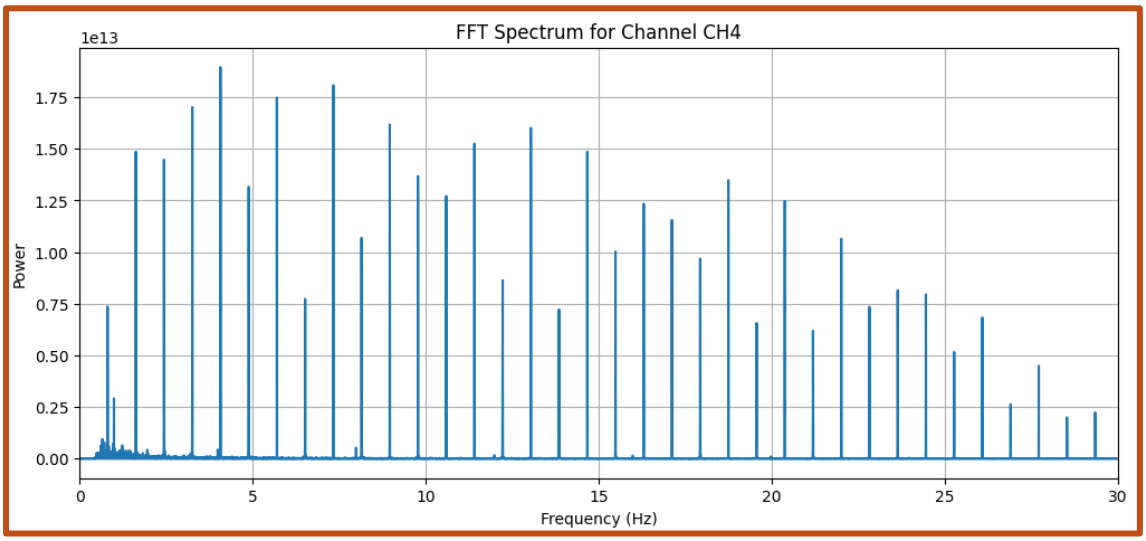

Figure 5.31: FFT for F4

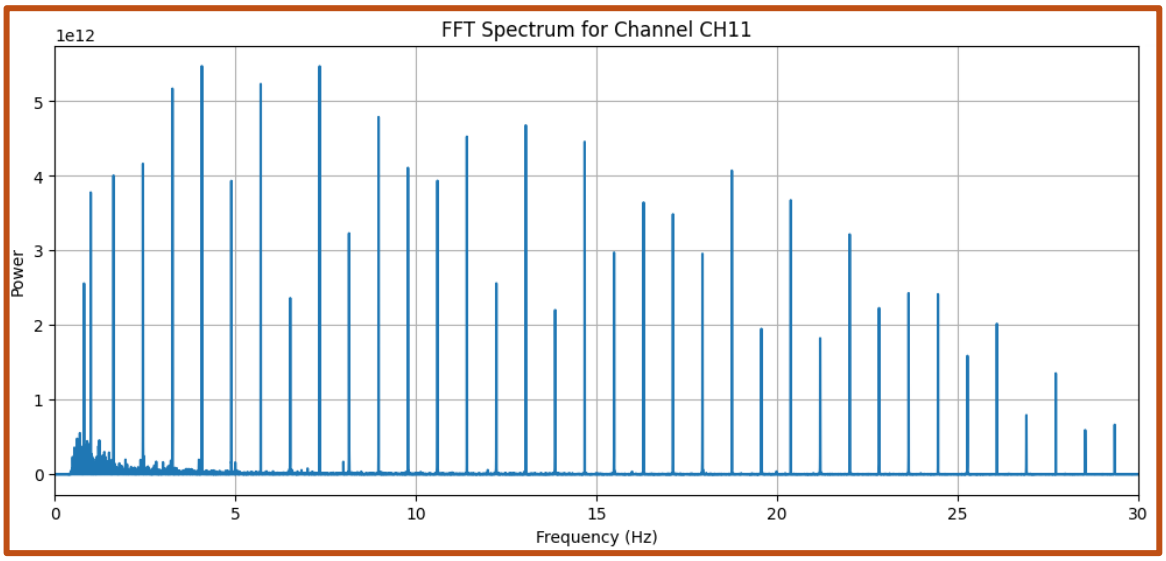


Figure 5.32: FFT for F7

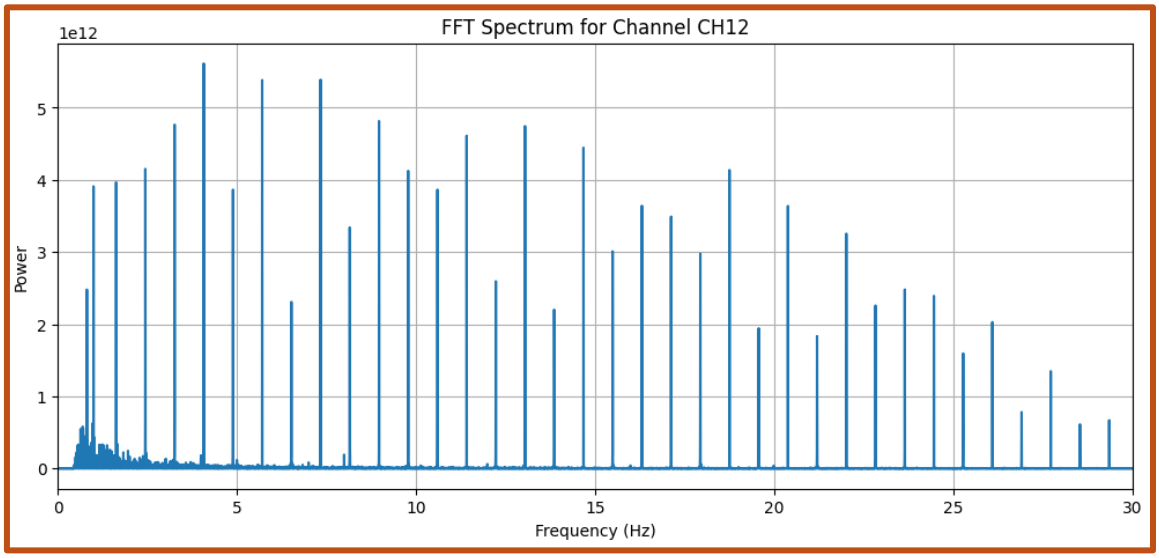


Figure 5.33: FFT for F8

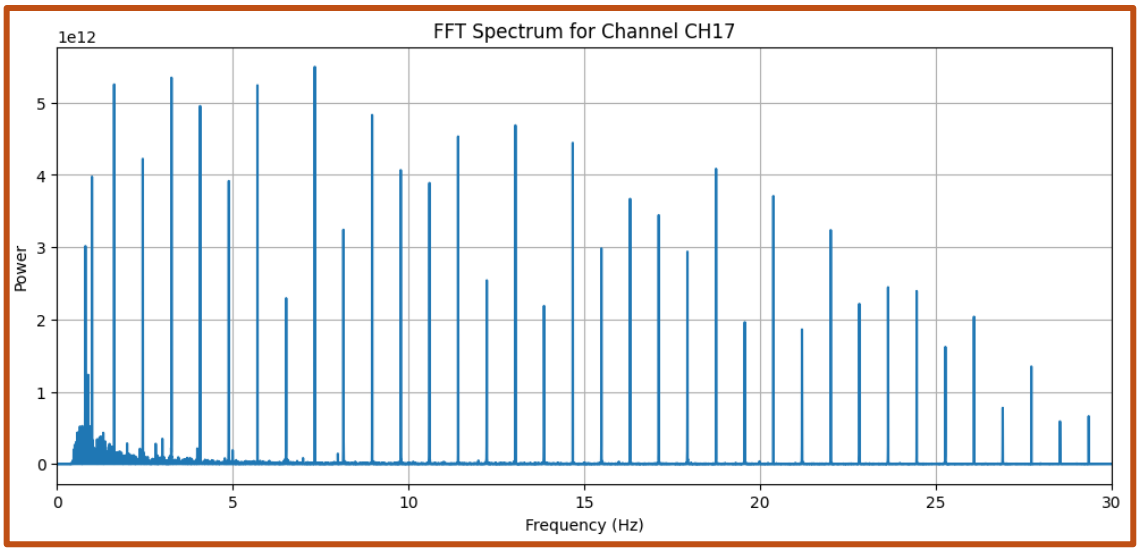

Figure 5.34: FFT for Sp1

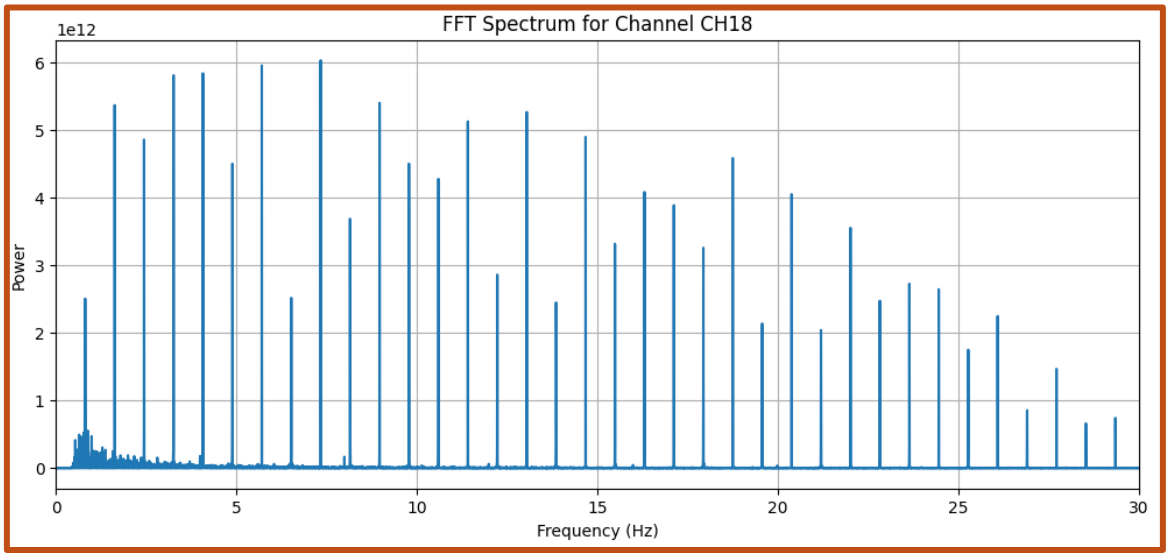

Figure 5.35: FFT for Sp2

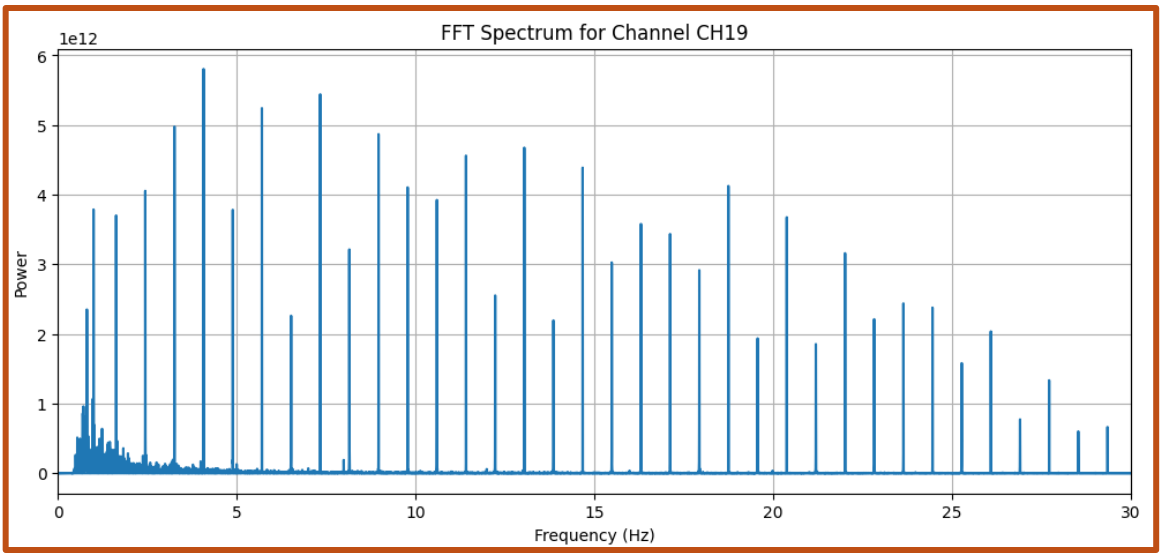

Figure 5.36: FFT for Fz

### 5.2.3. Statistical and time domain features of the EEG data

After performing the frequency domain analysis of the EEG data, a time domain analysis was also performed for extracting the statistical and time domain features from EEG data of desired channels. These features include:

- Mean: It is the average value of an EEG signal within a specific time frame.
- Variance: It indicates the signal variation within EEG data.
- Kurtosis: It indicates outliers and sharp spikes in the EEG data.
- Skewness: It indicates the direction of deviation from mean.
- Root mean square (RMS): It is the measure of amplitude of EEG signals.
- Zero Crossings: It refers to the number of times the EEG signals crosses baseline level.

The results for statistical and time domain features of the EEG data are shown in a subsequent series of figures below:

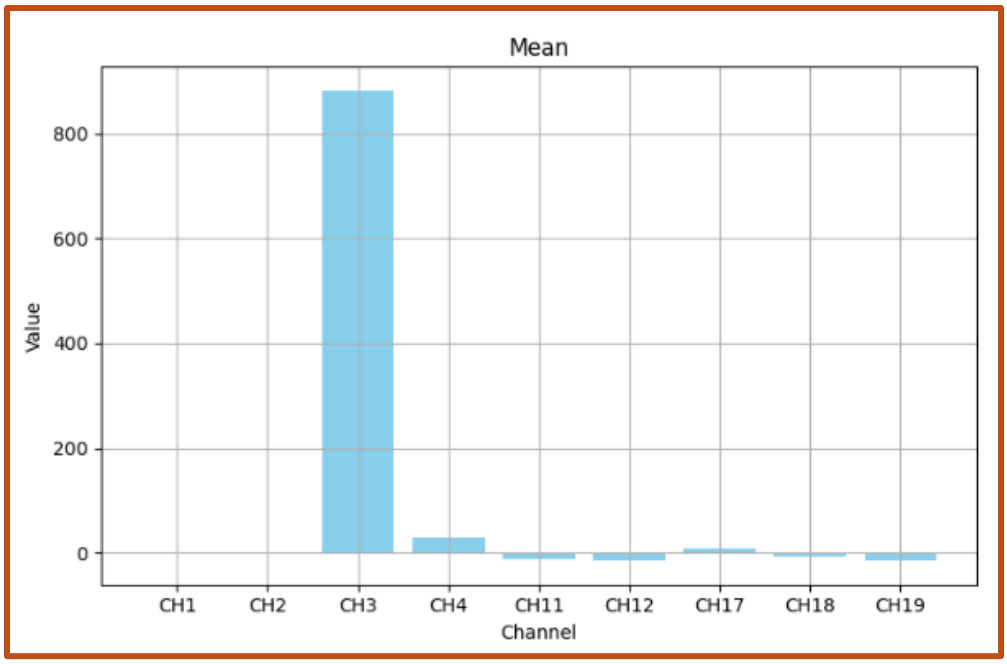


Figure 5.37: Mean for EEG data.

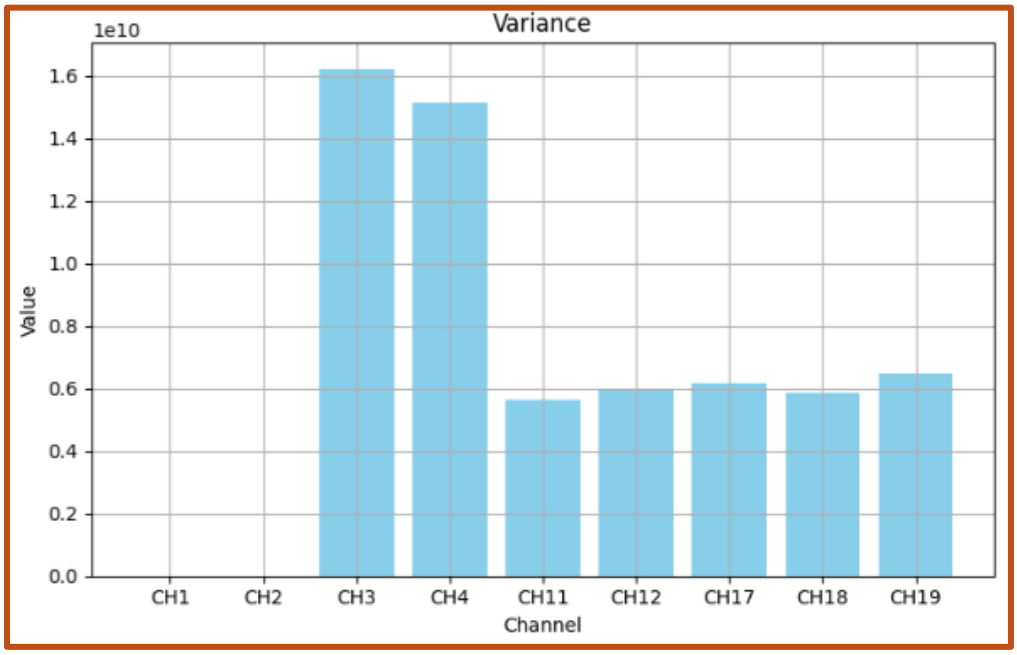


Figure 5.38: Variance within EEG data

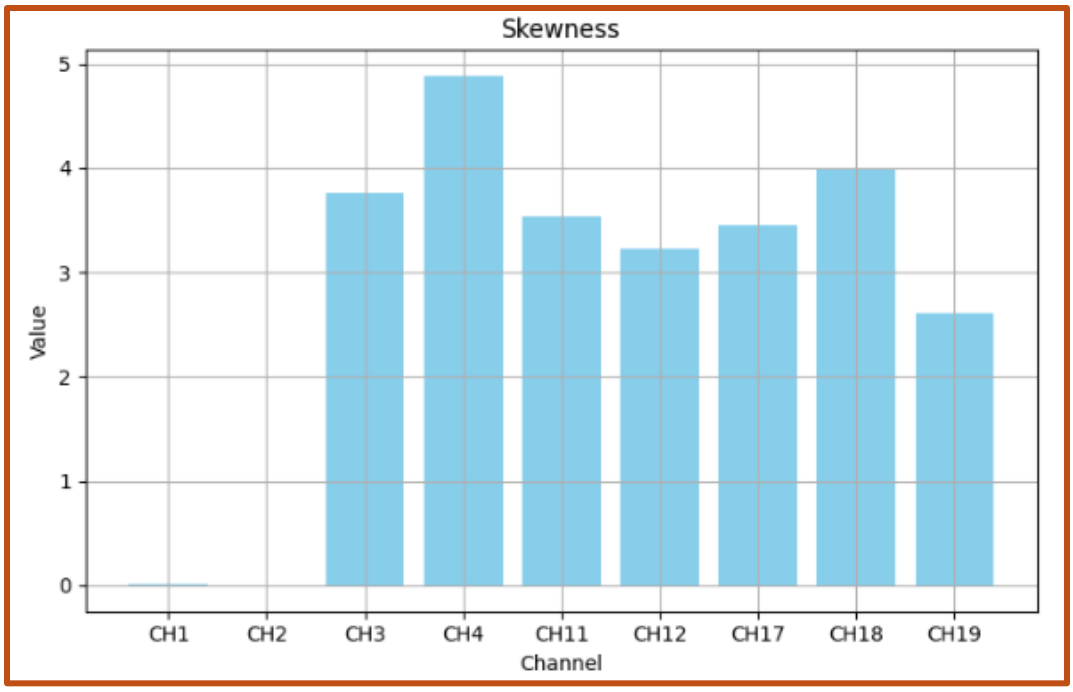

Figure 5.39: Skewness for EEG data

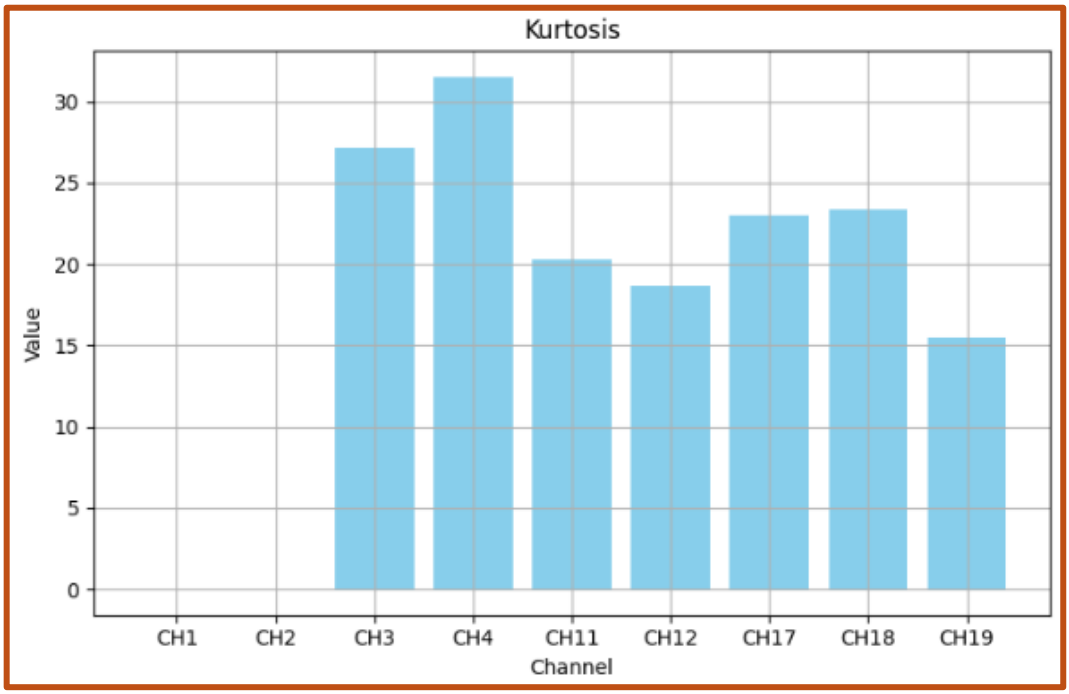

Figure 5.40: Kurtosis for EEG data

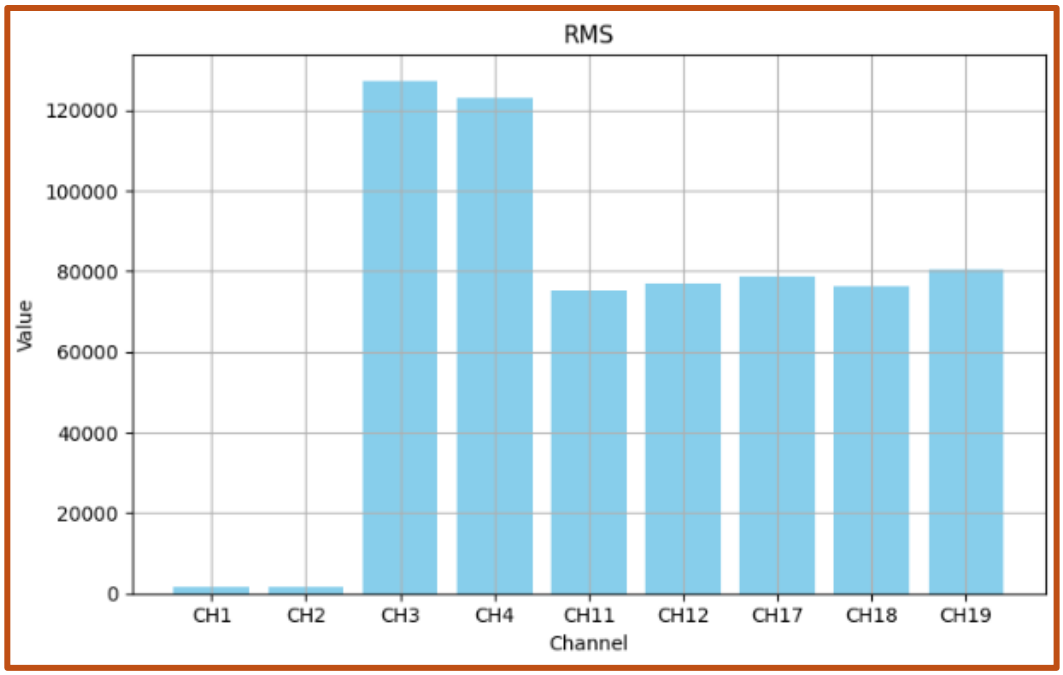

Figure 5.41: RMS for EEG data

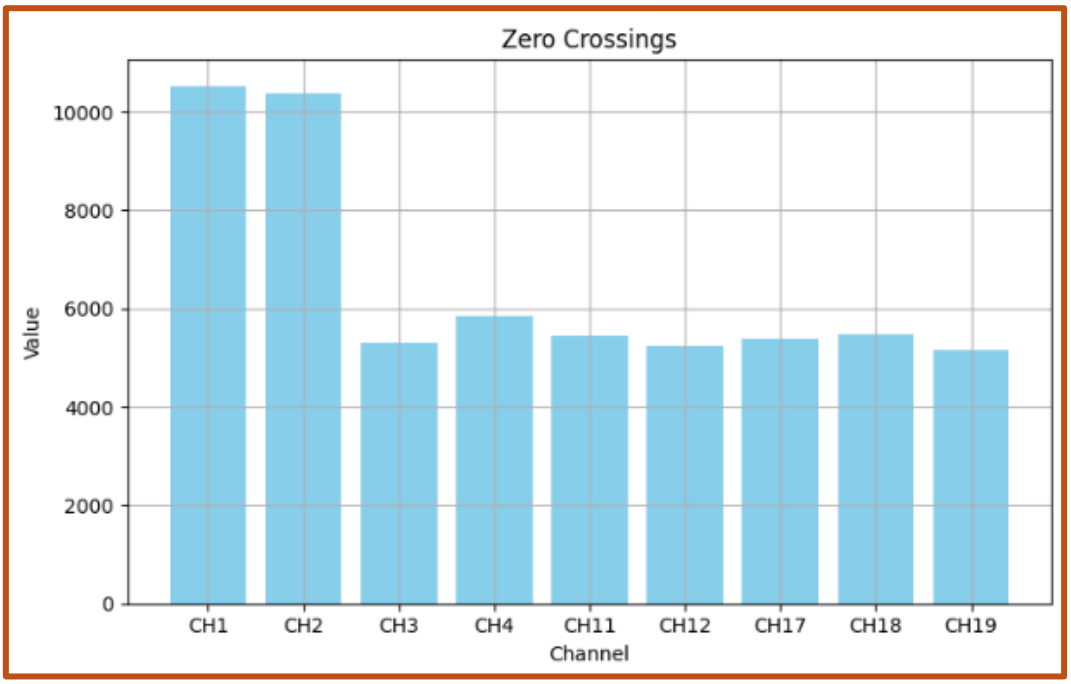

Figure 5.42: Zero crossings within EEG data

From the statistical results, it was concluded that:

- Channel F3 shows distinct characteristics with a high mean, high variance, high skewness, high kurtosis, and high RMS which indicates strong, variable, and asymmetric signal activity with potential transient spikes. This might indicate the presence of artifacts or significant brain activity in this region.

- Channel F4 has high variance, skewness, kurtosis, and RMS which indicates similarity with signal properties of channel F3.
- Channels Fp1 and Fp2 have high zero crossings but low other statistical measures which indicates high-frequency activity but with low amplitude and variability.
- Channels F7, F8, Sp1, Sp2 and Fz have moderate values for most of the statistical features which indicate moderate signal amplitude.

### 5.2.4. Analysis using machine learning models

After performing the preprocessing, frequency domain and time domain analysis, the next step is to analyze the EEG data using machine learning models. There are many machine learning models such as:

- Support Vector machine (SVM)
- Random Forest (RF)
- Linear Discriminant Analysis (LDA)
- Naive bayes
- KNN, RNN, CNN
- Regression
- Independent Component Analysis (ICA)

For our dataset, following machine learning models will be used:

- Support Vector machine (SVM)
- Random Forest (RF)
- Linear Discriminant Analysis (LDA)

#### 5.2.4.1. Support Vector machine (SVM)

The support vector machine is a supervised machine learning algorithm generally used for regression and classification of dataset. This algorithm works by identifying the best and optimal hyperplane that separates the data points of different classes within a dataset. The EEG data classification using SVM was done in following steps:

1. **Training Phase:** The SVM classifier learned a decision boundary that best separates the two classes (Fatigued and Non-Fatigued) based on the training data. In our case, the Support Vector Classifier was trained on the labelled training data.
2. **Prediction Phase:** For each data point in the test set, the trained SVM model predicted the class (Fatigued or Non-Fatigued) by determining which side of the decision boundary the data

point falls on.

3. **Evaluation Phase:** The predicted labels were compared to the actual labels in the test set to compute the evaluation metrics which provided insight into how well the model performed in distinguishing between Fatigued and Non-Fatigued data. After evaluation, the trained model predicted labels for the unlabeled data.

The working of SVM model for EEG data can be represented as:

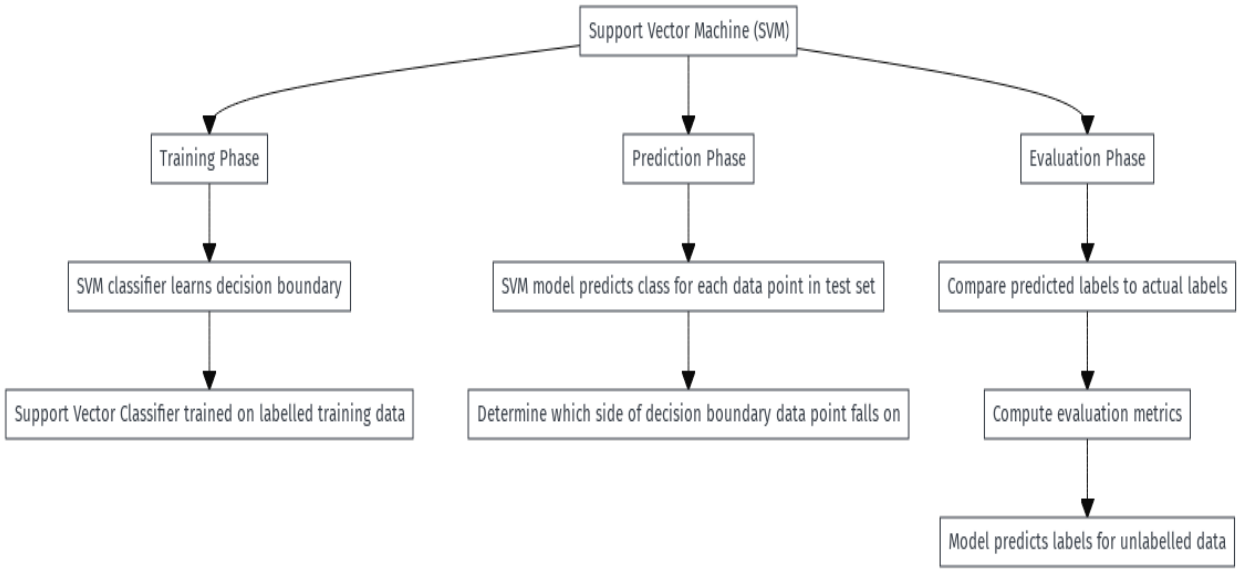


Figure 5.43: Flow chart for SVM algorithm

After following these steps, the SVM model predicted accuracy on labelled data as 98% as shown in the figure below:

```
Model Accuracy on Validation Set: 100.00%
Predicted Labels for Unlabeled Data:
[0 0 0 ... 0 0 0]
Model Accuracy on Unlabeled Data: 98.01%
```

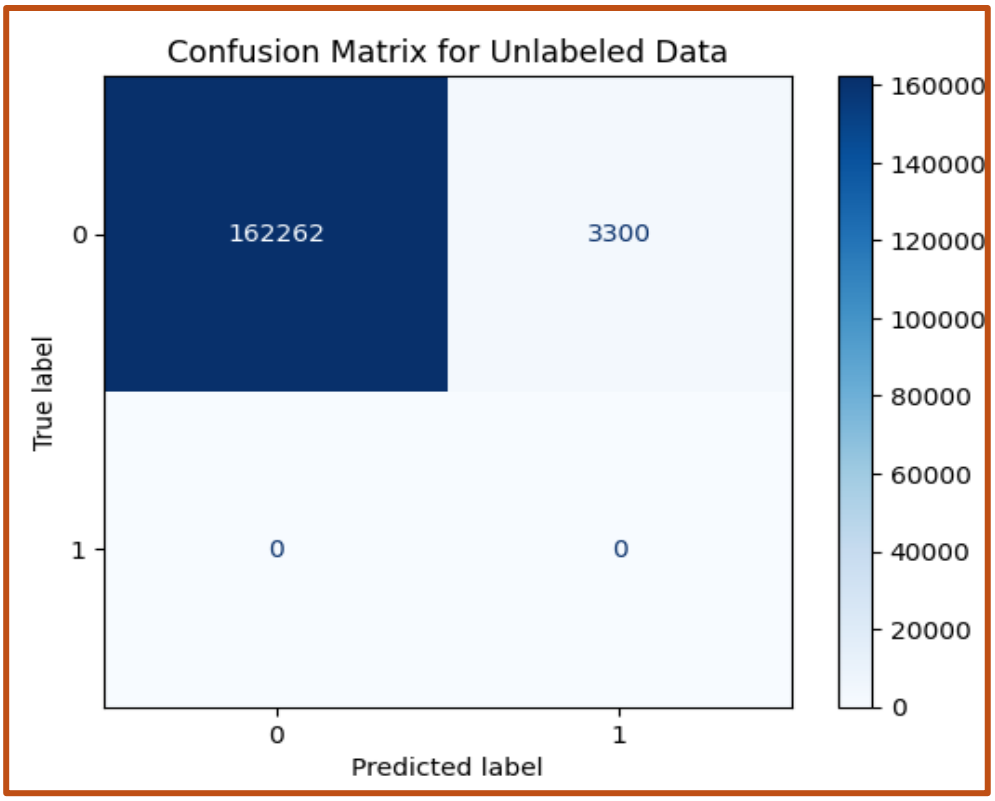

Figure 5.44: Model efficiency (top) and confusion matrix (bottom) by SVM algorithm

From above figure, we can conclude that:

- There are 162262 instances where the actual class was non-fatigued, and the model correctly predicted non-fatigued.
- There are 3300 instances where the actual class was non-fatigued, but the model incorrectly predicted Fatigued.
- There are 0 instances where the actual class was Fatigued but the model incorrectly predicted non-fatigued.
- There are 0 instances where the actual class was Fatigued, and the model correctly predicted Fatigued.

### 5.2.4.2. Random Forest (RF)

The Random Forest (RF) is an effective machine learning model which operates by constructing multiple decision trees during training and combines their output to improve predictive accuracy and control overfitting. It is widely used for classification and regression. This algorithm is also used to analyses the EEG data and predict the data accuracy. The working of Random Forest model for EEG data can be represented as:

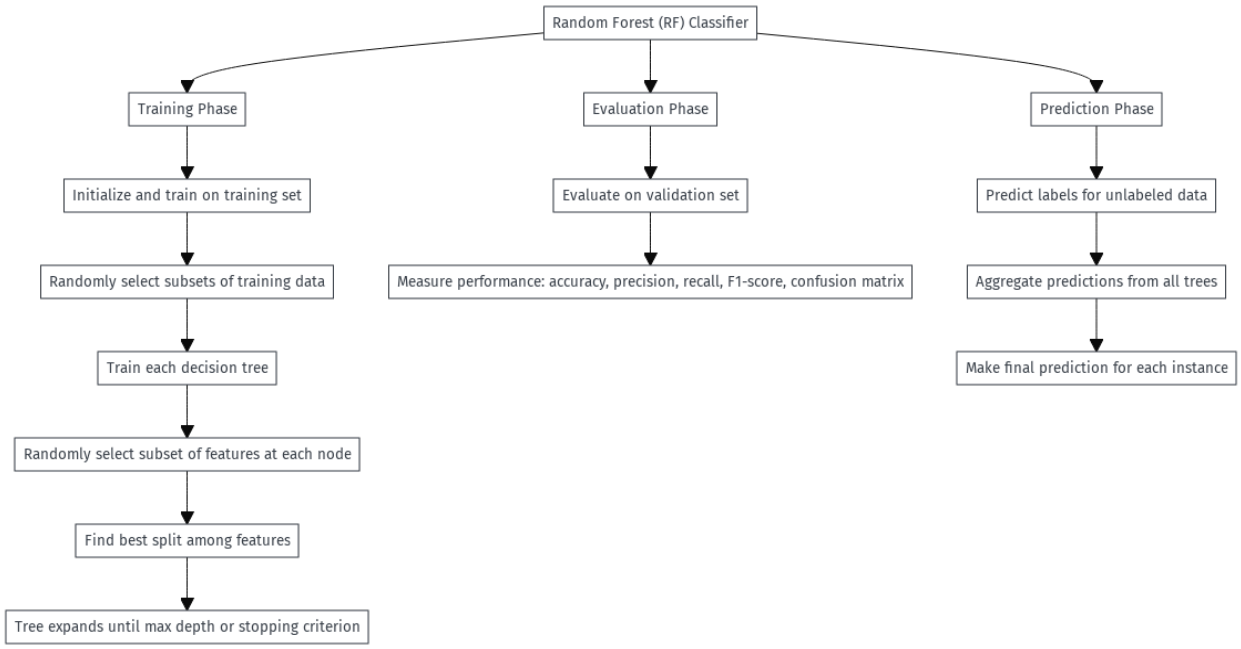


Figure 5.45: Flow chart for RF algorithm

For analyzing the EEG data, the Random Forest classifier was initialized and trained on the training set. During training, the random forest algorithm randomly selected subsets of the training data to train each decision tree. For each node in the tree, it randomly selected a subset of features and found the best spread among these features. Each tree expanded until it reached the maximum depth or another stopping criterion was met. The trained model was then evaluated on the validation set to check its performance. Metrics like accuracy, precision, recall, F1-score, and confusion matrix were used to measure the model's performance. The trained Random Forest model predicted the labels for the unlabeled data by aggregating the prediction from all individual trees to make a final prediction for each instance in the unlabeled data.

```
Model Accuracy on Validation Set: 100.00%
Predicted Labels for Unlabeled Data:
[0 0 0 ... 0 0 1]
Model Accuracy on Unlabeled Data: 85.83%
```

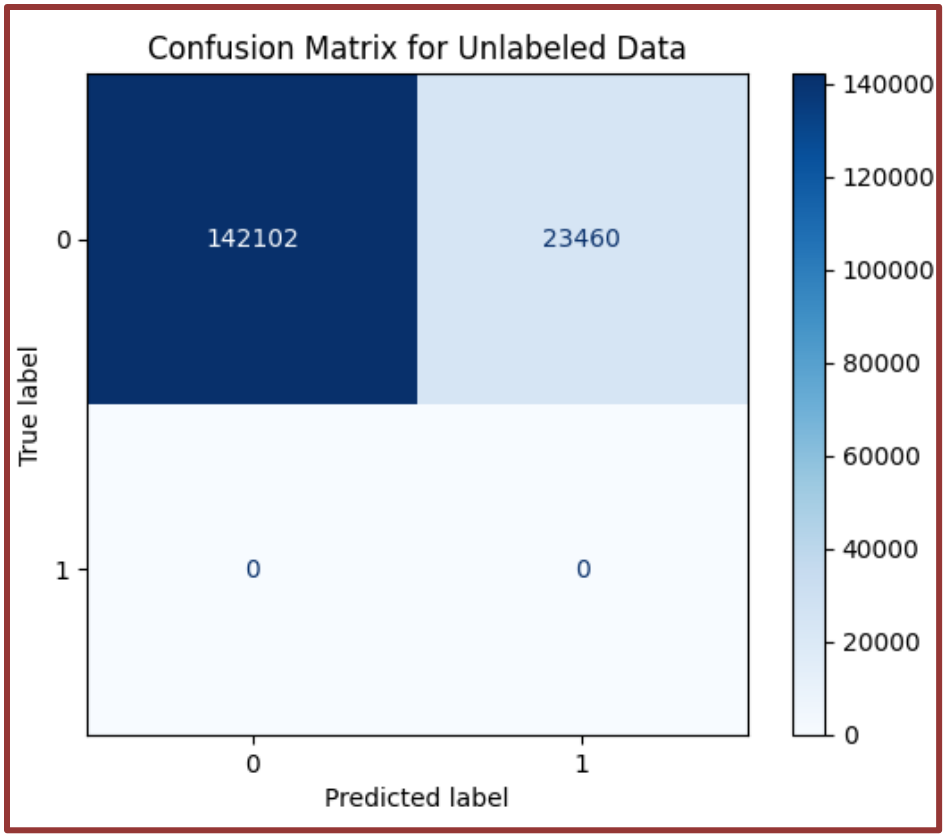

Figure 5.46: Model efficiency (top) and confusion matrix (bottom) by RF algorithm

From above figure, we can conclude that:

- There are 142102 instances where the actual class was non-fatigued, and the model correctly predicted non-fatigued.
- There are 23460 instances where the actual class was non-fatigued, but the model incorrectly predicted Fatigued.
- There are 0 instances where the actual class was Fatigued but the model incorrectly predicted non-fatigued.
- There are 0 instances where the actual class was Fatigued, and the model correctly predicted Fatigued.

### 5.2.4.3. Linear Discriminant Analysis (LDA)

The Linear Discriminant Analysis is a supervised machine learning algorithm which operates by determining the linear combinations of the features that segregate different classes in most effective and optimum way. This algorithm is widely used for classification and dimensionality reduction. The working of LDA model for EEG data can be represented as:

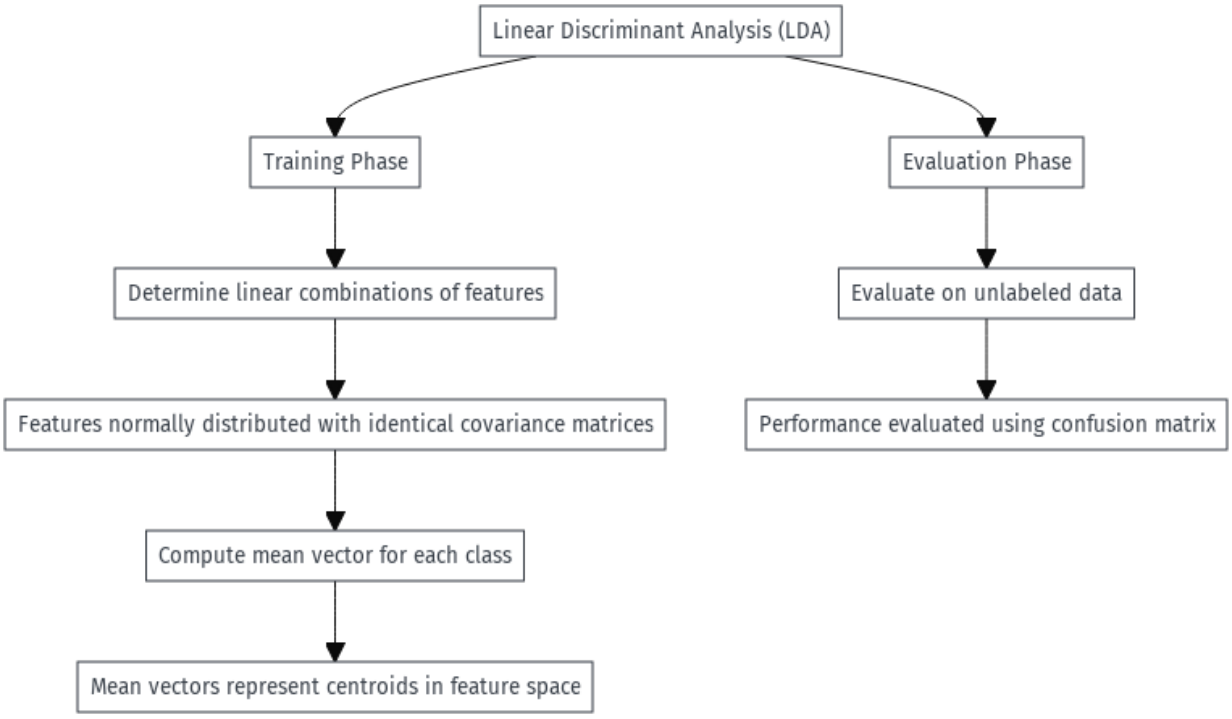


Figure 5.47: Flow chart for LDA algorithm

For analyzing the EEG data, the features in each class were normally distributed and had identical covariance matrices. This means that the features followed a Gaussian distribution and had the same spread across classes. For each class in the training data, LDA computed the mean vector of the feature values. These mean vectors represented the centroids of the classes in the feature space. Once the classifier was trained, it was evaluated for unlabeled data and the model's performance was evaluated in the form of a confusion matrix as shown in the figure below:

```
Model Accuracy on Validation Set: 100.00%
Predicted Labels for Unlabeled Data:
[0 0 0 ... 1 1 1]
Model Accuracy on Unlabeled Data: 29.62%
```

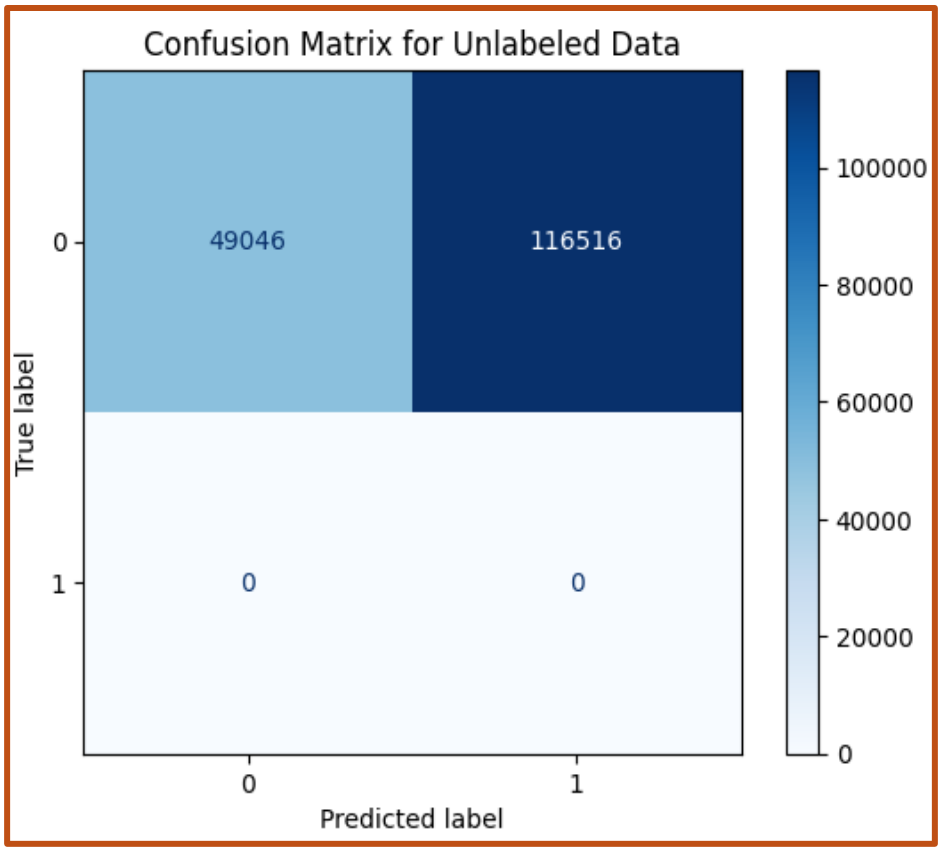

Figure 5.48: Model efficiency (top) and confusion matrix (bottom) by LDA algorithm

From above figure, we can conclude that:

- There are 49046 instances where the actual class was non-fatigued, and the model correctly predicted non-fatigued.
- There are 116516 instances where the actual class was non-fatigued, but the model incorrectly predicted Fatigued.
- There are 0 instances where the actual class was Fatigued but the model incorrectly predicted non-fatigued.
- There are 0 instances where the actual class was Fatigued, and the model correctly predicted Fatigued.

# Conclusion

This project was divided into four deliverables that were accomplished during the completion of this project. The first deliverable was to resolve the technical issues of the available EEG equipment. For this purpose, we contacted the equipment OEM to provide after sale service and assist in finding and resolving unidentified issues within the EEG equipment as mentioned in chapter 4. We conducted different tests to check for any issue within software, electrodes, and the amplifier/master box. During these tests, it was observed that there is no issue within the software and electrode caps. However, the issue exists within the amplifier box, but it was not clear within which component of the amplifier box the issue prevailed. Initially, it was an assumption that the issue lies within the amplifier IC, but it was confirmed by observing the results of impedance and ground zero test afterwards. The data for four channels i.e. Fp1, Fp2, C3 and C4 was found erroneous and had an impact on the EEG signals for other channels. These results were confirmed from OEM and the same conclusions were drawn for the channels mentioned earlier by the OEM R&D when the ground zero and impedance test results were shared with them.

The second deliverable was design of protocols. The data was acquired for three different protocols. The first protocol involved acquisition for SSVEP paradigm and the target region within brain was occipital lobe. The second protocol was followed for emotion capture paradigm and the target brain region was parietal lobe. The third protocol was followed for monitoring the short-term memory and brain cognitive activity and the target brain region was prefrontal lobe. During all these experiments, the protocols were strictly followed, and the instructions were made clear to test subjects so that data could be acquired accurately. Efforts were made to conduct these tests in an optimum environment.

The third deliverable involved data acquisition for these protocols and creation of a data repository for research purposes. The technique for EEG data acquisition is different because the electrodes had to be placed according to the 10-20 measurement system and electrode conduction gel had to be used to ensure contact between electrodes and the scalp. This is explained in chapter 3. Nonetheless, the data was acquired for the brain regions mentioned above while following the protocols. The subjects showed interest, dedication, and consistency for the EEG test. For the first test that involved signal acquisition from occipital region, the data was taken for 5 subjects. For the second test that involved signal acquisition from parietal region, the data was taken for 3 subjects. For the third test that involved signal acquisition from prefrontal region, the data was taken for 5 subjects. However, the data analysis presented in this thesis is for the third test which involved data acquisition for prefrontal region while following the third protocol. This is since proper testing environment and conditions were made

available for the third test. Another reason is that the time domain analysis, frequency domain analysis and results for ML algorithms showed better response as compared to the results for the other two testing paradigms. The data repository is available within the computer dedicated for available EEG equipment.

The fourth deliverable is the preprocessing of the EEG data. The preprocessing involved the filtering of the EEG data and afterwards the time domain and frequency domain analysis. During the initial stages of preprocessing, the EEG data was filtered using bandpass filter of 0.5-30 Hz and notch filter of 50 Hz. Upon analysis, it was observed that the response for channels Fp1 and Fp2 was erroneous because the waveform was same before and after bandpass and notch filtering. However, the response for other channels upon filtering was normal to some extent but erroneous too. After filtering the EEG data, the Fast Fourier Transform (FFT) was done to analyze the frequency domain response of the EEG data. Upon analysis, it was observed that the response for channels Fp1 and Fp2 was erroneous as it had multiple dominant frequencies. However, the response for other channels upon frequency analysis was normal to some extent but erroneous too. After filtering the EEG data, the statistical analysis was done to analyze the time domain response of the EEG data. Upon analysis, it was observed that the response for channels Fp1 and Fp2 was erroneous as it showed odd behavior for statistical parameters including the mean, variance, kurtosis, skewness, RMS and zero crossings. However, the response for other channels upon statistical analysis was normal to some extent but erroneous too. The reason for the other channels to show normal but erroneous data upon filtering, frequency and time domain analysis is the impact of channels Fp1 and Fp2. This observation is already mentioned in chapter 5 and the first paragraph. After these steps, the filtered and preprocessed EEG data was analyzed using machine learning algorithms including Support Vector Machine (SVM), Linear Discriminant Analysis (LDA) and Random Forest (RF) algorithms and the results are presented in chapter 5 for unlabeled data.

The equipment can be used for further experiments, but the data would be erroneous. The solution to this problem is to either repair the existing amplifier or decide on a new one. If the desired paradigm involves data acquisition from channels Fp1, Fp2, C3 and C4, swap the electrodes of these channels with ones that are not used for the current testing paradigm manually. This way, better quality of data can be ensured if environmental conditions and testing parameters are strictly followed along with the channel replacements too. The data would still be accurate up to some extent but erroneous due to the interference and impact of these four channels. Hence, we can conclude that channels Fp1, Fp2, C3 and C4 are faulty, and the amplifier needs repair/replacement to mitigate the effect of these channels.

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