ANALYSIS ON EEG MONTAGES TO IDENTIFY MENTAL DISORDERS USING MATLAB

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PREFACE

This research project explores EEG montages' potential in identifying mental disorders using MATLAB. EEG offers a non-invasive method to monitor brain activity, and its analysis can reveal patterns related to various mental conditions. The primary goal is to employ computational tools like ANN and CNN to extract meaningful insights from EEG data, aiding in early detection and effective management of mental health disorders.

The preface highlights the significance of EEG montages in mental health research and emphasizes the role of advanced algorithms in improving classification accuracy. By conducting a comprehensive analysis of existing literature, this study aims to contribute valuable knowledge to the field.

The work is original, and efforts have been made to avoid plagiarism by appropriately citing all sources and data. This research strives to advance the understanding of EEG montages' applications in mental health, ultimately benefiting healthcare and individuals affected by these conditions.

In conclusion, this preface sets the stage for a meaningful exploration of EEG montages' potential in identifying mental disorders using MATLAB. Through cutting-edge computational techniques, the study aims to enhance diagnostic accuracy and improve the lives of those impacted by mental disorders.

Dr. Ashok Vajravelu

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The authors express sincere gratitude to Universiti Tun Hussein Onn Malaysia (UTHM), Malaysia, Kongu Engineering College (KEC), India, and the National Institute for Empowerment of Persons with Multiple Disabilities (Divyangjan) in Chennai, India, for their unwavering support in conducting this research. Their contributions were invaluable in achieving the research objectives. The study focuses on using EEG montages and MATLAB to identify mental disorders. Advanced techniques like ANN and CNN are employed for accurate classification. The research aims to enhance early detection and management of mental health conditions. The collaboration with these esteemed institutions significantly shaped the study's outcomes. The authors acknowledge all sources and uphold academic integrity throughout the research. This study contributes to the advancement of mental healthcare and well-being.

Dr. Ashok Vajravelu

Dr. Wan Suhaimizan Bin Wan Zaki

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CHAPTER 1

INTRODUCTION TO EEG AND MENTAL DISORDERS

Dr. Ashok Vajravelu

Bio Medical Engineering and Measurement System (BioMEMS)

1.1 Background on EEG (Electroencephalography)

The field of electroencephalography (EEG) has a rich history dating back to the early 20th century. In 1924, Hans Berger, a German psychiatrist, conducted the pioneering experiment of recording the first human EEG (electroencephalogram). This groundbreaking study involved the measurement of electrical brain activity using electrodes placed on the scalp, leading to significant advancements in neuroscience and our understanding of brain function. signal, marking the beginning of a new era in neuroscience. Since then, EEG has emerged as a fundamental tool for studying brain activity and understanding the underlying mechanisms of various cognitive processes.

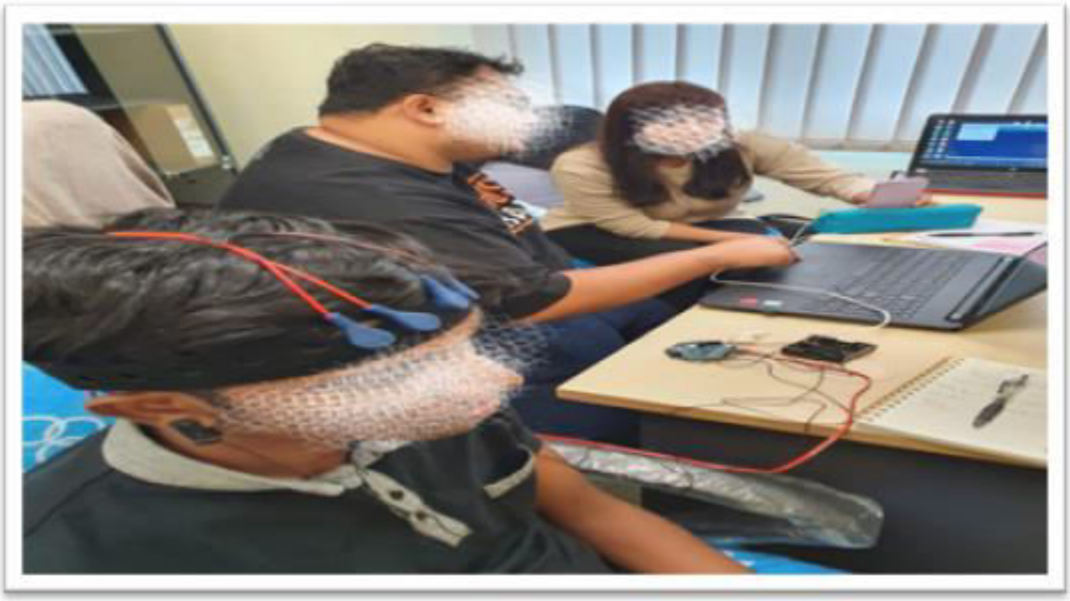

Figure 1.1: EEG setup captures neural patterns

Human organisms are precious in the universe. By nature, humans have some basic senses, which are hearing, sight, smell, touch, and taste. All the organs are interrelated and associated with each other for appropriate functioning sequentially and in parallel.

The organs have the capability of instantaneously communicating sensory information to the brain. All activities are executed by the neurons present in the brain. Due to chemical reactions inside the neurons, electrical impulses are generated. These electrical impulses are generated according to the activities of the human organisms. The electrodes placed on the head sense and capture these electrical impulses, and the equipment used for this purpose is called electroencephalography. The test conducted for analyzing the brain activities through the electrical impulses of brain neurons is known as, an electroencephalogram (EEG) is employed to detect possible abnormalities in the brain functioning. A montage refers to the arrangement of electrodes and their corresponding setup on the device designed to record the electrical signals generated by the brain. The electrodes are arranged logically and in a specific order. This article presents a comprehensive introduction to fundamental concepts concerning EEG montages, elucidating their operational principles across various montage types. For this study, 60 research articles related to EEG montages have been selected: 25 articles from 2020, 15 articles from 2019, 10 articles from 2018, 5 articles from 2017, 3 articles from 2016, and 2 articles from 2015.

Due to modernization of the world, pollution has increased. Human life has been changing as machine life in the fast-moving world. So, the brain activities of the humans have been changing as abnormal to the adults due to work burden as well as to the children too due to technology. Analyzing the brain activities in the abnormal stage is the challenging task to the medical professionals. In this work, an attempt has been planned to find an appropriate montage in the EEG analysis and disorder diagnosis as the first step in the signal analysis world. Because, the first stage of work in the EEG acquisition is montage.

1.2 Overview of Mental Disorders

Mental disorders are highly prevalent and can have a profound impact on individuals and society. They encompass a wide range of conditions, each characterized by distinct symptoms, etiology, and treatment approaches. Mental disorders can affect anyone regardless of age, gender, or socioeconomic background.

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Depression, one of the most common mental disorders, characterized by enduring emotions of sorrow, a diminished interest in activities, alterations in appetite and sleep habits, and challenges in maintaining focus. Anxiety disorders involve excessive and irrational worrying, fear, and avoidance behaviors. Schizophrenia is a severe mental disorder that affects cognition, emotion, and behavior, often leading to hallucinations, delusions, and social withdrawal. Bipolar disorder is characterized by extreme mood swings, alternating between periods of mania and depression. ADHD is a neurodevelopmental disorder that affects attention, impulsivity, and hyperactivity.

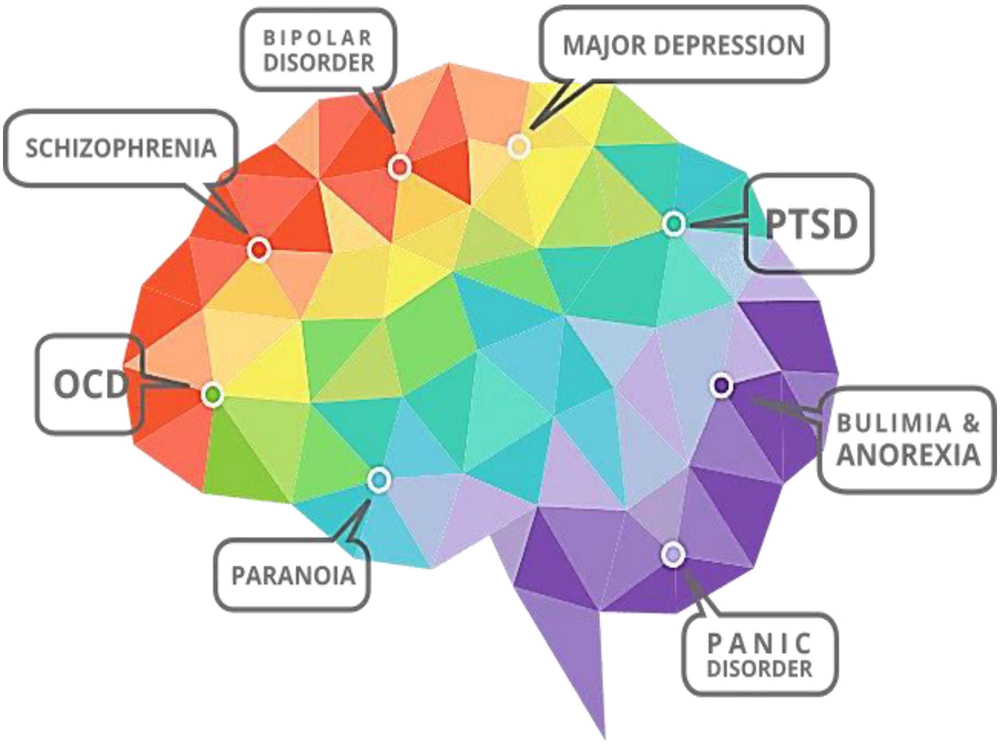

Figure 1.2: Co-occurring disorder exemplifies the intertwining of addiction and mental illness

1.3 Need for Accurate Diagnostic Tools

Accurate diagnosis of mental disorders is critical for appropriate treatment and intervention. However, diagnosing mental disorders can be challenging due to the subjective nature of symptoms and the overlap between different disorders. Clinicians heavily relying on self-reporting and subjective assessments, there is a possibility of introducing bias and inaccuracies, which may impact the validity of the results.

Objective diagnostic tools that provide quantifiable measures of brain activity can greatly enhance diagnostic accuracy. EEG, with its ability to capture real-time neural activity, offers a promising avenue for understanding the underlying neural signatures of mental disorders. By analyzing the unique patterns and abnormalities in EEG data, clinicians and researchers can gain valuable insights into the physiological mechanisms associated with specific disorders.

1.4 EEG Montages as Diagnostic Tools

EEG montages refer to specific electrode configurations used in EEG recordings. Different montages capture distinct aspects of brain activity by emphasizing specific brain regions or functional connections. For example, the standard 10-20 montage places electrodes at specific scalp locations based on a standardized measurement system. Other montages, such as bipolar and referential montages, focus on specific electrode pairs or reference electrodes, respectively.

By selecting appropriate EEG montages, researchers and clinicians can enhance the sensitivity and specificity of EEG analysis for mental disorder identification. Certain montages may be more relevant for detecting abnormalities in specific brain regions or networks associated with disorders. The choice of EEG montage depends on the research question or clinical objective, and it plays a crucial role in extracting meaningful information from EEG data.

In recent years, the development of advanced signal processing techniques and machine learning algorithms has been facilitated by the utilization of these methods. EEG-based diagnostic tools for mental disorders. These tools leverage the unique information contained within EEG signals to identify patterns and biomarkers indicative of specific disorders.

1.5 Objectives of the Book

The primary aim of this book is to investigate the application of EEG (electroencephalography). montages in identifying mental disorders and provide a comprehensive analysis using MATLAB, a widely used software platform for signal processing and data analysis. By combining the knowledge of EEG montages, signal processing techniques, and machine learning algorithms, this book aims to equip readers with the necessary skills to effectively analyze EEG data for mental disorder identification.

Specifically, the Book Aims To:

- Provide a thorough understanding of EEG signal processing techniques, artifact removal methods, and feature extraction algorithms.
- Explore the selection and significance of different EEG montages for various mental disorders.
- Discuss using machine learning algorithms to classify EEG signals is a practical approach for categorizing brainwave patterns, data and identifying mental disorders.
- Present case studies and real-world applications showcasing the utility of EEG montages and MATLAB analysis techniques.
- Discuss the challenges, limitations, and potential future directions in the field of EEG-based mental disorder identification.
- By accomplishing these objectives, this book aims to enhance the current understanding of mental disorders and promote progress in their diagnosis and treatment by employing EEG montages and MATLAB analysis techniques.

1.3 Significance of EEG in Mental Disorder Research

EEG has emerged as a valuable tool in mental disorder research due to its unique advantages. Firstly, EEG provides excellent temporal resolution, allowing researchers to examine the dynamic changes in brain activity over milliseconds. This temporal precision enables the identification of fast neural processes associated with mental disorders for instance, event-related potentials (ERPs) can be cited as an example of brain responses to specific events. oscillatory activity.

Secondly, EEG is non-invasive and relatively affordable in comparison to other neuroimaging techniques like functional magnetic resonance imaging (fMRI), electroencephalography (EEG) offers greater accessibility, making it a feasible option for conducting extensive studies and implementing in clinical settings.

Moreover, EEG is well-suited for studying the interactions between different brain regions and the dynamic patterns of neural communication within the brain. By analyzing the synchronization patterns and coherence between different brain regions, researchers can gain insights into the functional alterations and disruptions underlying mental disorders.

1.4 Ethical Contemplations

When conducting any study involving human participants, ethical considerations are of utmost importance play a crucial role in EEG-based mental disorder research. The use of EEG montages for diagnostic purposes should adhere to ethical guidelines, ensuring the protection of participants' rights, privacy, and confidentiality.

Informed consent is essential, and participants should receive comprehensive details about the research, including its aims, methodologies, and possible advantages and disadvantages. Furthermore, it is essential to be informed about the potential hazards and benefits associated with participating in the study. Confidentiality and data protection measures must be in place to safeguard participants' privacy and ensure that their data is used solely for research purposes.

Furthermore, researchers must ensure that the research design and procedures do not cause harm or distress to participants. Ethical review boards, also known as institutional review boards, have a crucial function in assessing and granting approval for research protocols, ensuring that they adhere to ethical standards.

1.5 Advancements in EEG Technology

Over the years, significant advancements have been made in EEG technology, enhancing its potential for mental disorder research. These advancements have improved the quality and reliability of EEG data, enabling researchers to capture more precise and detailed information about brain activity.

One notable advancement is the development of high-density EEG systems. Traditional EEG systems typically use a limited number of electrodes (e.g., 19 or 32) placed on specific scalp locations. High-density EEG systems, On the flip side, they encompass a significantly greater quantity of synonymous terms electrodes (e.g., 64, 128, or even 256), allowing for more extensive coverage of the scalp and better spatial resolution.

High-density EEG facilitates the detection of subtle changes in neural activity, providing a more comprehensive understanding of brain dynamics associated with mental disorders.

Another significant advancement is the incorporation of neuroimaging techniques with EEG, such as EEG-fMRI and EEG-TMS (transcranial magnetic stimulation). These hybrid techniques combine the strengths of EEG's temporal resolution with the spatial information provided by fMRI or the ability to modulate brain activity with TMS. By integrating multiple modalities, researchers can gain an in-depth comprehension of the neural substrates of mental disorders and the fundamental mechanisms contributing to their development.

Furthermore, the evolution of wireless and portable EEG devices. systems have increased the accessibility and convenience of EEG recordings.

These systems eliminate the need for tethered connections, allowing participants to move more freely during EEG data collection.

Wireless EEG technology has enabled research in naturalistic settings, such as studying brain activity during real-life activities or in clinical environments where mobility is essential.

1.6 Limitations of EEG in Mental Disorder Research

While EEG offers numerous advantages, it also has certain limitations that researchers must consider. One limitation is the difficulty in precisely localizing the source of the recorded electrical activity. EEG provides a measure of electrical potentials on the scalp, but accurately pinpointing the exact brain regions responsible for the recorded signals can be challenging. Additional techniques, such as source localization algorithms or combining EEG with other neuroimaging modalities, may be used to improve spatial localization.

Another limitation is the presence of artifacts in EEG data. Artifacts can arise from various sources, including muscle movements, eye blinks, electrical interference, and environmental

Sound. These disturbances can mask the fundamental neural activity and impact the precision of the results of mental disorder identification. Careful preprocessing and artifact removal techniques are necessary to mitigate the impact of artifacts on EEG data analysis.

Additionally, EEG has inherent limitations in capturing deep brain structures due to the signal attenuation as it passes through the scalp, skull, and other tissues. This limitation restricts the examination of certain brain regions and may lead to a biased representation of brain activity.

1.7 Potential of EEG Montages for Mental Disorder Identification

EEG montages play a crucial role in enhancing the diagnostic potential of EEG for mental disorders. Different montages highlight specific brain regions or functional networks, allowing researchers to focus on the neural activity most relevant to a particular disorder. For instance, montages that emphasize frontal brain regions may be useful for studying disorders involving executive functions and emotion regulation.

Moreover, the selection of appropriate EEG montages can aid in the identification of specific biomarkers or neural signatures associated with mental disorders.

For example, certain oscillatory patterns or event-related potentials (ERPs) may serve as potential biomarkers for schizophrenia or depression.

By leveraging the unique information provided by EEG montages, researchers can develop robust and targeted analysis approaches to identify reliable markers of mental disorders. These markers can contribute to more accurate diagnosis, personalized treatment plans, and enhancing comprehension of the fundamental mechanisms behind mental disorders.

1.8 CONCLUSION

In conclusion, EEG is a powerful resource for studying brain activity and has significant potential in the identification and understanding of mental disorders. Its excellent temporal resolution, accessibility, and ability to capture functional connectivity make it an attractive option for researchers and clinicians. By utilizing specific EEG montages and advanced analysis techniques, researchers can extract valuable information from

EEG data and uncover neural signatures associated with mental disorders. However, it is crucial to consider the constraints of EEG and address challenges related to artifacts and spatial resolution. Through continued advancements in EEG technology and methodologies, EEG capacity to make a substantial impact in the field exists of mental disorder research, ultimately leading to improved diagnosis, treatment, and overall mental health outcomes.

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CHAPTER 2

LITERATURE REVIEW - EEG MONTAGES AND MENTAL DISORDER

Dr. Ashok Vajravelu
Bio Medical Engineering and Measurement System (BioMEMS)

2.1 INTRODUCTION

While doing research, studying, or developing a new product, as guidance, literature review is very important and it promotes the act of done the analysis. Analysis of literature is a research or study collected from the reference sources, such as journals, case studies, books, and electronic media, as well as internet sources. For this study, a total of 60 articles were used to study about the process of feature extraction from the year 2015 to 2020. The focus is to get all the necessary parameters needed and compare them accordingly.

Once all the articles are obtained, they are short-listed to 12 articles based on the availability of the parameters such as the frequency range, type of classifier used, accuracy of the study and so on.

EEG is the most common option used in tracking physiological signals from the human body because of its features such as the ability capturing neuronal activity of the brain, higher temporal, and spatial resolutions.

2.2 Signals vs. Images: A Comparative Analysis in EEG

When analyzing EEG data, two main approaches are commonly employed: signal-based analysis and image-based analysis. These approaches offer distinct perspectives and serve different purposes in investigating brain activity.

In this segment, we will delve into the contrast between signals and images when conducting EEG analysis, examining their respective applications and advantages. Table 2.1 presents a thorough overview findings from multiple sources, shedding light on the utility and considerations associated with these approaches.

Signal-based analysis focuses on the direct examination of raw EEG data, typically represented as voltage-time series.

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This approach emphasizes the temporal dynamics of brain activity, enabling researchers to investigate event-related potentials, oscillatory activity, and other time-domain features. Signal-based analysis involves preprocessing steps, such as filtering and artifact removal, to improve the accuracy and clarity of the captured information.

Conversely, image-based analysis involves transforming the raw EEG data into spatial representations commonly known as brain maps or topographic maps. These maps visualize the distribution of electrical activity across various scalp locations, offering insights into the spatial patterns and regional differences in brain activity. Image-based analysis techniques employ methods such as EEG source localization or scalp mapping algorithms to generate these maps.

The choice between signal-based and image-based analysis depends on the specific research question and the information of interest. Signal-based analysis excels in examining temporal dynamics, event-related responses, and changes in oscillatory activity over time. It allows for the precise characterization of the timing and sequencing of neural events. However, it may have limitations in spatial specificity, as the recorded electrical potentials represent the collective activity of multiple underlying sources.

In contrast, image-based analysis provides a more holistic view of brain activity, highlighting the spatial distribution of electrical potentials. It is particularly valuable for studying the connectivity between brain regions and identifying patterns of activation or abnormalities across the scalp. Image-based analysis facilitates the investigation of specific brain regions' involvement in different tasks or mental disorders. However, it may sacrifice some temporal resolution and might not capture fast temporal dynamics as effectively as signal-based analysis.

The choice between signal-based and image-based analysis depends on the research question, the specific goals of the study, and the available resources. Researchers and clinicians must carefully consider the trade-offs between temporal resolution and spatial specificity when selecting the most appropriate approach for their investigations.

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In the subsequent sections, we will conduct an extensive literature review encompassing both signal-based and image-based approaches in EEG analysis for mental disorder identification.

This comprehensive analysis will provide valuable insights into the strengths, limitations, and applications of these approaches and highlight the advancements made in the field.

EEG can measure in two different method which is through signals and images. Table 2.1 shows the summarized data from several sources on comparison between the application of signals and images in EEG.

Table 2.1: Comparison between application of signals and image in EEG

No.	Author(s)	Signal	Image	Application	Accuracy
1	**Kural et al., (2020) [15]**	/		Interictal Epileptiform discharges in EEG	**91%**
2	**Chatzichristos et al., (2020) [5]**		/	Epileptic Seizure Detection	**NA**
3	**Das et al., (2020) [8]**	/		Epileptic Seizure Detection	**98.75%**
4	**Cox et al., (2020) [7]**	/		Analysing Human Sleep EEG	**96%**
5	**Malfilâtre et al., (2020) [17]**	/		Interpretation guidelines for premature and full-term new-borns	**93.50%**
6	**Hill et al., (2020) [11]**	/	/	Alteration of functional network characteristics.	**88%**
7	**Azuma et al., (2019) [2]**	/		Comparing linear and non-linear EEG analyses in patients with epilepsy before and after experiencing psychosis.	**91%**

8	**Mansouri et al., (2019) [18]**	/		EEG Seizure Detection and Localization	**99%**
9	**Brihadiswaran et al., (2019) [4]**	**NA**	**NA**	Approaches to the Processing and Categorization Techniques in Autism Spectrum Disorder	**100%**
10	**Stevenson et al., (2018) [21]**	/		Modifying the number of EEG electrodes influences the visual interpretation of neonatal seizure detection by human experts.	**NA**
11	**Baroumand et al., (2018) [3]**	/	**/**	Automated EEG source imaging	**61%**
12	**Mohammadi et al., (2015) [19]**	/		Analysing EEG signals in individuals with depression using data mining techniques.	**80%**

Based on [3], it shows that both image and signals were implemented in EEG but the level of accuracy is only 61%. Whereas according to [11], it shows 88% of accuracy level by implementing both signals and image in EEG.

Based on [18], the accuracy level is shown as 99% by only implementing the signals in EEG. Hence to summarize the Table 2.1, the accuracy level records by EEG signals is higher compared to the EEG images.

2.2.1 EEG Signals

EEG signals enable the observation of the brain's electrical activity. Seizures can be detected through variations in the EEG signals, as epileptic seizure events display atypical patterns in the EEG readings. The examination of EEG signals with paroxysmal abnormality includes identifying spikes, spike-and-slow waves, and sharp waves [8].

2.2.2 EEG Images

In EEG source imaging (ESI), the goal is to estimate the EEG signals' inherent brain activity can be better understood by integrating an electrical conduction model from the patient's MRI data. The process of Electroencephalography Source Imaging (ESI) includes multiple stages, such as automatically detecting spikes and grouping them based on their shape. There are two primary methods for implementing automated ESI: a fully automated one and a semi-automated one.

❖ **Fully Automated Approach:**

In the fully automated approach, the analysis pipeline is designed to quantitatively define a dominant cluster based on specific criteria. This cluster represents the most relevant and consistent spike activity in the EEG data. Typically, the automated spike detection algorithm identifies individual spikes or epileptiform discharges in the EEG recordings. These detected spikes are then grouped or clustered based on their morphological characteristics, such as shape, duration, and amplitude. The quantitatively defined dominant cluster is selected as the representative activity for the analysis. This cluster is often chosen based on predetermined criteria, such as the highest number of spikes, a specific threshold for spike similarity, or other relevant parameters. The analysis is then performed on this dominant cluster, which provides information about the underlying brain activity associated with the identified spikes.

❖ **Semi-Automated Approach:**

The semi-automated approach involves a combination of automated spike detection and manual or expert-driven intervention. The automated spike detection algorithm is applied to identify spikes or epileptiform discharges in the EEG data. However, instead of relying solely on the automated clustering and selection of spikes, the results are further refined and validated by an expert or researcher. In the semi-automated approach, the expert reviews the detected spikes and manually verifies or adjusts the clustering results based on their expertise and knowledge. This intervention helps to ensure the accuracy and reliability of the spike clusters identified in the EEG data. The expert may consider additional factors such as the clinical context, patient history, and other relevant information during the refinement process. The semi-automated approach allows for more flexibility and expert input in the analysis, which can be beneficial in situations where automated algorithms may not capture the full complexity or subtleties of the spike activity.

Both the fully automated and semi-automated approaches have identical implications, their advantages, and limitations. The choice between these approaches depends on various factors, including the research or clinical objectives, available resources, expertise of the researchers or clinicians, and the nature of the EEG data being analyzed. It is crucial to emphasize that the sentence's meaning remains unchanged specific implementation and details of automated ESI may vary depending on the software, algorithms, and research protocols being used.[8]

2.3 Frequency Range Vs Sampling Rate

The EEG database includes information of the sampling frequency, the quantity of electrodes and their placement the electrode, the EEG setup, the length of the recording and data types [4]. Table 2.2 shows the accuracy level of EEG database which includes the Frequency range and sampling rate.

Table 2.2: Frequency range and Sampling rate

No.	Author(s)	Sampling Rate (Hz)	Frequency Range (Hz)	Application	Accuracy
1	**Kural et al., (2020) [15]**	**256**	**NA**	Interictal Epileptiform discharges in EEG	**91%**
2	**Chatzichristos et al., (2020) [5]**	**200**	**0-1**	Epileptic Seizure Detection	**NA**
3	**Das et al., (2020) [8]**	**256**	**0.1-70**	Epileptic Seizure Detection	**98.75 %**
4	**Cox et al., (2020) [7]**	**400**	**0.5-4**	Analyzing Human Sleep	**96%**

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				EEG	
5	**Malfilâtre et al., (2020) [17]**	**256**	**0-70**	Interpretation guidelines for premature and full-term new-borns	**93.50 %**
6	**Hill et al., (2020) [11]**	**10k**	**1.0 - 55**	Modulation of functional network properties	**88%**
7	**Azuma et al., (2019) [2]**	**500**	**4.0 - 30**	Comparing linear and non-linear EEG analyses in patients with epilepsy before and after experiencing psychosis.	**91%**
8	**Mansouri et al., (2019) [18]**	**256**	**0.5-25**	EEG Seizure Detection and Localization	**99%**
9	**Brihadiswaran et al., (2019) [4]**	**500**	**0.4-60**	Approaches to the Processing and Categorization Techniques in Autism Spectrum Disorder	**100%**
10	**Stevenson et al.,**	**256**	**0.5-70**	Modifying the	**NA**

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	(2018) [21]			number of EEG electrodes influences the visual interpretation of neonatal seizure detection by human experts	
11	**Baroumand et al., (2018) [3]**	**256**	**0.5-30**	Automated EEG source imaging	**61%**
12	**Mohammadi et al., (2015) [19]**	**500**	**1.0 - 30**	Analyzing EEG signals in individuals with depression using data mining techniques.	**80%**

According to [15], the electroencephalogram (EEG) was captured at a frequency of 256 Hz and shows 91% of accuracy level. Based on the [4], the accuracy when the EEG captured with a frequency of 500 Hz samples per second, and frequency rate of 0.4-60 Hz is 100%. Whereas, study shows that 61% of accuracy when the sampling rate is 256 Hz and frequency rate is 0.5-30 Hz [3]. To summarize the Table 2.2, increasing the sampling rate and frequency range of an EEG (Electroencephalogram) leads to improved EEG accuracy.

2.3.1 Frequency Range

EEG waveforms placed on the scalp classify electrical signals based on their frequency range, amplitude, and spatial position. The frequency, measured in Hertz (Hz), is a fundamental parameter used to distinguish between normal and abnormal brain

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rhythms. Grouping of waveforms will be based on the frequency range [14]. Table 2.3 shows the brain wave frequencies with their characteristics.

Table 2.3: Brain wave frequencies with their characteristics [14]

Type	Frequency (Hz)	Behavioral /Psychological State	Neurotransmitter/ Hormone	Location
Delta	0- 4	Deep rest, dreamless sleep	Human Growth Hormone, Melatonin	Frontally in adults, Posteriorly in children
Theta	4 – 8	Deeply relaxed	Serotonin, Acetylcholine, Anti-cortisol, Endorphins,Human Growth Hormone	Thalamic region
Alpha	8 – 13	Day dream, calm	Serotonin, Endorphins, Acetylcholine	Posterior regions
Beta	13 – 30	Alert, active thinking, anexity, panic attack, focus, concentration	Adrenaline, Cortisol, Norepinephrine, Dopamine	Frontal and Parietal
Gamma	30 - 100	combination of two senses	Serotonin, Endorphins	Somatosensory cortex

2.3.2 Sampling Rate

The frequency at which data points are collected per second (sampling rate, f in Hz) is crucial for various analyses, such as seizure analysis, sleep analysis, or cognition-related studies. The nominal sampling rate of the recording device holds significant importance, as it directly impacts the performance of automated software detection tools that rely on algorithms to assess the time-frequency characteristics of the EEG recording [22].

2.4 Frequency vs Sampling vs Filter

The frequency and sampling play a crucial role in filtering process. Filtering is the main pre-processing step when analyzing EEG data. There are few types of filters widely used in EEG such as spatial, bandpass, notch and anti-aliasing passband. Table 2.4 shows the comparison based on the frequency, sampling and filters used in EEG.

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Table 2.4: The comparison based on the frequency, sampling and filters used in EEG

No	Author(s)	Frequency Range (Hz)	Sampling Rate (Hz)	Filter Type	Application	Accuracy
1	**Kural et al., (2020) [15]**	**NA**	**256**	Spatial	Interictal Epileptiform discharges in EEG	**91%**
2	**Chatzichristos et al., (2020) [5]**	**0-1**	**200**	Bandpass	Epileptic Seizure Detection	**NA**
3	**Das et al., (2020) [8]**	**0.1-70**	**256**	Notch	Epileptic Seizure Detection	**98.75%**
4	**Cox et al., (2020) [7]**	**0.5-4**	**400**	Bandpass	Analysing Human Sleep EEG	**96%**
5	**Malfilâtre et al., (2020) [17]**	**0-70**	**256**	Anti-aliasing passband	Interpretation guidelines for premature and full-term new-borns	**93.50%**
6	**Hill et al., (2020) [11]**	**1.0 – 55**	**10k**	Butter Worth	Modulation of functional network properties	**88%**
7	**Azuma et al., (2019) [2]**	**4.0 – 30**	**500**	Low pass	Linear and non-linear EEG analyses before and after	**91%**

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					psychosis in patients with epilepsy	
8	**Mansouri et al., (2019) [18]**	**0.5-25**	**256**	Analog bandpass	EEG Seizure Detection and Localization	**99%**
9	**Brihadiswaran et al., (2019) [4]**	**0.4-60**	**500**	Bandpass	Processing and Classification Methodologies for Autism Spectrum Disorder	**100%**
10	**Stevenson et al., (2018) [21]**	**0.5-70**	**256**	Butterworth high-pass	Reducing EEG electrode number on the visual interpretation of the human expert for neonatal seizure detection	**NA**
11	**Baroumand et al., (2018) [3]**	**0.5-30**	**256**	Band-pass	Automated EEG source imaging	**61%**
12	**Mohammadi et al., (2015) [19]**	**1.0 – 30**	**500**	amplifier bandpass	Data mining EEG signals in depression	**80%**

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According [8], notch filter is used on 256 Hz sampling rate at the frequency level of 0.1-70 Hz and shows 98.75% level of accuracy. EEG records 100% accuracy when the bandpass filter used when using a sampling rate of 500 Hz, 0.4-60 Hz of frequency range [4]. Moreover as [3], EEG records the lowest accuracy level among others which 61% when butter worth filter used at the frequency range of 1.0-55 Hz.

2.4.1 Filters

Digital filters encompass a diverse range of techniques extensively employed to accentuate or diminish specific frequencies in discrete, numerical representations of continuous waveforms. In clinical EEG, three commonly used filter types are low-frequency filters, high-frequency filters, and notch filters. The primary function of a low-frequency filter is to suppress lower frequencies while preserving higher frequencies unchanged. Due to their ability to attenuate low frequencies and pass high frequencies, engineers occasionally colloquially label low-frequency filters as high-frequency filters [4].

2.5 Montages and Classifiers

Classifier is to analyses the output of waveform-level from the EEG and through classifier, the type of montages can be identified. Table 2.5 shows the data of montages and classifiers from several studies.

Table 2.5: Data of montages and classifiers

No.	Montage	Sub Types	Classifiers	Application	Accuracy
1	3	Common Average, Longitudinal, Source Space	NA	Interictal Epileptiform discharges in EEG	91%
2	1	Double banana	CNN	Epileptic Seizure Detection	NA
3	1	Mono-polar	CNN	Epileptic Seizure Detection	98.75%
4	3	Common average	NA	Analysing Human Sleep	96%

		reference, Common linked mastoids reference, Surface Laplacian		EEG	
5	4	Monopolar, Monopolar reference, Longitudinal, Transverse	CNN	Interpretation guidelines for premature and full-term newborns	93.50%
6	2	Bilateral, Unilateral	CNN	Modulation of functional network properties	88%
7	1	longitudinal bipolar	NA	Linear and non-linear EEG analyses before and after psychosis in patients with epilepsy	91%
8	2	Bipolar, Ipsilateral referential	ANN	EEG Seizure Detection and Localization	99%
9	5	average reference, Bipolar, common electrode	ANN	Processing and Classification Methodologies for Autism Spectrum	100%

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		reference, Laplacian, weighted average reference		Disorder	
10	2	Bipolar	ANN	Reducing EEG electrode number on the visual interpretation of the human expert for neonatal seizure detection	NA
11	2	Bipolar, referential	NA	Automated EEG source imaging	61%
12	2	Bipolar, unipolar	ANN	Data mining EEG signals in depression	80%

According to [19], two kinds of montages were analyzed which is Bipolar and unipolar through ANN with the accuracy of 80%. However, ANN also records the 100% of accuracy by determined five types of montages such as average reference, Bipolar, common electrode reference, Laplacian, weighted average reference [4]. ANN also records 99% of accuracy by determined two types of montages which is Bipolar and Ipsilateral referential [18]. In accordance with reference [8], a Convolutional Neural Network (CNN) is a type of deep learning model which was used to analyzed the mono-polar with accuracy level of 98.75 %.

2.5.1 Montages

In Table 2.6, montages can be classified into three main categories based on their electro-anatomical arrangement: unpaired, paired channels (where similar channels

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from both sides are displayed one below the other), and paired groups (involving chains or groups of channels on one side placed above a corresponding chain on the other side) [1].

Table 2.6: Montage arrangement

Montage Arrangement	Longitudinal	Transverse
Unpaired	Bipolar, referential	Bipolar, referential
Paired group	Bipolar, referential	
Paired channel	Bipolar, referential	

2.5.2 Classifiers

There are several classifiers that can be employed in EEG analysis, including Convolutional Neural Network (CNN), Artificial Neural Network (ANN), and K-nearest neighbor (KNN).

CNNs are often favored in EEG classification due to their ability to learn distinctive features from local receptive fields. They excel in handling complex EEG recognition tasks and have received positive feedback in research. ANN is extensively utilized to process neurobiological signals obtained from EEG data. On the other hand, KNN is commonly applied in differentiating between seizure and non-seizure events for automated seizure detection using EEG signals.

2.6 Accuracy Vs Classifiers Vs Application

To summarize the Table 2.7, Convolutional Neural Network (CNN) classifier used in the Epileptic Seizure Detection shows 98.75% of accuracy level. Based on [4], ANN used to analyse in approaching and categorization techniques for autism spectrum disorder (ASD) records 100% level of accuracy. Also, ANN classifier used in EEG Seizure Detection and Localization shows 99% of accuracy level [18]. Table 2.7 shows the reviewed data from several studies which shows the accuracy level and type of classifies used in application.

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Table 2.7: Accuracy level and type of classifiers used in application

No.	Author(s)	Accuracy	Classifier	Application
1	Kural et al., (2020) [15]	91%	NA	Interictal Epileptiform discharges in EEG
2	Das et al., (2020) [8]	98.75%	CNN	Epileptic Seizure Detection
3	Cox et al., (2020) [7]	96%	NA	Analysing Human Sleep EEG
4	Malfilâtre et al., (2020) [17]	93.50%	CNN	Interpretation guidelines for premature and full-term newborns
5	Hill et al., (2020) [11]	88%	CNN	Modulation of functional network properties
6	Azuma et al., (2019) [2]	91%	NA	Linear and non-linear EEG analyses before and after psychois in patients with epilepsy
7	Mansouri et al., (2019) [18]	99%	Artificial Neural Network (ANN)	EEG Seizure Detection and Localization
8	Brihadiswaran et al., (2019) [4]	100%	ANN	Processing and Classification Methodologies for Autism Spectrum Disorder
9	Stevenson et al., (2018) [21]	NA	ANN	Reducing EEG electrode number on the visual interpretation of the human expert for neonatal seizure detection

10	Baroumand et al., (2018) [3]	61%	NA	Automated EEG source imaging
11	Mohammadi et al., (2015) [19]	80%	ANN	Data mining EEG signals in depression

2.7 Future Directions in EEG Montage Research

Exploration of emerging trends and advancements in EEG montage research for mental disorder identification.

Discussion regarding the amalgamation of sophisticated analysis methods, machine learning and deep learning, in EEG montage analysis. Overview of potential directions for future studies, including multimodal approaches, longitudinal investigations, and real-time monitoring using EEG montages.

By conducting a comprehensive literature review on EEG montages and their application in mental disorder identification, this chapter aims to provide readers with an in-depth comprehension of the present state of research, the advantages limitations of different montages, and potential avenues for future investigation.

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CHAPTER 3

FEATURE EXTRACTION AND SELECTION

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Bio Medical Engineering and Measurement System (BioMEMS)

3.1 INTRODUCTION

Methodology serves as a roadmap, ensuring that the process is executed in a systematic and appropriate manner, leading to reliable and compelling outcomes. It keeps us aligned and enables a profound focus on our study's scope while avoiding any plagiarism concerns. It is the simplest way to monitor and tells us every step in this study and how the study is carried out from all sorts of sources.

Methodology represents a collection of practices employed in various industries or scientific fields. It pertains to the techniques utilized in a specific research investigation or the methods adopted to achieve a particular project's objectives. Some individuals may even use the term "methodology" to denote the study of such methods, rather than the methods themselves.

The significance of a well-defined methodology is particularly emphasized in the scientific community. Clearly delineated directions and procedures enhance consistency and facilitate the replication of work in different settings, a crucial aspect of robust scientific research. For this reason, scientific research methodologies are always thoroughly described, enabling others to replicate the study independently and identify any potential errors that could have influenced skewed results.

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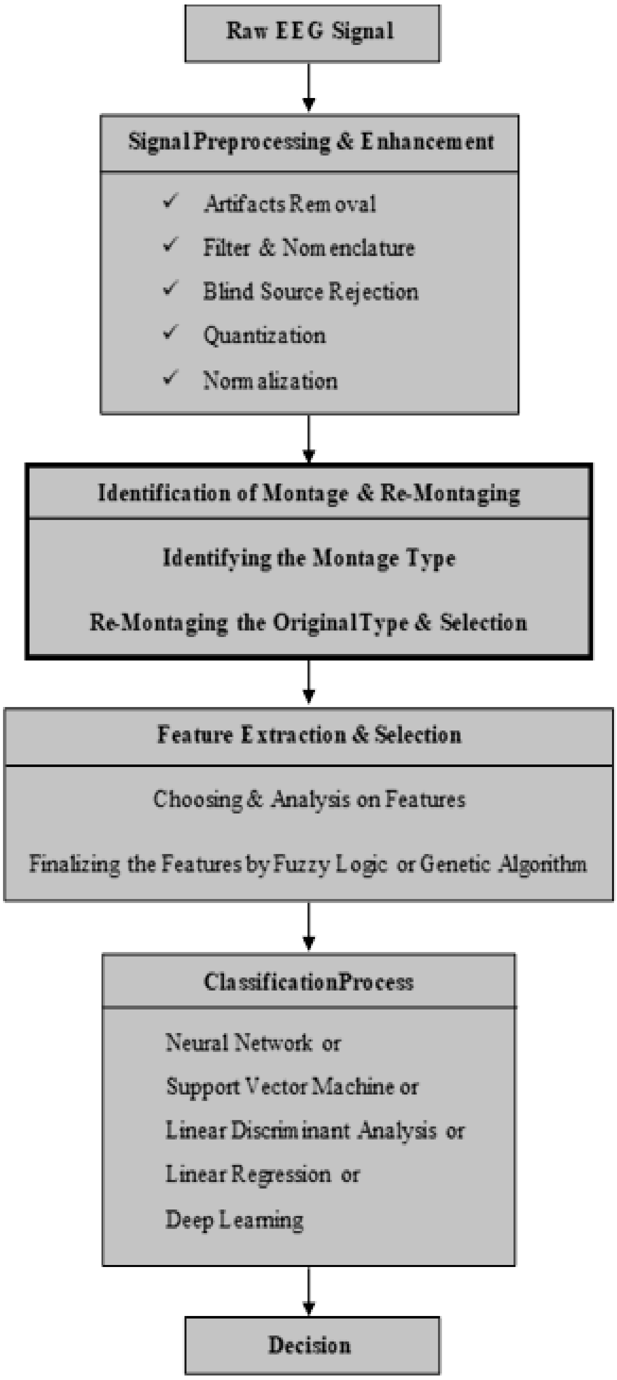

Figure 3.1: Methodology Flowchart

The main component of this system is Neural Network which processes the input data enables machine learning models to autonomously learn and identify patterns inherent within the dataset. Subsequently, these models can use their acquired knowledge to make predictions for novel and akin datasets. The electrodes from the EEG helmet are used to detect the brain impulse signals.

The raw EEG data is pre-processed and converted into a logarithm measurement of the rate of transform of information called entropy. These are the features and its results are classified and compared base on the type of disorder.

The most recent methods for recording EEG data and relevant datasets are being analyzed in this article, along with the formulation of the problem statement using assessment matrices.

3.2 EEG Recording Methods

Non-invasive EEG signaling is a preferred option for clinical epilepsy management due to ethical issues and health risks [12]. Usually, EEG signals are obtained with devices by the potential difference between scalp surface-placed pairs of electrodes. A test is called an EGG channel between the two electrodes.

3.3 EEG Datasets

An EEG archive with well-established epileptic recordings is important to establish an automated seizure monitoring system.

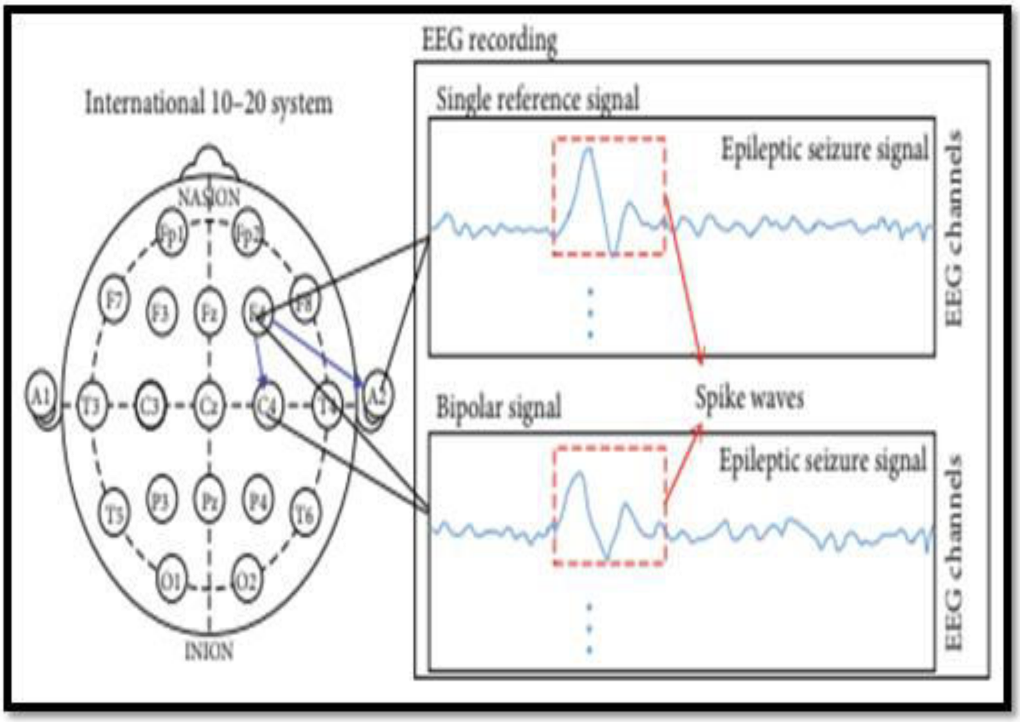

Figure 3.2: Common EEG recording method used for epileptic seizure detection

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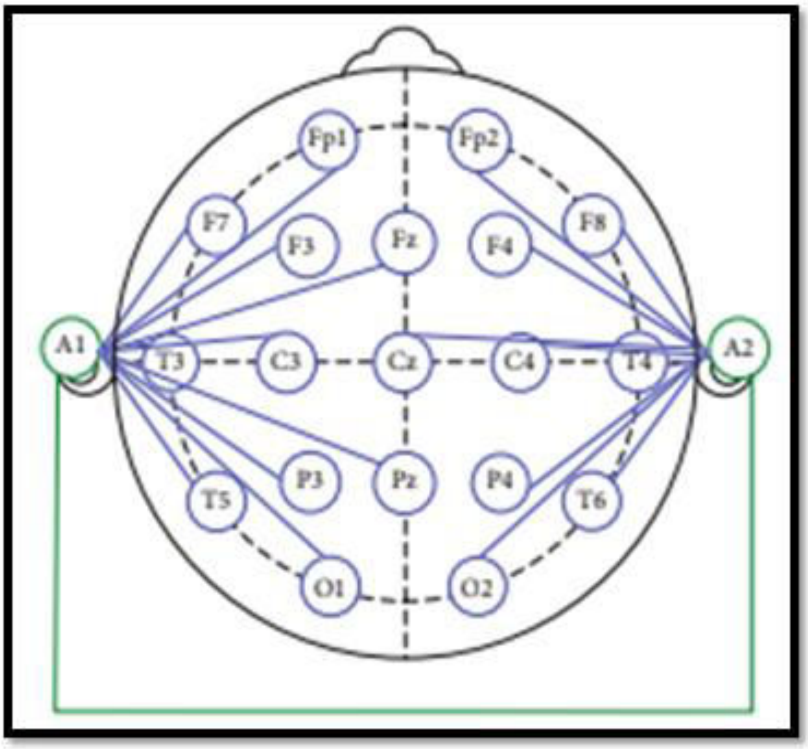

Figure 3.3: The auricular reference montage that uses electrodes on ears as referential electrodes

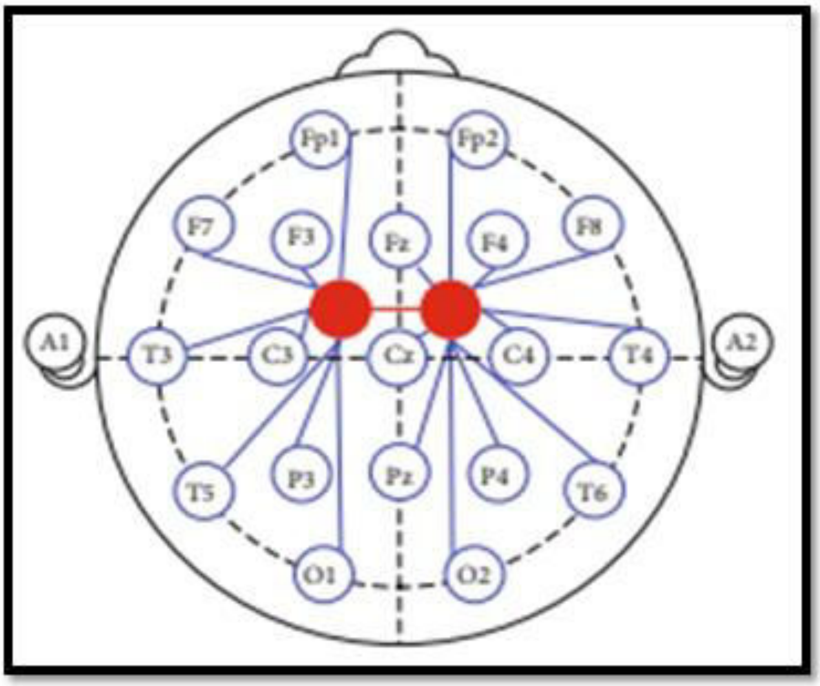

Figure.3.4: Common average montage that uses averaged potential of all the electrodes as the referential electrode.

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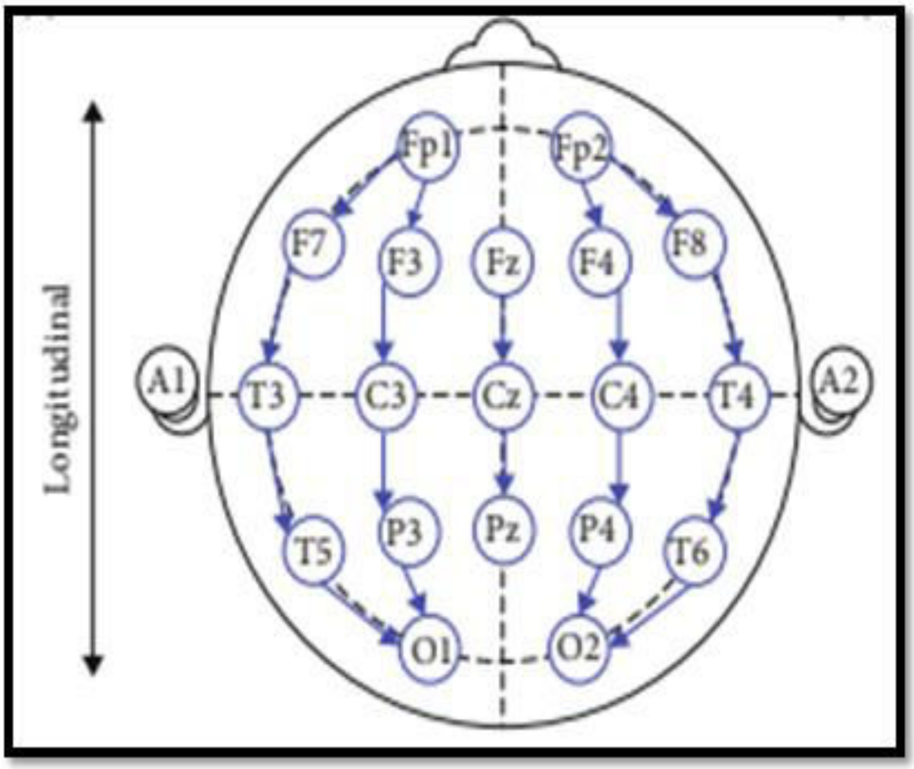

Figure 3.5 The longitudinal bipolar montage that records the potential difference between pairs of recording electrodes.

3.4 Pre-processing

Pre-processing and denouncing of reported EEG data therefore is quite necessary. In general, pre-processing processes require transformations and redevelopments of the reported EEG data by the elimination of erroneous or data containing artifacts without altering the pristine dataset (manipulation). The use of pre-processing measures depends primarily on many factors, including the purpose of the research, the experimental design specifics, the equipment used for recording EEG raw signals, along with sophisticated data analysis techniques.

In most cases, the pre-processing of the EEG signal preparation is a crucial stage in EEG analysis. While the conventional EEG pre-processing pipeline is still missing, it usually includes any needed digital signal processing operations to polish raw EEG signals in order to leave only brain activity signals for subsequent study [26, 13, 20]. The effects of EEG pre-processing on subsequent data analysis outcomes have been seen in a variety of studies [26, 10, 33].

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3.4.1 Descriptive Statistics Analysis

EEG pre-processing involves the systematic and semi-automated organization of signal processing functions during the initial stages. Unlike typical procedures focused on artifact removal, this pre-processing phase is entirely agnostic to specific artifacts. Its primary elements encompass noise reduction, artifact removal, and the elimination of problematic channels.

3.4.2 Characteristics of Background EEG

The EEG background activity has specific characteristics [18]. It operates within a limited frequency range of approximately 0.01 to 100 Hz, and brain-generated amplitudes fall between ±100 μV. Given the absence of authentic EEG measurements, it is reasonable to consider the EEG signal as nonlinear [23]. The oscillatory frequency can be categorized into five bands as follows: delta (0.5 to 4 Hz), theta (4 to 8 Hz), alpha (8 to 13 Hz), beta (13 to 30 Hz), and gamma (30 to 100 Hz).

3.4.3 Line Noise Removal

The primary emphasis lies in attenuating 60 Hz line noise to effectively eliminate interference from the EEG signal. However, conventional notch filtering may inadvertently introduce distortions to signal components within the 50 to 70 Hz range. To address this concern, an alternative approach is proposed: accurately estimating the embedded line noise in the recorded EEG signals and subtracting it from the results [26].

3.4.4 Re-Referencing

An essential component in EEG recordings is the reference electrode, also known as the common reference, which is typically connected to the earlobes. Proper placement and a strong signal are crucial for reference electrodes as any noise in this electrode can result in the scalp electrodes picking up unwanted interference. To ensure accurate readings, the electrode montage should cover nearly the entire head, employing many electrodes. Researchers often recommend utilizing an average comparison [34]. This approach becomes particularly meaningful when the EEG recording device includes enough evenly distributed channels, leading to a total operation average that tends towards zero.

3.4.5 Filtering

In the initial stages of the pre-processing pipeline, it is essential to incorporate filtering techniques to address various issues such as the presence of line noise, high frequency noise, and low frequency noise in raw EEG recordings. By employing digital filters on the continuous EEG data, we can significantly improve the clarity of the EEG signals that might have been affected by artifacts.

There are four main types of digital filters: band-pass filter, high-pass filter, low-pass filter, and band-stop filter. A band-pass filter allows frequencies within a specific range to pass through while rejecting frequencies beyond that range. On the other hand, a high-pass filter allows signals with frequencies higher than a certain cut-off frequency to pass through, while attenuating signals with frequencies lower than the cut-off frequency. Conversely, a low-pass filter permits signals below the selected cut-off frequency to pass through and attenuates signals with frequencies higher than the cut-off frequency. Lastly, a band-stop filter functions to allow frequencies within a certain range to be excluded while transmitting all others.

To ensure optimal results, it is highly recommended to apply these filtering techniques to the continuous EEG data before dividing it into epochs during the pre-processing phase. This helps to mitigate potential issues and enhance the quality of subsequent analyses.

3.4.6 Digital Filtering of EEG

A computer programmer or algorithm would be a digital filter which can eliminate undesirable frequency components from a signal. Digital filters can be classified into different categories such as low-pass filters, high-pass filters, bandpass filters, or notch filters, just like their analog counterparts. The advantages of using digital filters over analog filters are manifold. Firstly, they allow for a much sharper reduction in frequency. Secondly, being software applications rather than hardware devices, they can be quickly designed and updated. Moreover, when constructed correctly, digital filters do not introduce any delay in the signal (phase shift), which is often a concern with ordinary analog filters. This ensures that time relationships between different channels remain intact even when separate filters are used.

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There are two widely employed types of digital filters: Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) filters. FIR filters compute the output based on the current and past input signal values only, while IIR filters consider both the current input signal and past input signal values ("feed forward" data flow) as well as past output signal values ("feedback" data flow). Designing FIR filters is simpler, but IIR filters require fewer calculations and generally work more efficiently than FIR filters with similar functionality. As a result, most EEG digital devices provide regular IIR filters for low, high-frequency, and line-frequency notch filtering, benefiting from their superior computing speed.

3.4.7 Spatial Filtering Using Principal Component Analysis

Principal component analysis (PCA) can be used in multiple linear, autonomous components/features by single value decomposition (SVD) for evaluating a period of multichannel EEG.

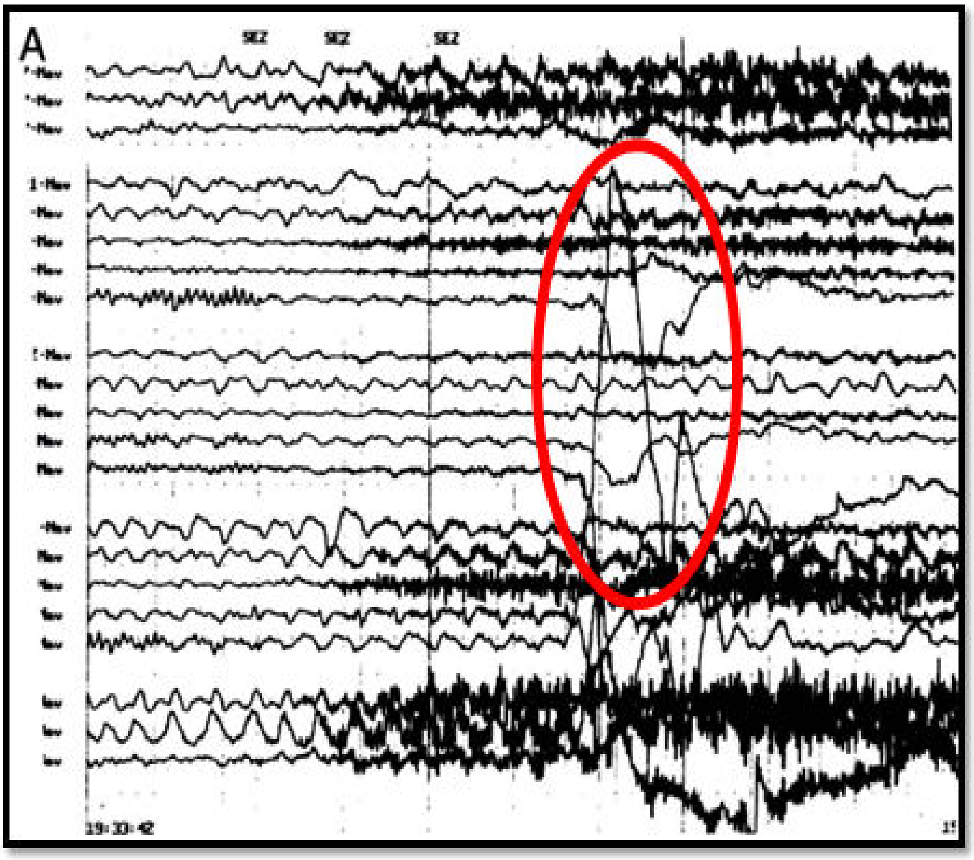

Figure 3.6: Without filtering

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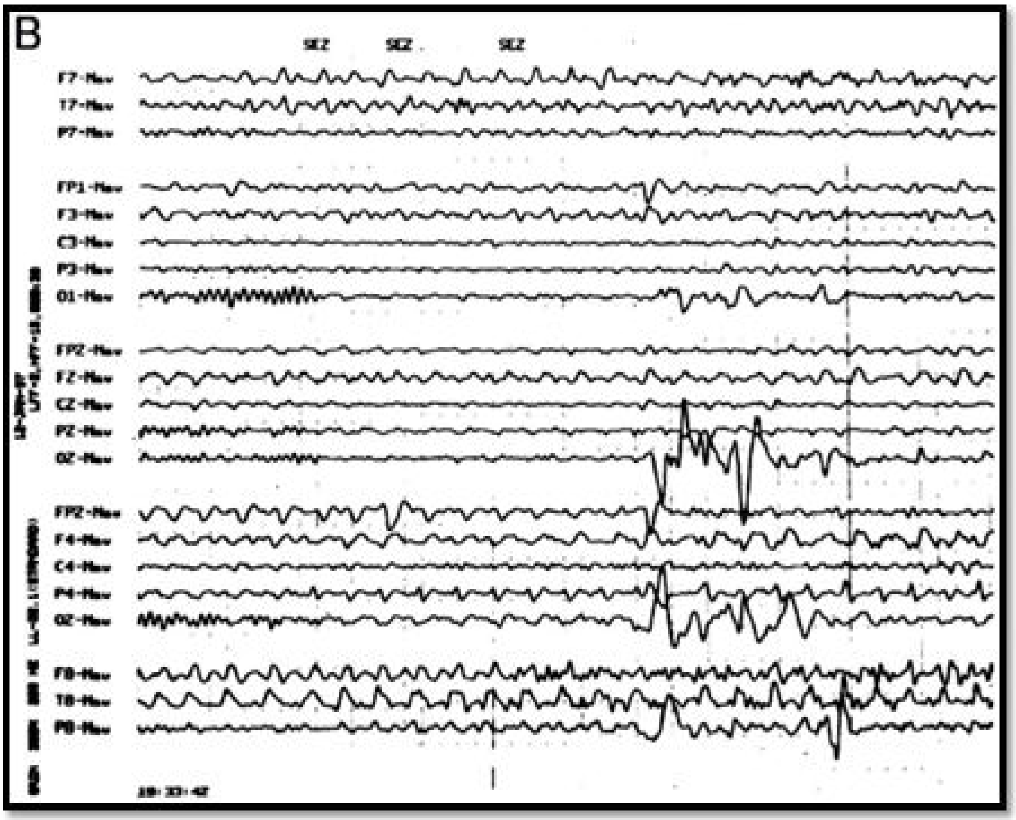

Figure 3.7: After use of a 2 to 15Hz digital band-pass filter to reduce unwanted muscle and electrode artifact.

3.4.8 Correcting and Filling in Data from Faulty Channels

Some EEG channels, particularly high-density EEG channels, have been unable to accurately provide neurophysiological information on brain activity for distinct reasons, such as if they are not properly positioned on the scalp. These signals that are obtained can be referred as bad channels and it is important to ignore the bad channels for future analysis. Some of the reasons are because of:

I. The channel malfunctions

II. The channel is poorly located or has no contact with the scalp

III. There are two or more channels linked.

IV. The channel becomes saturated

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3.4.9 Extracting Data Epochs and Removing Baseline Values

EEG data is being used to investigate cognitive event-related abilities by examining changes in EEG behaviors that are time-locked to the start of specific events of interest. These events can be sensory stimuli or cognitive tasks. The selection of the event onset (time point '0') is crucial for segmenting the data in order to classify EEG changes associated with the onset of these events or tasks. Specifically, brain responses related to both the stimulus presentation and the behavioral response are analyzed.

To ensure accurate analysis, a mean baseline value is subtracted from each epoch of the data after extracting the data epochs that correspond to specific experimental events. This step is necessary because the electrical potential at baseline can vary between these data epochs, and the baseline correction helps to account for these variations.

It is important to note that data epoch extraction and baseline correction are not performed for the resting-state dataset. In the resting-state dataset, the brain is not subjected to specific experimental events or tasks, so there is no need for epoch extraction and baseline correction in this case.

3.4.10 Removal of Bad Epochs

EEG epochs that are flagged as poor epochs, which is significantly corrupted by artifacts (e.g., eye blinks and movements), can be dismissed. Visually inspecting the data using an interactive viewer and labelling the bad segments in the data manually is the common approach to removing bad epochs. The automatic rejection method, for example, based on peak-to-peak signal amplitude values, is another standard and simple approach involving the rejection of bad epochs [11, 27, 15].

3.4.11 Interpolation of Digital EEG

Digital EEG has been commonly used as an alternative to traditional and analogue EEG, but whether clinical EEGs are represented more accurately with digital rather than conventional technologies remain a mystery. The EEGs recorded in this analysis were interpreted in three separate ways on a digital EEG system: Whether on a paper printout, on-screen without utilizing digital features such as montage reformatting or filtering, or on-screen using the full array of digital EEG capabilities, the information remains unchanged.

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Figure Fehler! Kein Text mit angegebener Formatvorlage im Dokument.**8:** A 12-s epoch of EEG on the same subject

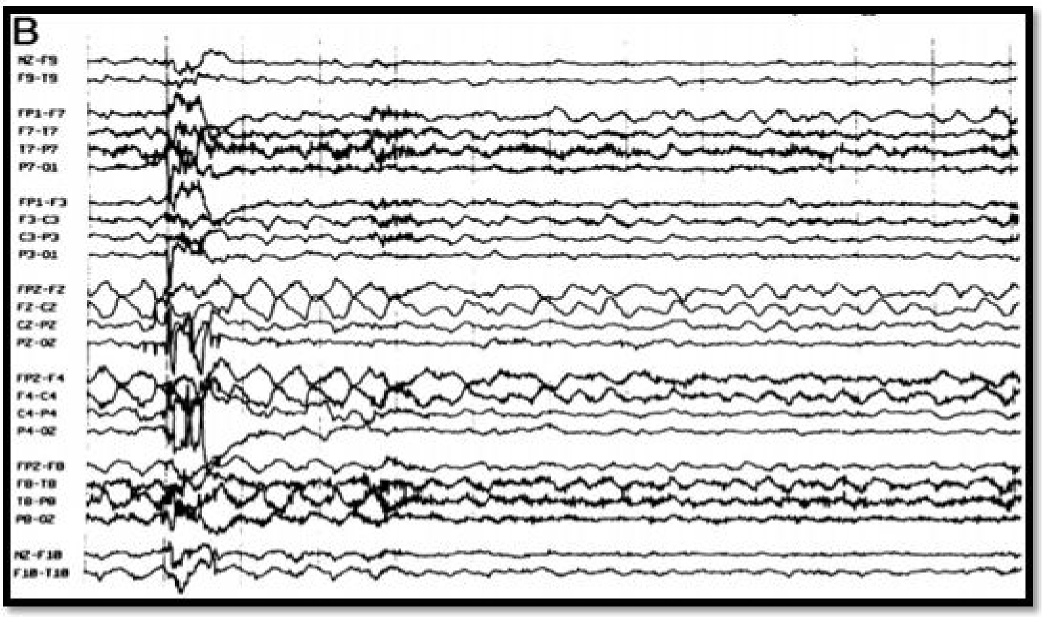

Figure 3.9: B The same EEG after applying the spatial filter

3.4.12 Artifacts in EEG

Furthermore, artifacts present in EEG signals can be categorized into two groups: physiological and non-physiological. Physiological artifacts arise from electrical activities inherent to the individual, predominantly originating from physical components near the head, such as eye movements, muscle contractions, and heart activity, or from subject movements. On the other hand, non-physiological artifacts encompass those arising from factors like the interface between the electrodes and the scalp, external devices, and environmental interference occurring throughout the EEG recording process.

3.4.13 Sources of Artifacts

EEG sources can be categorized into two main types: internal and external sources. Internal sources refer to the physiological activities of the body, such as electromagnetic signals from the heart, eyes, and muscles. On the other hand, external sources include practical interferences like wireless signals, electrode attachments, recording equipment, and cable movement that contaminate the EEG signals [23]. Internal artifacts, stemming from physiological processes, are challenging to avoid and have been the primary focus of artifact removal methods. Among the internal artifacts, the most notable ones that are typically addressed using EEG removal processes are ocular artifacts caused by eye movements and blinks, muscle artifacts resulting from contractions of various body parts like the face, head, neck, and arms, as well as heart artifacts generated by the electrical activity of the heart. Heart artifacts usually exhibit low amplitudes compared to other types of artifacts.

3.4.14 Removal of EEG Artifacts Using ICA

The process of independent component analysis (ICA) is utilized in the analysis of electroencephalographic (EEG) signals. ICA's primary objective concerning a random vector is to find a linear transformation that maximizes the statistical independence between the components associated with the signal [3]. EEG data, which consists of the summation of real EEG signals and unrelated objects, is recorded from scalp electrodes. Therefore, ICA represents a valuable technique in theory for distinguishing objects from

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EEG signals [19, 32]. Typically, components that are relevant to artifacts can be identified based on their temporal distributions, topographies, and frequency distributions across trials.

In particular, the use of ICA tends to be especially helpful in eliminating blinks and other oculomotor objects [16]. The use of ICA to correct objects is usually considered the strongest, because the individual signals do not presume orthogonal or gaussian behavior [17].

3.4.15 Physiological Artifacts

Physiological artifacts typically come from body origins. Eyeblinks, eye motions, head motions, heartbeats and muscle noise are among the most common physiological artifacts.

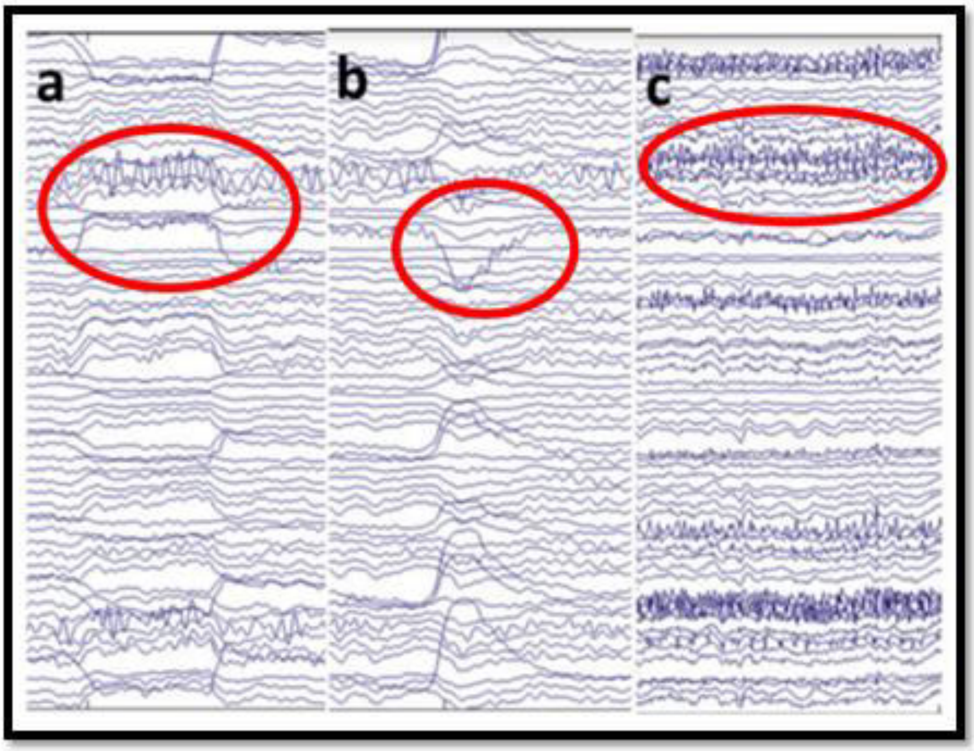

Figure 3.10: Examples of ocular and electromyography artifacts.

The electrical potential of ocular artifacts, such as eye movements (a) and blinking (b), is usually characterized by a synchronized appearance, bilateral distribution, and anterior location. On the other hand, electromyography artifacts (c) like those caused by muscle tension exhibit high-frequency activities and are observed to have a spiky nature.

3.4.16 Non-Physiological Artifacts

Non-physiological artifacts are typically the result of disturbances originating outside the brain. Among these, electrical disruptions are a prevalent factor. Another common source of non-physiological artifacts is the improper placement of electrodes on the scalp. Additionally, any malfunction within the EEG recording system can also lead to the occurrence of artifacts.

Table 3.8: Physiological and non-physiological artifacts

No.	Physiological artifacts	Non-physiological artifacts
1	Eyes gestures and blinks among artifacts related to the ocular.	Interference artifacts caused by power lines at 60 Hz are prevalent in Malaysia.
2	Artifacts in electromyography related to frontal and temporal activity of muscles.	Electrode artifacts because electrode is not positioned correctly in the scalp
3	Electrocardiographic artifacts due to heartbeats	Any role of the EEG machine failure, for example, amplifiers
4	Scalp abruptness and motions	Digital artifacts like easing of wires or easing of circuit board links

3.5 Montage

The International 10–20 System is an internationally accepted method throughout the context of EEG experiments for describing and applying the scalp electrode position. The relation in between electrodes position and sub-areas, especially cerebral cortex, of the brain are focused on this system.

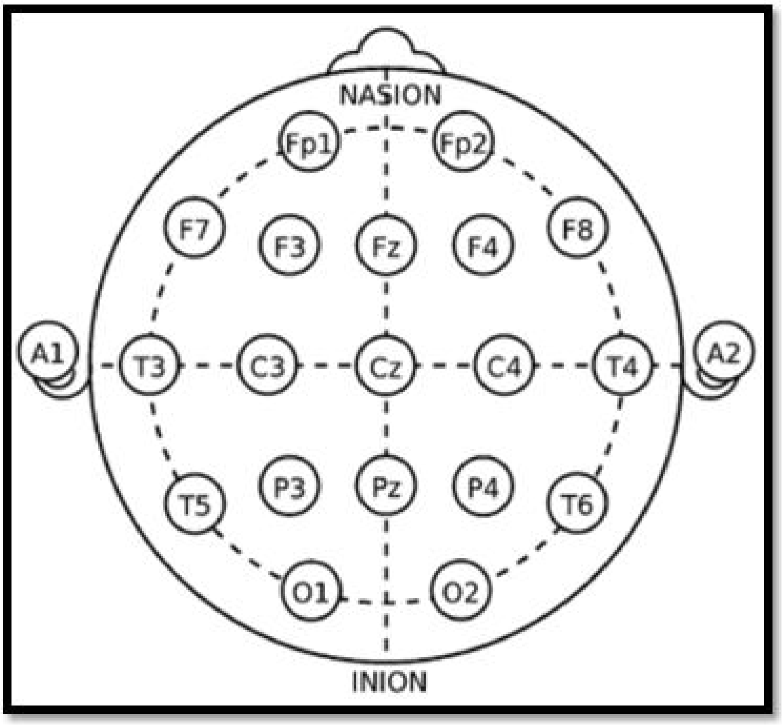

Figure 3.11: The International 10–20 EEG Placement System

This current system of naming electrodes is more complex, which contributes to the adjusted combinatorial nomenclature, which is MCN. Each position on this MCN scheme includes a letter representing the brain lobe or area: frontal (F), temporal (T), parietal (P) and occipital (O), and central (C). Electric potential variations between electrodes form the channels and most are known as assemblies of the combinations of the various channels. Two major montages are available: the bipolar and the referential montages. Channels are formed in a bipolar montage in chains following an anterior or a transverse configuration. In the referential montage, the separate electrode potential within each electrode reflects each channel with one electrode selected (reference electrode).

3.5.1 Reformatting to Referential or Bipolar Montages

The EEG show application scans two current channels, one with an electrode reference O1 and the other with a O2 reference, which subtracts the 2 channels. That is, O1 - O2 = (O1 - R) - (O2 - R), where R is the reference. This makes it possible to produce new bipolar and referential montages. Suppose, for instance, that the EEG data entered include the following channels:

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Table 3.9: Technique of reformatting to referential or bipolar montages

Channel	Channel Derivation
1	Fp1 - Cz
2	Fp2 - Cz
3	F3 - Cz
4	F4 - Cz
5	C3 – Cz
6	C4 – Cz
7	P3 – Cz
8	P4 – Cz
9	O1 – Cz
10	O2 – Cz

A new bipolar montage can be formed by subtracting pairs of channels as follows:

Table 3.10: Subtracting pairs of channels as follows can create a new bipolar montage

Channels	Channels Derivation
Ch 1 - Ch 3	Fp1 - F3
Ch 3 - Ch 5	F3 - C3
Ch 5 - Ch 7	C3 - P3
Ch 7 - Ch 9	P3 – 01
Ch 2 - Ch 4	Fp2 - F4
Ch 4 - Ch 6	F4 - C4
Ch 6 - Ch 8	C4 - P4
Ch 8 - Ch 10	P4 - 02

Let us consider an electroencephalogram (EEG) recorded with a Cz reference. We can establish a new derivation, for instance, O1 - Ab, by calculating it in the following manner: Here, Ab represents the average of ear electrodes that are combined due to the "tied ear" effect.

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O1 - Ab = (O1 - Cz) - 0.5(Al - Cz) - 0.5(A2 – Cz) ………………… (3-1)

3.5.2 The Laplacian (Source Current Density) Montage

For all points in the brain, the potential is not identified since only at electrode positions can an EEG instrument record potential. In this case Laplacian exact calculation is impossible but however a simple approach method is available for Laplacian at the site of electrodes matching locations. The method which is called as nearest neighbor method is The Laplacian montage commonly derives. Electrode X can be about the total of the potentials at the four nearest neighbors to X minus four times the potential at X. For instance, Cz will be appropriate formula that required formula:

Cz - Nav = (Cz - R) - 0.25[(C3 - R) + (C4 - R) + (Fz - R) + (Pz - R)] ……….. (3-2)

The reference R here is for which Cz, C3, C4, Fz and Pz were calculated. A theoretical reference electrode is the notation "Nav," which stands for the "neighborhood average," where it indicates the average of four neighboring electrodes.

3.6 Problem Formulation and Definitions

Definition 1, (seizure density function). Each should label an ideal seizure sensor system or human marker with exact start and end time in the videos.

Definition 2, (sensitivity (Sen)). The sensitivity is measured as the proportion of the overall number of seizure occurrences observed to the overall number with all labelled EEG activities reported,

$$\text{Sen} = \frac{\text{Total number of correctly recognized seizure events}}{\text{Total number of labelled seizure events}}$$

……………………………… (3.3)

Definition 3, (specificity (Sp)). Specificities are defined by specifying the ratio from the number of normal events observed to the total number of known events labelled in the EEG record,

$$\text{Sen} = \frac{\text{Total number of recognized normal events}}{\text{Total number of labelled normal events}},$$

………………………………… **(3.4)**

Definition 4, (true positive rate (TPR)). The true positive rate is the ratio between the number of seizure occurrences observed and the overall number of seizure occurrences,

$$\text{TPR} = \frac{\text{Total number of correctly recognized seizure events}}{\text{Total number of detected seizure events}}$$

…………………………………… **(3.5)**

Definition 5, (false alarm rate (FAR)). A false alarm is made if the seizure density integral function crosses the seizure density threshold p for a nausea case. The false alarm rate over a 24-hour period is specified as the ratio of the number of wrong alarm events to the EEG length of 24 hours.

$$\text{FAR} = \frac{\text{Total number of false alarm events}}{\text{Total duration}}.$$

………………………………………………… **(3.6)**

3.7 Classification

There are many types of classifiers available, namely Artificial Neural Network (ANN), Convolution Neural Network (CNN), k-nearest neighbor (KNN), Support Vector Machine (SVM) and so on. The data are to be run through deep learning technique for the classification process.

3.8 Summary

Table 3.11: Summary of pre-processing procedures

No.	Process	Remarks
1	Import data	From. Excel file
		Manual import of event and electrode information in the form of PYTHON arrays.
2	Import channel	Load the channel location file describing channel

	locations	positions
3	Remove empty channels	Remove HEOG, VEOG, M1, M2
4	Re-reference data	Compute common average
		Or reference to a specific channel(s)
5	Filter data	Low-pass filter at 30 Hz – >100 Hz
		High-pass filter at 1 Hz – >0.3 Hz
6-1	Extract epochs with correct responses	Extract epochs [3.5 s, 0 s] around "correct responses"
6-2	Extract epochs around stimulus one	Extract epochs [0.5 s, 1 s] around events
7	Baseline correction	Baseline latency range: [0.5 s, 0.1 s] around events, that is, during fixation
8	Epoch rejection	Reject epochs with extreme values outside +/ 40 microvolts (higher threshold, e.g., 65/100uV)
		Reject epochs with abnormal trend >50 microV/epoch or R-squared >0.3
		Reject epochs with improbable data, outside 6 SD of single electrode or 5 SD of all electrodes
		Reject epochs with abnormal distribution, kurtosis outside 5 SD of mean kurtosis
		Aim to remove only small number of epochs (<10%)
9	Artifact removal	ICA on EEG epochs
		Manual component removal (see if it is inconsistent across trials and activation concentrate in frontal areas)
		2 components for eye and 1 component for sine wave
		Either remove as much epoch as possible or 2–4 components

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CHAPTER 4

CLASSIFICATION ALGORITHMS FOR MENTAL DISORDER IDENTIFICATION

Dr. Ashok Vajravelu

Bio Medical Engineering and Measurement System (BioMEMS)

4.1 INTRODUCTION

This chapter focuses on result obtained for the development of this project. The results represent the 10-20 system and the electrode actions, also represent the output of the Montages signals using MATLAB software. For the simulation, a total of 33 pre-processed signals are obtained from Erode Neuro Centre, Chennai. All the EEG signals were recorded from subjects who are induced with anesthesia where 9 subjects' signals have been involved in this study. The 9 subjects are divided into 2 normal subjects, 1 normal subject with hypertension condition, 2 general epilepsy subjects and 4 autism spectrum disorder subjects. The signals vary from normal controlled subjects, subjects with general epilepsy and subjects with autism spectrum disorder (ASD). The signals are then executed through the MATLAB module and the results obtained are classified and tabulated based on the type of subjects. Kuppuswamy socioeconomic scale is used to classify the score of the obtained values for each type of subjects.

4.2 10 – 20 System

The 10-20 system is a widely adopted approach for positioning electrodes in electroencephalography (EEG) research. It defines specific locations on the scalp where electrodes allow it to record the brain's electrical activity. The system is named after the distances between these electrode positions, which are either 10% or 20% of the total distance between specific anatomical landmarks on the scalp.

In your case, it seems that different simulations were conducted using MATLAB software, and the results were obtained for electrode placements based on different channel configurations.

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The numbers 31 channels, 56 channels, 61 channels, and 64 channels indicate the number of electrodes used in each simulation. The figures you mentioned likely depict the different electrode placements for each channel configuration. These plots can provide valuable information about the spatial distribution of electrical activity recorded from the brain. By visualizing the electrode positions on the scalp, researchers can gain insights into the brain regions that were targeted in each simulation.

The electrode placements obtained from the simulations using MATLAB software can serve a multitude of purposes across various domains, including studying brain activity patterns, analyzing functional connectivity, and identifying abnormal electrical patterns associated with neurological disorders. It is important to note that without specific details or additional context about the simulations or the research objectives, it is challenging to provide more specific information. If you have any questions or need further clarification, please feel free to ask.

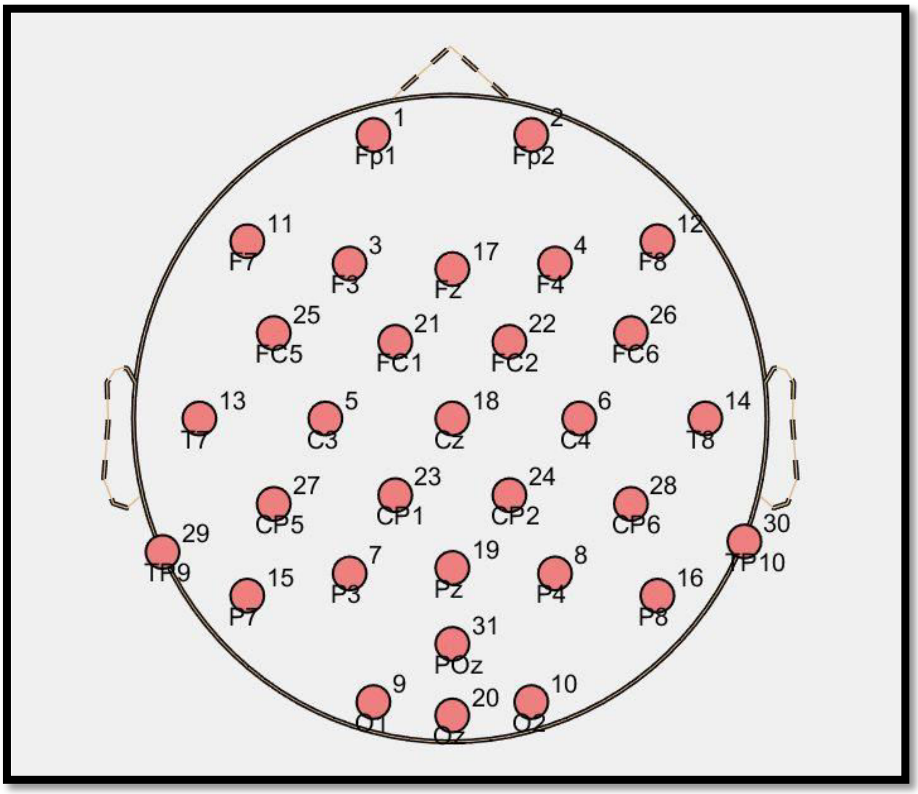

Figure 4..12: Electrode placement of 31 channels

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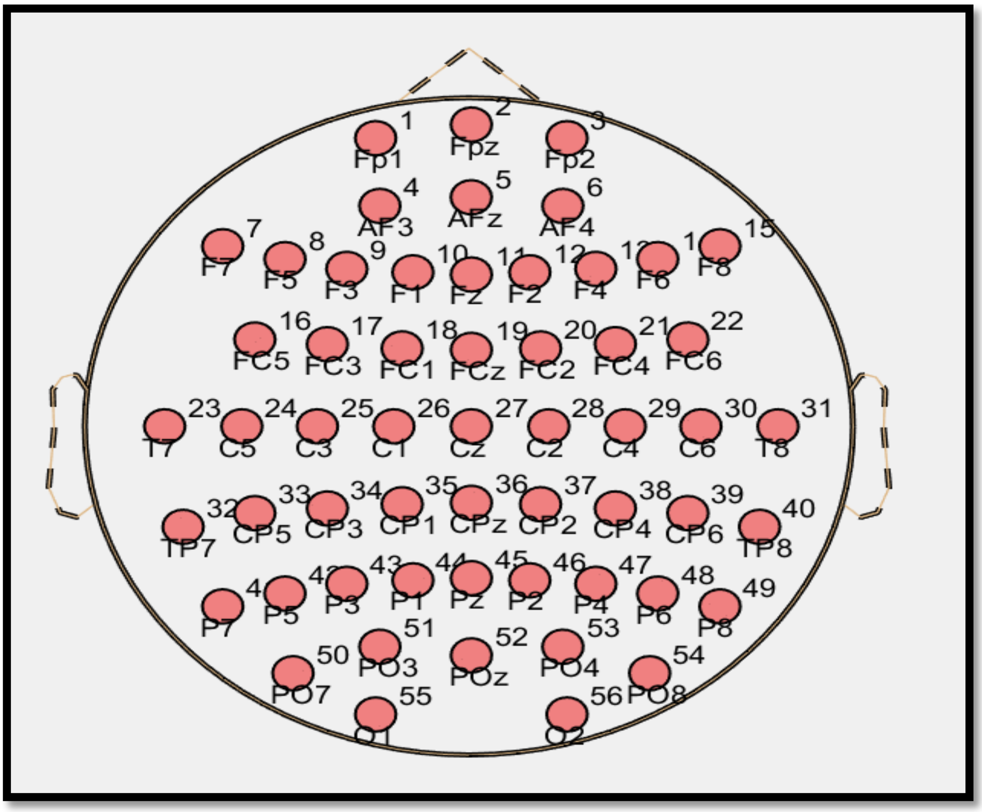

Figure 4.13: Electrode placement of 56 channels

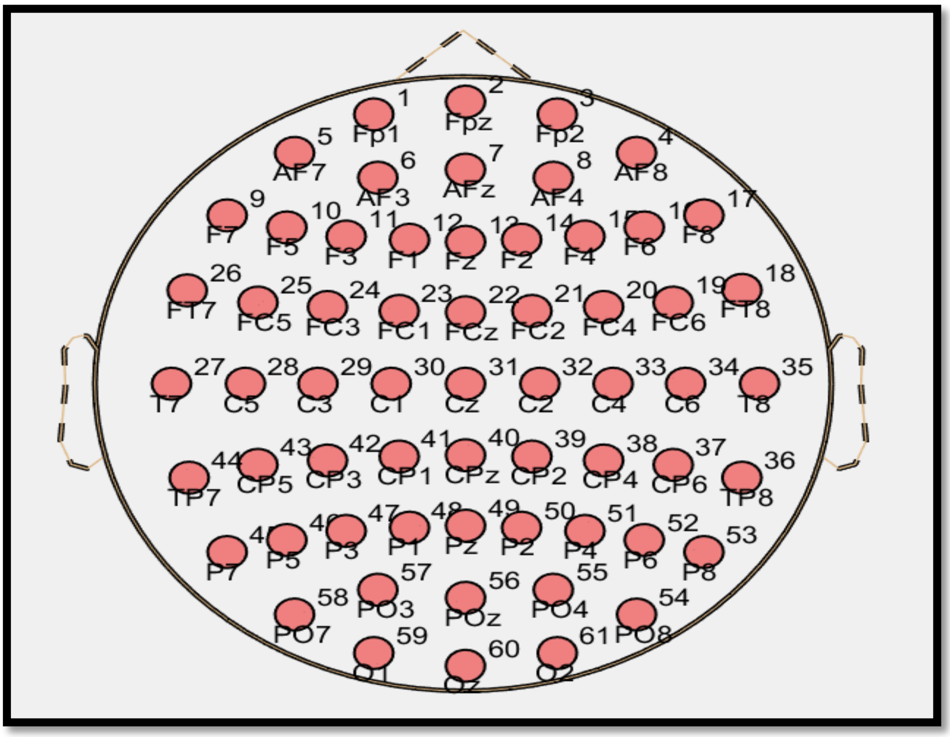

Figure 4.14: Electrode placement of 61 channels

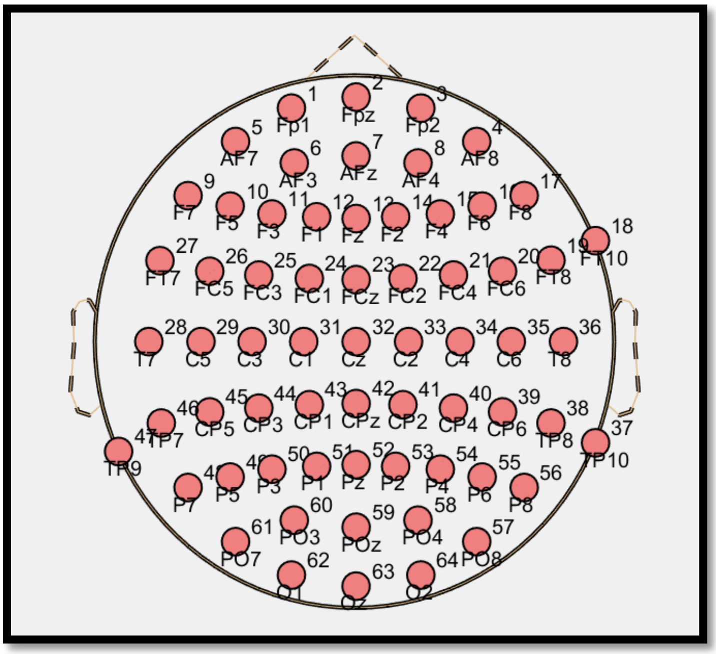

Figure 4.15: Electrode placement of 64 channels

4.2.1 Channel Impulse Reactions

After the electrode placement plotting, the system will simulate the digital signal data to rectify the channel impulse reaction. In this process it will show the electrodes that have reacted. The below figures show the set of electrode placement.

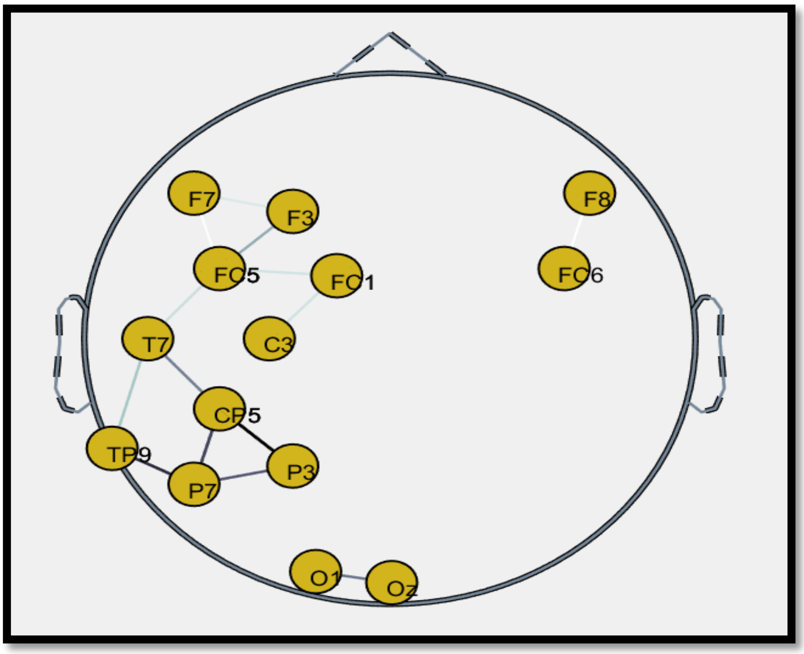

Figure 4.16: The formed pattern of electrode

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After this plotting it continues to plot the reaction between the electrodes which shows in which channel the signals spikes up for later reading and observation. The below figure shows the reactions between electrodes. The darker lines are reacted to the signal readings.

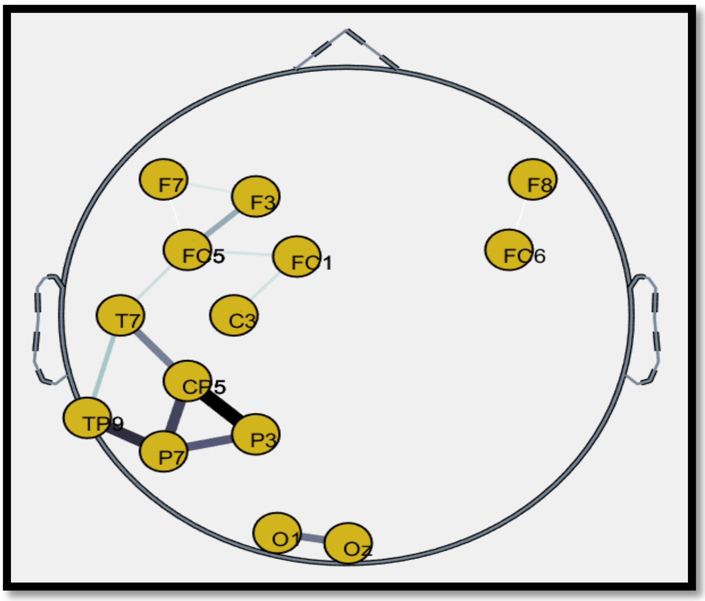

Figure 4.17: The reaction between electrodes

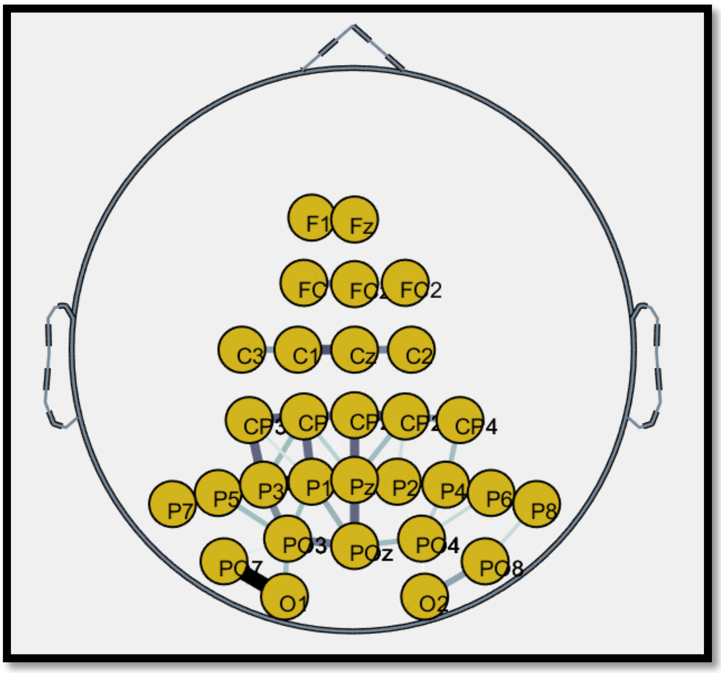

Figure 4.18 : The reaction between electrodes

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4.3 Analysis of Normal Subjects

The results of controlled subjects are filtered to 3 subjects randomly and tabulated. However, one of the controlled subjects has hypertension condition (Male, 22-year-old) compared to the other 2 subjects who has no such complexity. That reading is chosen in order to differentiate the subject's condition with the other normal subject and to avoid the results to be classified as someone with general epilepsy or autism syndrome disorder. The Table 4.1 will show the details of the subjects, montages that has been used, the affected channels and lobes, finally will show the Kuppuswamy's socio-economic status scale 2019 score. The image of the obtained signals will be illustrated below the Table 4.1.

Table 4.12: Reading of normal subjects based on their signal montages

No.	Subject	Montage	Channel	Lobe	Signal	Kuppuswamy's socio-economic status scale 2019 score
1.	S1	Bipolar	NA	NA	(Figure 4.8)	26-29
		Monopolar			(Figure 4.9)	26-29
2.	S2	Bipolar	NA	NA	(Figure 4.10)	26-29
		Monopolar			(Figure 4.11)	26-29

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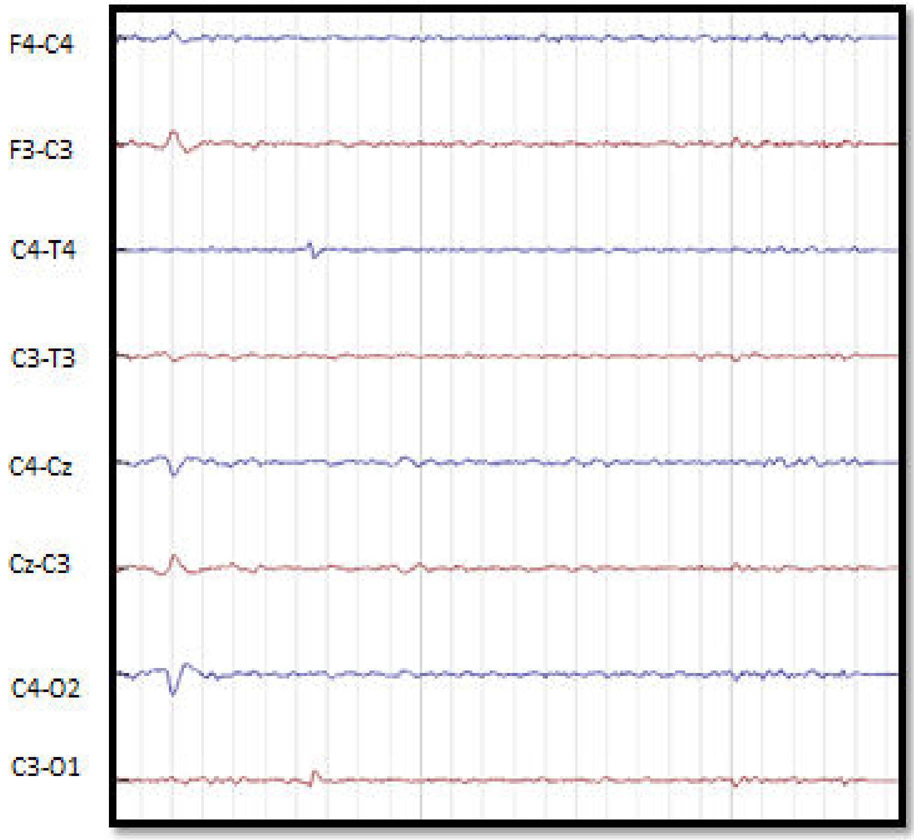

Figure 4.19: Bipolar montage of normal subject, male 9 years old

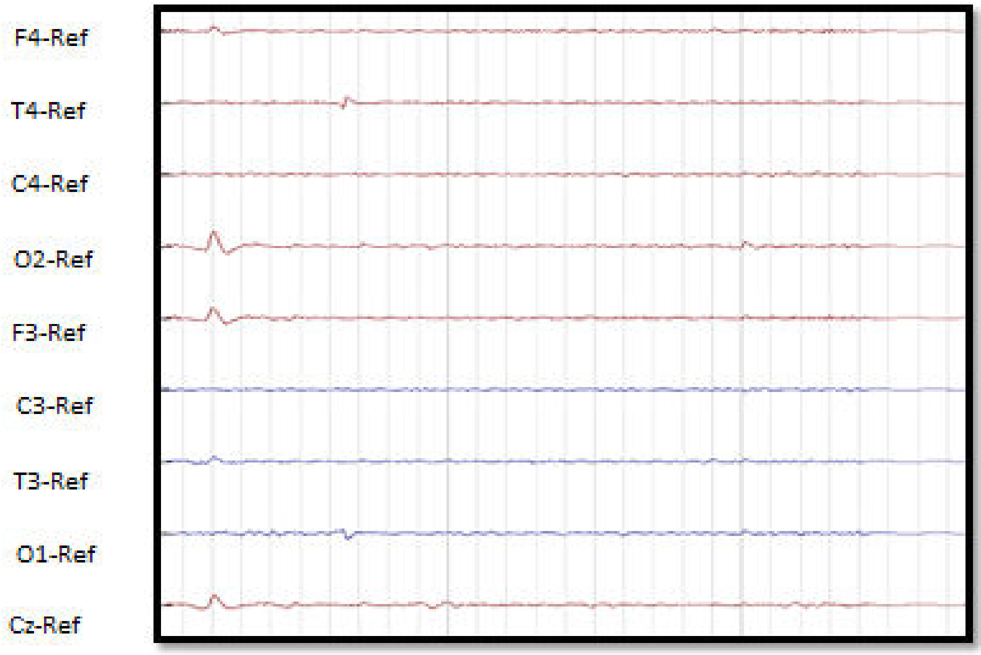

Figure 4.20: Monopolar montage of normal subject, male 9 years old

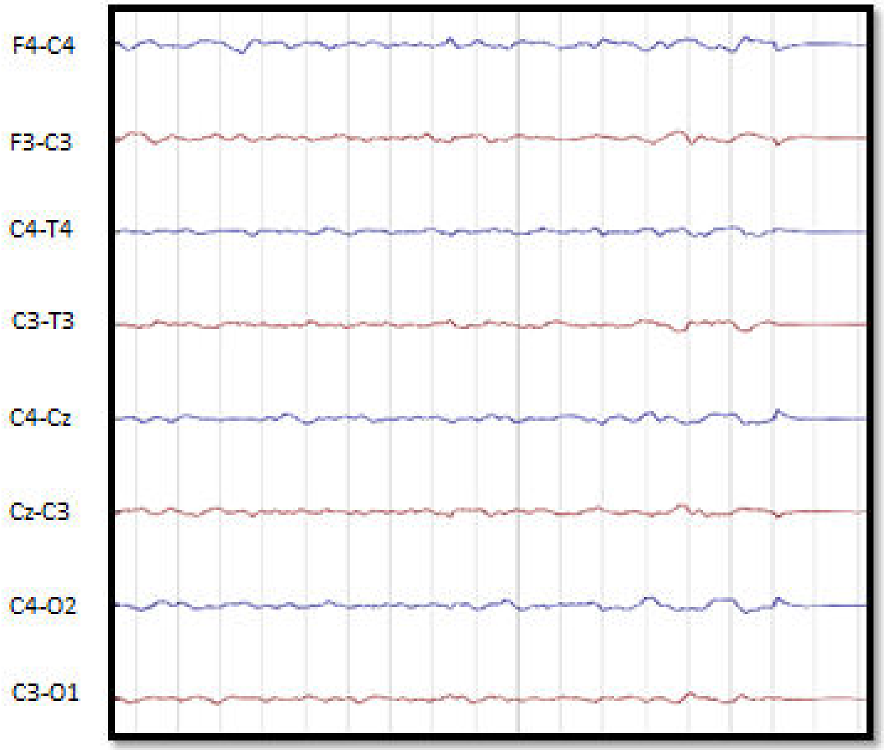

Figure 4.21: Bipolar montage of normal subject, male 8 years old

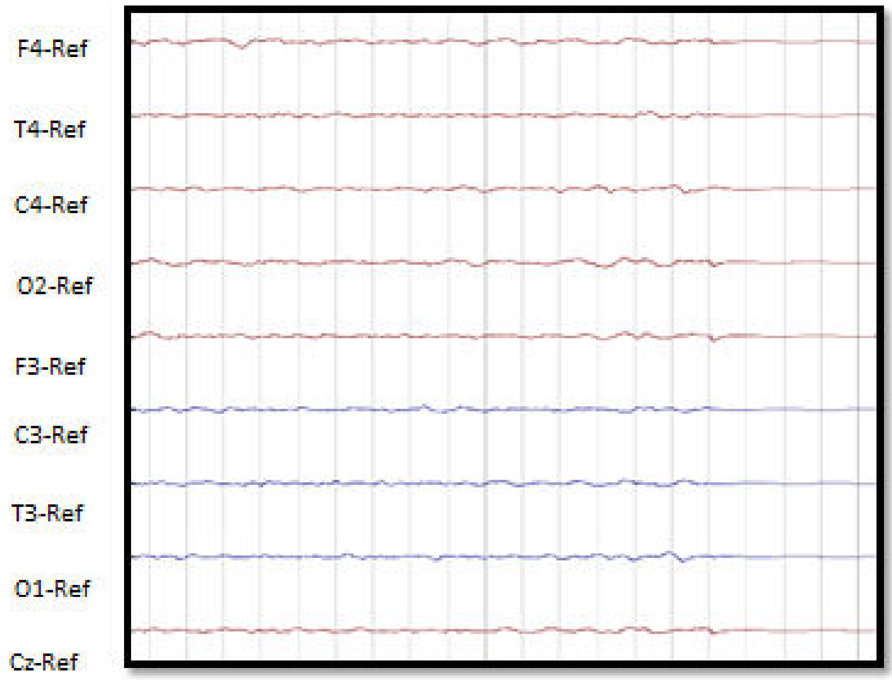

Figure 4.22: Monopolar montage of normal subject, male 8 years old

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From the above figures, Figure 4.8, Figure 4.9, Figure 4.10 and Figure 4.11, the signals shown are obtained from digital EEG signals has been run a simulation using MATLAB software. As the signal displayed, there are no any fluctuations in the signals from the both subjects. This shows the brain activity is very normal and they are classified as a normal subject.

Table 4.2 shows the details of a normal subject but with hypertension condition. The Table 4.2 will show the details of the subjects, montages that has been used, the affected channels and lobes, finally will show the Kuppuswamy's socio-economic status scale 2019 score. The image of the obtained signals will be illustrated below the Table 4.2.

Table 4.13: Reading of normal subjects with hypertension condition based on their signal montages

No.	Subject	Montage	Channel	Lobe	Signal	Kuppuswamy's socio- economic status scale 2019 score
1.	S1	Bipolar	F4-C4, F3-C3, C3-T3	Frontal, Central, Temporal	(Figure 4.12)	15-25
		Monopolar	F3-Ref, T3- Ref,		(Figure 4.13)	15-25

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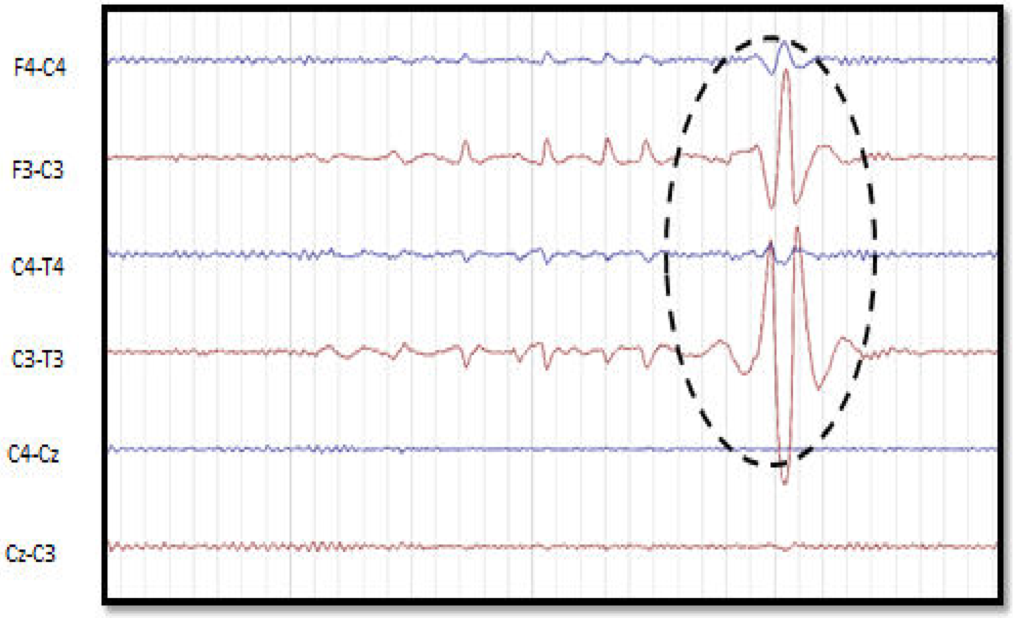

Figure 4.23: Bipolar montage of normal subject with hypertension condition, male 22 years old

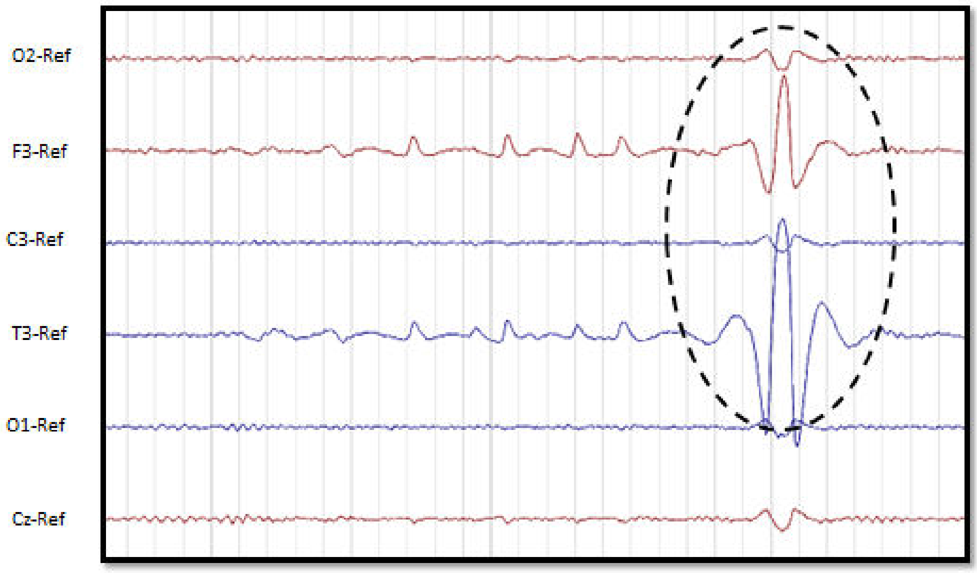

Figure 4.24: Monopolar montage of normal subject with hypertension condition, male 22 years old.

From the above figures, Figure 4.12 and Figure 4.13, the signals shown are obtained from digital EEG signals that has been run a simulation using MATLAB software. Both the bipolar montage and monopolar montage has fluctuation from the signal obtained and which affects the Frontal, Central and Temporal lobes.

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4.4 Analysis of General Epilepsy Subjects

The results of general epilepsy subjects are filtered to 2 subjects randomly and tabulated. When compared to the signals of normal controlled subjects, the recordings of EEG signals of general epilepsy can be observed in the below results, tends to have fluctuated signals while for the EEG recoding of controlled subjects have a more even and controlled values. The Table 4.3 will show the details of the subjects, montages that has been used, the affected channels and lobes, finally will show the Kuppuswamy's socio-economic status scale 2019 score. The image of the obtained signals will be illustrated below the Table 4.3.

Table Fehler! Kein Text mit angegebener Formatvorlage im Dokument.**.14: Reading of general epilepsy subjects based on their signal montages**

No.	Subject	Montage	Channel	Lobe	Signal	Kuppuswamy's socio-economic status scale 2019 score
1.	S1	Bipolar	F4-C4, F3-C3, C3-T3, C4-Cz, Cz-C3, C4-O2	Frontal, Central, Occipital	(Figure 4.14)	26-29
		Monopolar	F4-Ref, O2-Ref, F3-Ref, T3-Ref, Cz-Ref	Frontal, Central, Occipital	(Figure 4.15)	26-29
2.	S2	Bipolar	F4-C4, F3-C3, C4-T4,	Frontal, Central, Temporal,	(Figure 4.16)	15-25

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			C3-T3, C4-Cz, Cz-C3, C4-O2, C3-O1	Occipital		
		Monopolar	C4-Ref, C3-Ref, O1-Ref	Central, Occipital	(Figure 4.17)	26-29

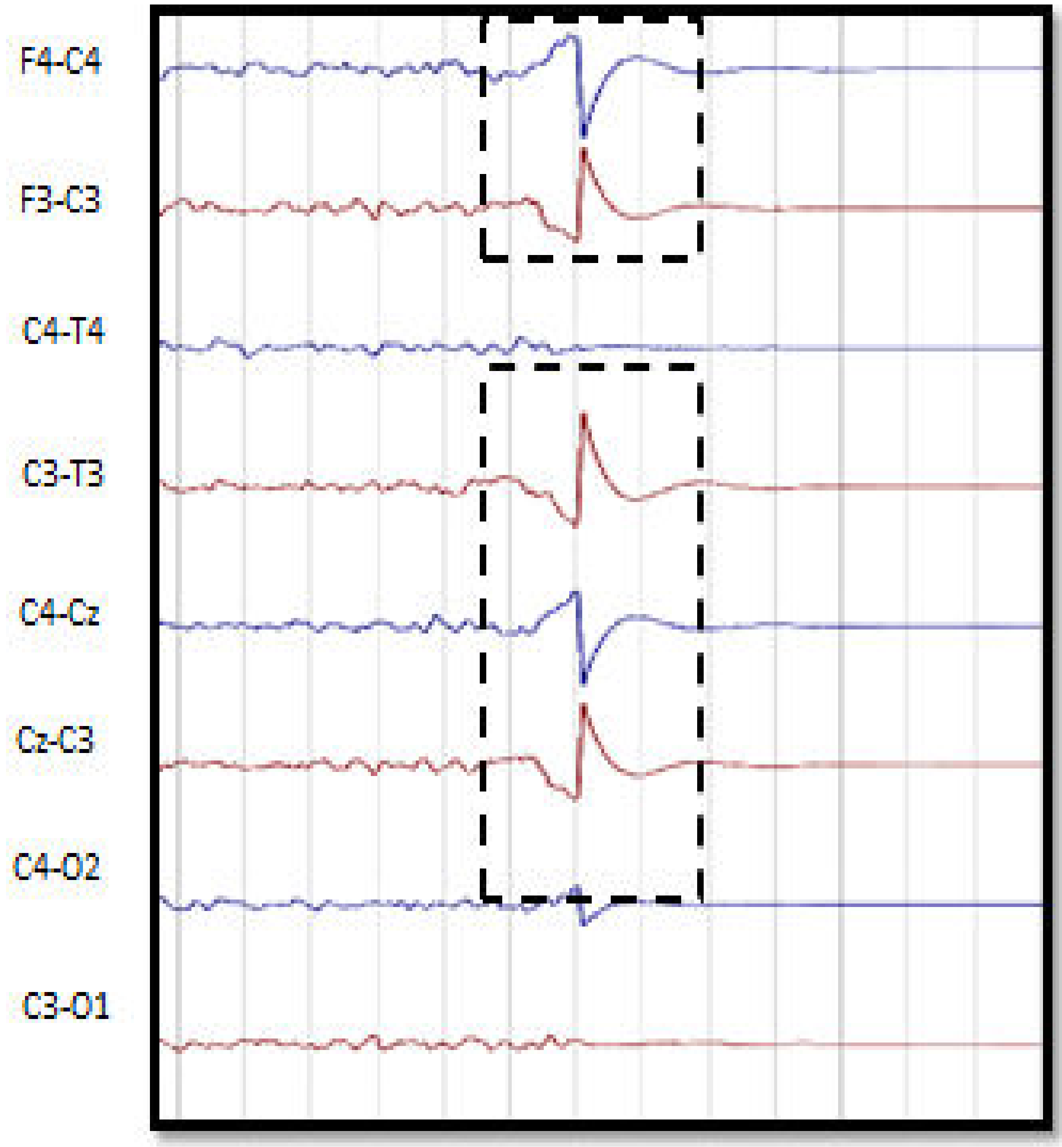

Figure 4.25: Bipolar montage of general epilepsy subject, male 6 years old

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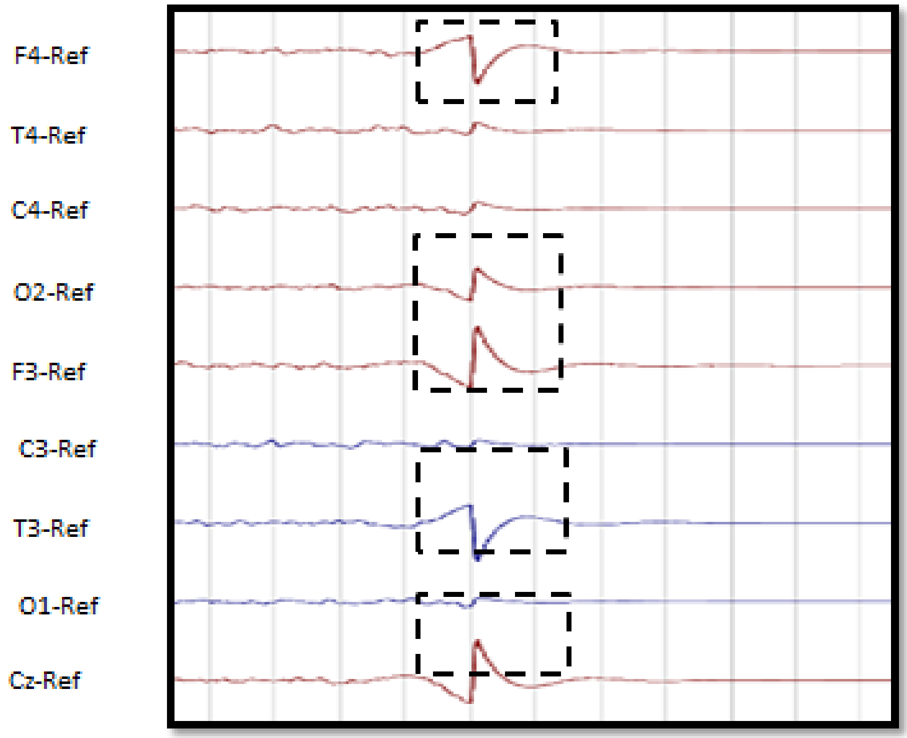

Figure 4.26: Monopolar montage of general epilepsy subject, male 6 years old

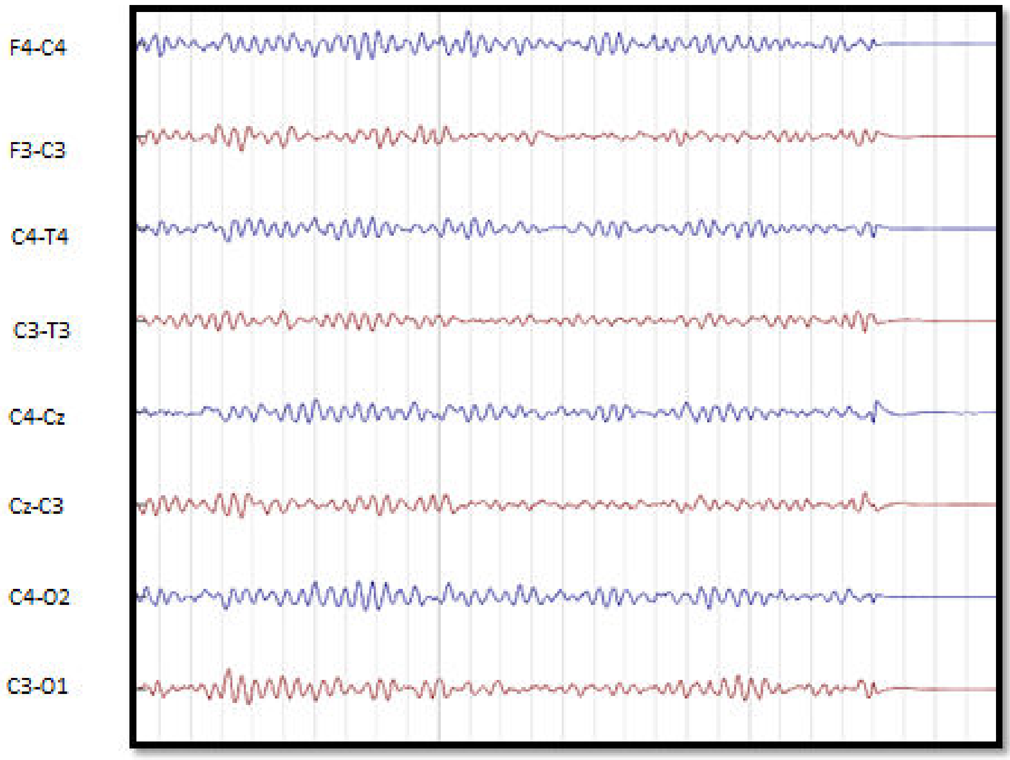

Figure 4.27: Bipolar montage of general epilepsy subject, male 8 years old

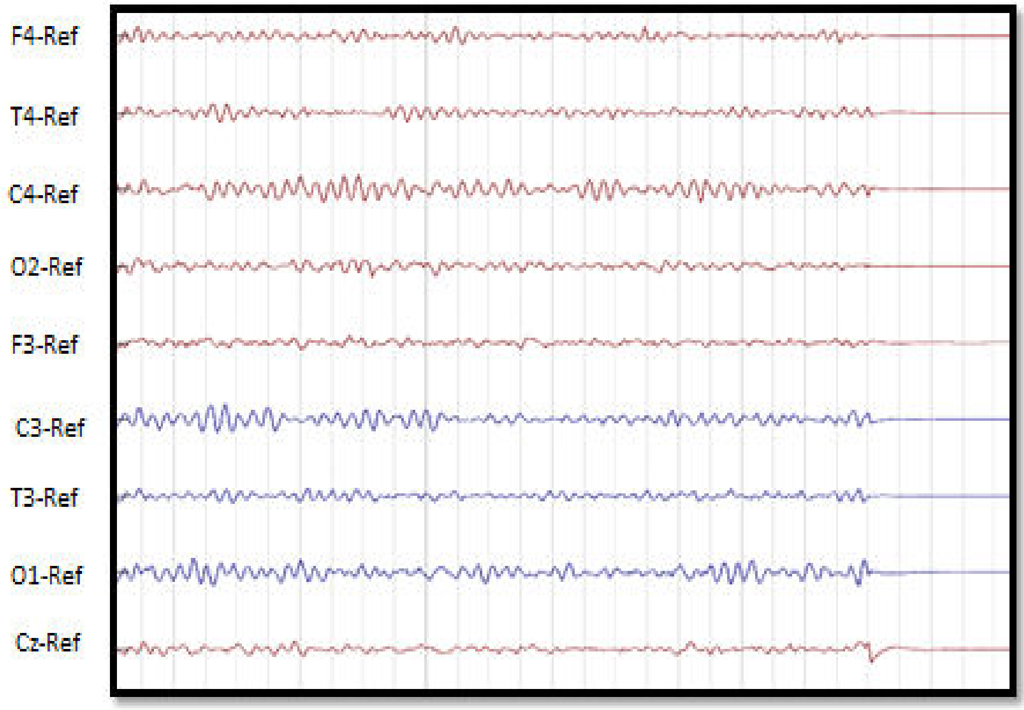

Figure 4.28: Monopolar montage of general epilepsy subject, male 8 years old

From the above figures, the signals shown are obtained from digital EEG signals that has been run a simulation using MATLAB software. Comparing subject 1 who is 6 years old and subject 2 who is 8 years, the Figure 4.14 and Figure 4.15 shows different fluctuations in signals when compared to Figure 4.16 and Figure 4.17. This is because different types of lobes have been affected to the subjects. To subject 1, the affected lobes are Frontal, Central and Occipital for both montages. Meanwhile for subject 2, the affected lobes are Frontal, Central, Temporal and Occipital in bipolar montage but for monopolar montage, Central and Occipital lobes are affected.

4.5 Analysis of Autism Spectrum Disorder (ASD) Subjects

The results of autism spectrum disorder subjects are filtered to 4 subjects randomly and tabulated. When compared to the signals of normal controlled and general epilepsy subjects, the recordings of EEG signals of autism spectrum disorder subjects can be observed in the below results, tends to have even more fluctuated signals while for the EEG recoding of controlled subjects have a more even and controlled values. The Table 4.4 will show the details of the subjects, montages that has been used, the affected channels and lobes, finally will show the Kuppuswamy's socio-economic status scale 2019 score. The image of the obtained signals will be illustrated below the Table 4.4.

Table 4.15: Reading of autism spectrum general subjects based on their signal montages

No.	**Subject**	**Montage**	**Channel**	**Lobe**	**Signal**	**Kuppuswamy's socio-economic status scale 2019 score**
1.	S1	**Bipolar**	F4-C4, C4-T4, C3-T3, C4-Cz, C4-02, C3-01	Frontal, Central, Temporal, Occipital	**(Figure 4.18)**	**26-29**
		Monopolar	F4-Ref, T4- Ref, C4- Ref, C3- Ref, T3- Ref, O1- Ref	Frontal, Central, Temporal, Occipital	**(Figure 4.19)**	**26-29**
2.	S2	**Bipolar**	F4-C4, F3-C3, C4-T4, C3-T3, C4-Cz, Cz-C3, C4-02, C3-01	Frontal, Central, Temporal, Occipital	**(Figure 4.20)**	**26-29**
		Monopolar	F4-Ref,	Frontal,	**(Figure**	**26-29**

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			T4- Ref, C4- Ref, C3- Ref, T3- Ref, O1- Ref	Central, Temporal, Occipital	**4.21)**	
3.	S3	**Bipolar**	C4-T4, C3-T3, C4-Cz, C4-02, C3-01	Central, Temporal, Occipital	**(Figure 4.23)**	**26-29**
		Monopolar	F4-Ref, T4- Ref, C4- Ref, C3- Ref, T3- Ref, O1- Ref	Frontal, Central, Temporal, Occipital	**(Figure 4.24)**	**26-29**
4.	S4	**Bipolar**	C4-T4, C3-T3, C4-Cz, C4-02, C3-01	Central, Temporal, Occipital	**(Figure 4.25)**	**26-29**
		Monopolar	F4-Ref, T4- Ref, C4- Ref, C3- Ref, T3- Ref, O1- Ref	Frontal, Central, Temporal, Occipital	**(Figure 4.26)**	**26-29**

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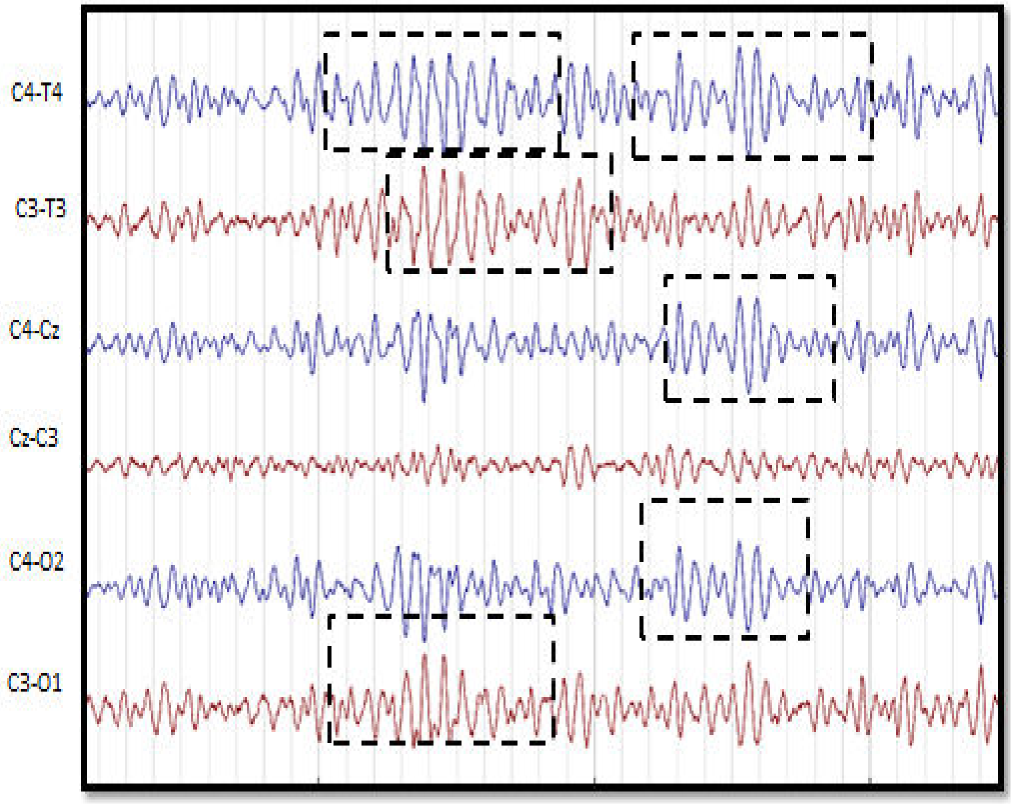

Figure 4.29: Bipolar montage of autism spectrum disorder subject, male 8 years old.

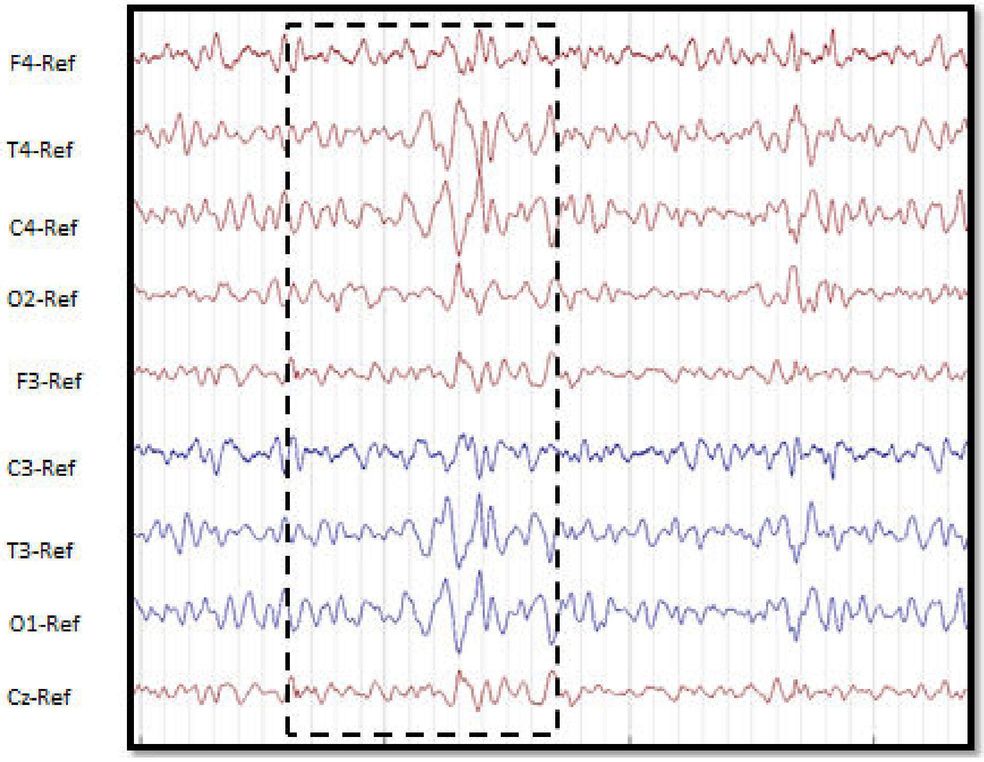

Figure 4.30: Monopolar montage of autism spectrum disorder subject, male 8 years old

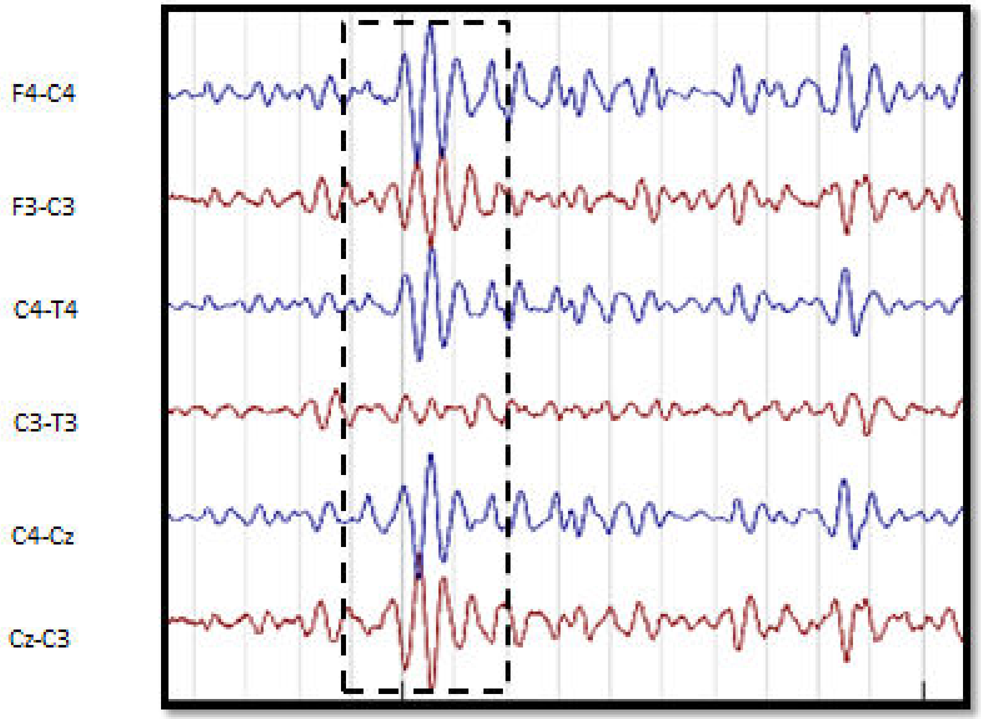

Figure 4.31: Bipolar montage of autism spectrum disorder subject, male 8 years old.

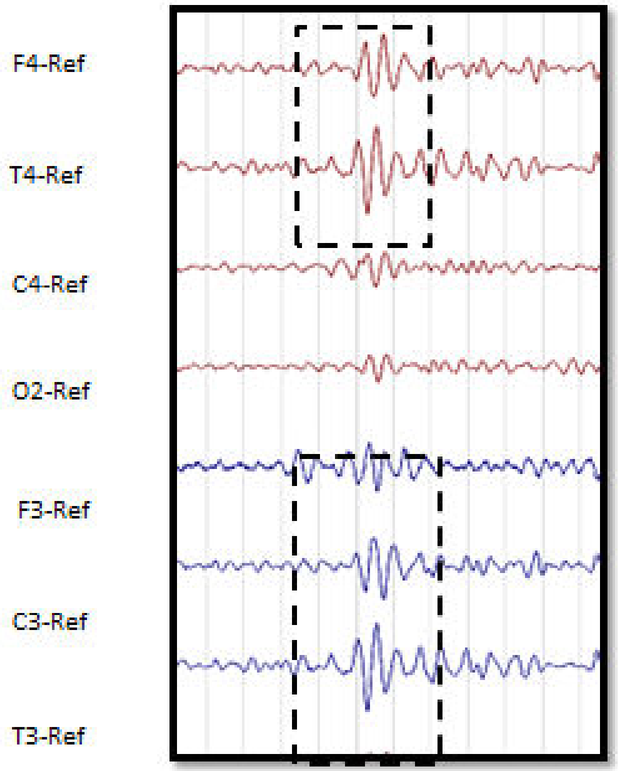

Figure 4.32: Monopolar montage of autism spectrum disorder subject, male 8 years old

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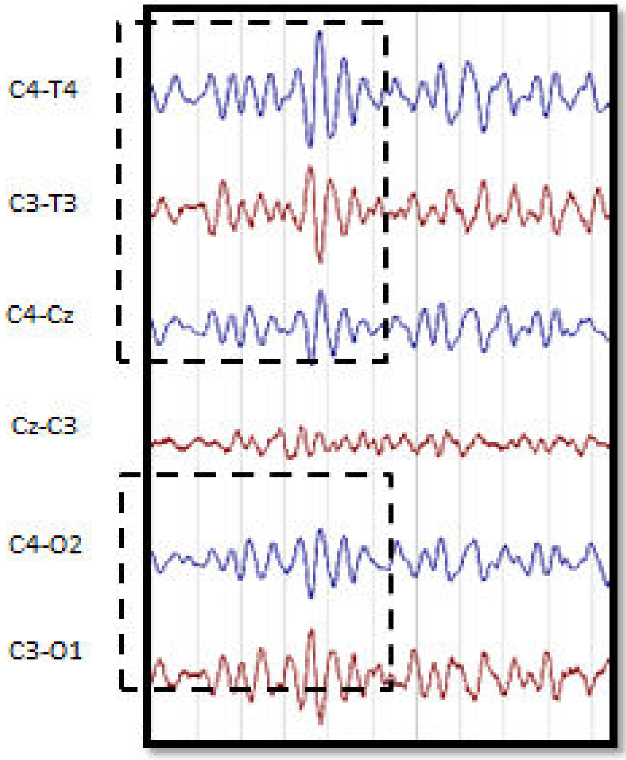

Figure 4.33: Bipolar montage of autism spectrum disorder subject, male 8 years old

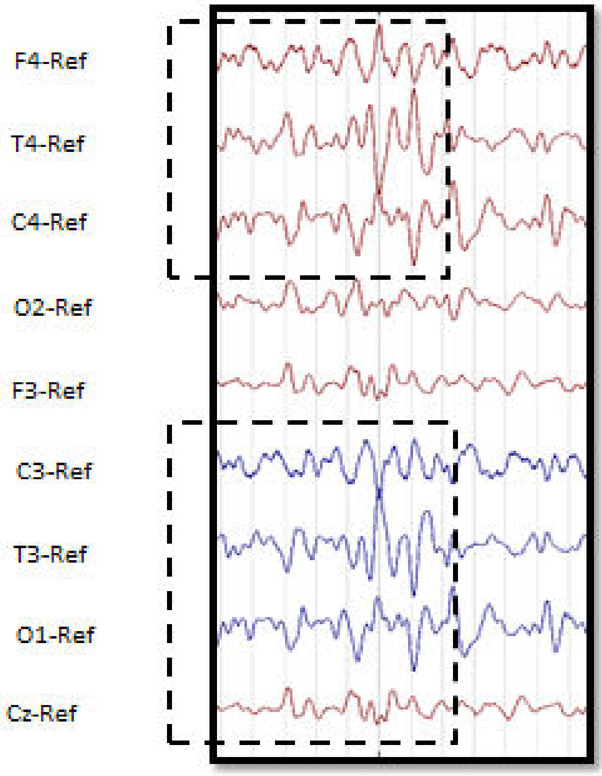

Figure 4.34: Monopolar montage of autism spectrum disorder subject, male 8 years old

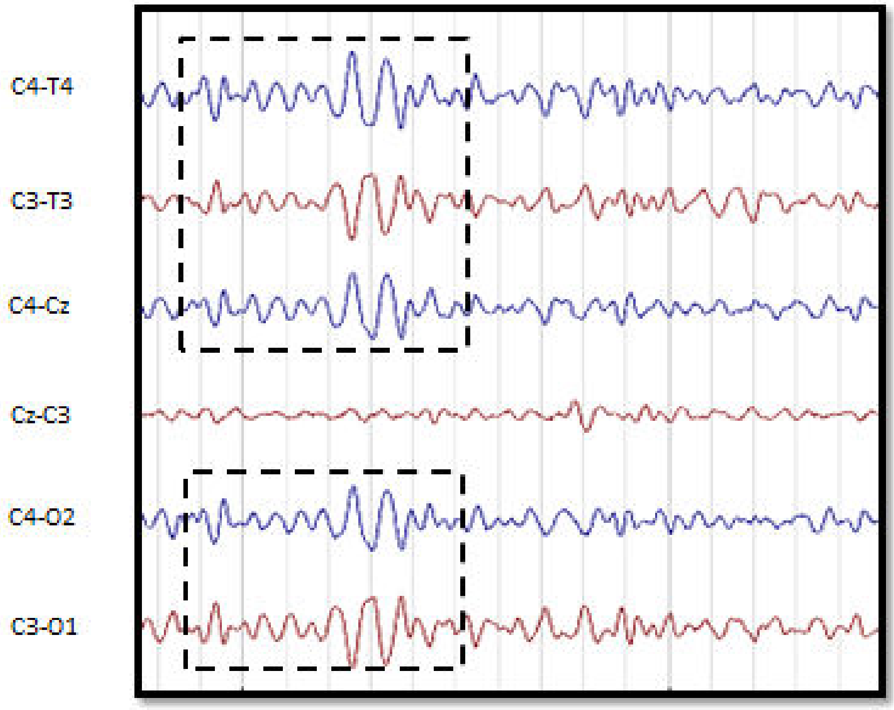

Figure 4.35 Bipolar montage of autism spectrum disorder subject, male 5 years old

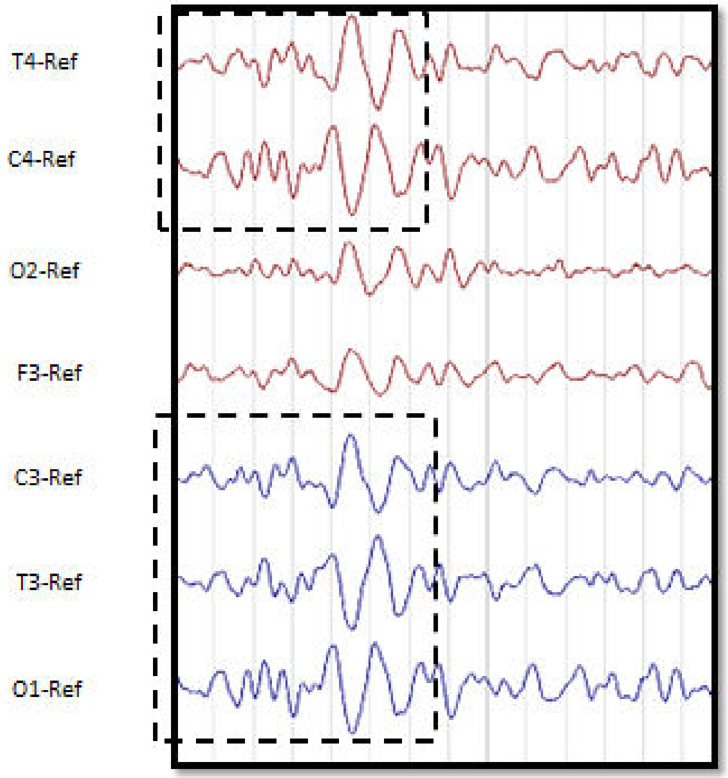

Figure 4.36 Monopolar montage of autism spectrum disorder subject, male 5 years old

From the above figures, the signals shown are obtained from digital EEG signals that has been run a simulation using MATLAB software. Comparing subject 1, 2, 3 and 4 who, subject 1, 2 and 3 is 8 years old and subject 4 is 5 years old, where the signals that are obtained and processed does not show much difference compared to the previous analysis. It can be observed that the autism spectrum disorder signals have high amplitude throughout the whole recordings compared to the general epileptic which has a few spikes while the readings of normal subjects are obtained in an even manner. The lobes which are affected in this disorder is more and stronger affects when it is compared to the controlled subjects and general epilepsy subjects.

4.6 DISCUSSION

The digital EEG signals that are extracted into waveform signals after running simulation in MATLAB software can be compared into two montages which are bipolar and monopolar. In this both recordings, the signals can be differentiated by analyzing the channels of electrodes. By this, it is also able to identify which lobes are affected by observing which channels of electrode is reacted to the brain activity of the disorders.

The Kuppuswamy's socio-economic status scale score is used to categories the level of sternness of the recordings. This level is useful to indicate whether the subject is prone to the type of mental disorder although the readings might vary.

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CHAPTER 5

CASE STUDIES AND APPLICATIONS

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5.1 INTRODUCTION

Welcome to an exciting journey into the world of EEG montage analysis for identifying mental disorders! In this chapter, we will delve into various case studies and applications that showcase the incredible potential of using MATLAB to analyze EEG data and gain insights into mental health conditions. These real-life examples illustrate the diverse range of mental disorders and the methodologies employed to extract meaningful information from EEG data, all while providing a friendly and accessible tone to make the topic approachable.

5.2 Case Study 1: Detecting Depression through EEG

Let us start by exploring a fascinating case study centered around the detection of depression using EEG montages. In this study, researchers recorded EEG data from individuals diagnosed with depression and compared it with data from healthy controls. The aim was to identify specific EEG features that differentiate between the two groups. To begin, the EEG data was loaded into MATLAB, where it underwent essential preprocessing steps. These included filtering to remove noise and artifacts, as well as channel selection to focus on relevant brain regions. Once the data was prepared, statistical analysis and machine learning algorithms like Support Vector Machines (SVM) or Random Forests were utilized to differentiate between EEG data of individuals in the depressed group and those in the control group.

The classification model's performance was assessed using cross-validation methods to ensure its reliability. The results of this study revealed intriguing insights. Certain frequency bands, such as alpha and theta, exhibited significant differences between depressed individuals and controls. These findings indicated that specific EEG patterns could serve as potential biomarkers for depression. The classification model built using

MATLAB achieved high accuracy in distinguishing between the two groups, showcasing the promising potential of EEG montage analysis for depression detection.

5.3 Case Study 2: Unraveling Schizophrenia through EEG

Our next case study takes us into the realm of schizophrenia identification using EEG montages. Researchers embarked on a journey to uncover distinctive EEG markers associated with schizophrenia by recording EEG data during cognitive tasks from patients diagnosed with schizophrenia and healthy individuals.

Using MATLAB, the researchers conducted preprocessing steps to clean the EEG data, including artifact removal, epoch extraction, and baseline correction.

To extract relevant EEG characteristics, they employed Methods for extracting features, like power spectral density, are utilized to analyze signals or data and capture relevant information from them without any duplication of content or event-related potentials. Statistical analysis and machine learning algorithms were then employed to differentiate between the two groups.

The results of this study were captivating. They revealed aberrant neural oscillations, reduced gamma band activity, and altered event-related the potentials in individuals diagnosed with schizophrenia exhibit differences when compared to those found in healthy control subjects. These EEG patterns provided valuable insights into the neurophysiological underpinnings of schizophrenia. The classification model built using MATLAB showcased significant accuracy, further affirming the potential of EEG montage analysis for schizophrenia identification.

5.4 Case Study 3: Assessing ADHD through EEG

Our final case study focuses on the assessment of attention deficit hyperactivity disorder (ADHD) investigating sleep patterns in children through EEG montages.

Researchers recorded EEG data during a sustained attention task from children diagnosed with ADHD and those without the disorder. The objective was to identify specific EEG features associated with attention deficits.

In MATLAB, the researchers embarked on preprocessing the EEG data, employing techniques such as artifact removal, filtering, and segmentation to ensure clean and reliable data. They then utilized feature extraction techniques, including spectral power, coherence, or event-related potentials, to capture relevant EEG markers. Statistical analysis and machine learning algorithms were employed to classify the EEG data into ADHD and control groups.

The outcomes of this research were captivating. They revealed reduced theta/beta ratios, altered frontal theta power, and decreased coherence in children with ADHD compared to controls. These findings shed light on the neural correlates of attention deficits in ADHD. The classification model built using MATLAB exhibited promising accuracy, highlighting the potential of EEG montage analysis for ADHD assessment.

5.5 Recommendation

Future research should investigate these EEG discoveries in conjunction with other clinical and neuroimaging traits to enhance comprehension and enhance management. In addition to the accomplished objective, it is suggested to incorporate classifiers like ANN (Artificial Neural Network), CNN (Convolution Neural Network), and deep learning to further enhance the proposed system. This will enable the system to achieve more precise classification of brain signals.

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5.6 MATLAB Coding

```
clc
clear all
close all
da=xlsread('M16 5Y (ASD).xlsx');
channels=da;
ad=da(3:200,:);
size(ad)
bt=ad(:);
a=ad(:,1)
first_channel=a;
Fs = 64;
mins = 60*Fs;
%      x = rand(9,3*mins).*rand(9,3*mins).*(100);        % 9-channels of 10
disp('Second Channel')
disp('Type 1')
dist_type='chebychev';
n=1;
r=.01;
a1=min(a);
a2=max(a);
a3=mean(a);
a4=median(a);
a5=std2(a);
```

```
a6=skewness(a);
a7=kurtosis(a);
a8=var(a);
a9=wentropy(a,'log energy');
a10=wentropy(a,'threshold',0.2);
a11=renyi_entropy(a,2);
a12 = wentropy(bt,'shannon');
a13=sample_entropy(bt, n, r, dist_type);
% a14=Fuzzy_MI(a(1:500))
a15=wentropy(a,'norm',1.1)
a16=permutation_entropy(a,2,5);
a17=approximate_entropy(n,r,a(1:100));
a18=spectral_entropy(a);
a19=svd(a);
[Pxx,a20] = pburg(a,4,1024,1);
F=rand(512,1);
% figure,plot(F,10*log10(Pxx(1:512,1)))
% legend('True Power Spectral Density','pburg PSD Estimate')
% xlabel('Frequency (Hz)')
% ylabel('PSD (dB/Hz)')
a21= wentropy(a,'sure',3);
a22=jAutoRegressiveModel(a,4);
a23=jfeeg('mcl',a)  %% more subdivision
a24=jFirstDifference(a)
```

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```
a25=jHjorthComplexity(a)

a26=jHjorthMobility(a)

a27=jLogRootSumOfSequentialVariation(a)

a28=jMeanCurveLength(a)

a29=jMeanTeagerEnergy(a)

%%

disp('Second Channel')

disp('Type 2')

ad=da(3:200,:);

bt2=ad(:);

b=ad(:,2);

first_channel=bt2;

dist_type='chebychev';

n=1;

r=.01;

b1=min(b);

b2=max(b);

b3=mean(b);

b4=median(b);

b5=std2(b);

b6=skewness(b);

b7=kurtosis(b);

b8=var(b);

b9=wentropy(b,'log energy');
```

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```
b10=wentropy(b,'threshold',0.2);

b11=renyi_entropy(a,2);

b12 = wentropy(bt2,'shannon');

b13=sample_entropy(bt2, n, r, dist_type);

% a14=Fuzzy_MI(a(1:500))

b15=wentropy(b,'norm',1.1)

b16=permutation_entropy(b,2,5);

b17=approximate_entropy(n,r,b(1:100));

b18=spectral_entropy(b);

b19=svd(b);

[Pxx,b20] = pburg(b,4,1024,1);

F=rand(512,1);

% figure,plot(F,10*log10(Pxx(1:512,1)))

% legend('True Power Spectral Density','pburg PSD Estimate')

% xlabel('Frequency (Hz)')

% ylabel('PSD (dB/Hz)')

b21= wentropy(b,'sure',3);

b22=jAutoRegressiveModel(b,4);

b23=jfeeg('mcl',b)  %% more subdivision

b24=jFirstDifference(b)

b25=jHjorthComplexity(b)

b26=jHjorthMobility(b)

b27=jLogRootSumOfSequentialVariation(b)

b28=jMeanCurveLength(b)
```

```
b29=jMeanTeagerEnergy(b)

%%

disp('Third Channel')

disp('Type 3')

ad=da(3:200,:);

c=ad(:,3);

ct=ad(:);

first_channel=c;

dist_type='chebychev';

n=1;

r=.01;

c1=min(c);

c2=max(c);

c3=mean(c);

c4=median(c);

c5=std2(c);

c6=skewness(c);

c7=kurtosis(c);

c8=var(c);

c9=wentropy(c,'log energy');

c10=wentropy(c,'threshold',0.2);

c11=renyi_entropy(ct,2);

c12 = wentropy(b,'shannon');

c13=sample_entropy(ct, n, r, dist_type);
```

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```
% a14=Fuzzy_MI(a(1:500))
c15=wentropy(c,'norm',1.1)
c16=permutation_entropy(c,2,5);
c17=approximate_entropy(n,r,c(1:100));
c18=spectral_entropy(c);
c19=svd(c);
[Pxx,a20] = pburg(c,4,1024,1);
F=rand(512,1);
% figure,plot(F,10*log10(Pxx(1:512,1)))
% legend('True Power Spectral Density','pburg PSD Estimate')
% xlabel('Frequency (Hz)')
% ylabel('PSD (dB/Hz)')
c21= wentropy(c,'sure',3);
c22=jAutoRegressiveModel(c,4);
c23=jfeeg('mcl',c)  %% more subdivision
c24=jFirstDifference(c)
c25=jHjorthComplexity(c)
c26=jHjorthMobility(c)
c27=jLogRootSumOfSequentialVariation(c)
c28=jMeanCurveLength(c)
c29=jMeanTeagerEnergy(c)
channel_labels = {'F3','F4','C3','C4','Cz','T3','T4','O1','O2'};
x=channels';
size(x)
```

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```
eeg_plotgui_withannos('signals',x, ...
'fs',Fs, ...
'channel_labels',channel_labels, ...
'epoch_length',mins./60, ...
'insert_ta_scale',1 ...
```

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CONCLUSION

EEG is a widely renowned technique used to gain insight into brain neurophysiology. It plays a crucial role in studying brain activity to determine various mental illnesses. This thesis aims to achieve its goals by classifying brain signals from different subjects based on the type of disorders they have. MATLAB Toolbox is utilized for analyzing brain waves and signal designs, providing a detailed functional method for EEG signal modeling.

By processing brain signals, EEG allows for the comprehension of complex brain systems, enabling the detection of abnormalities and related illnesses. Brainwave studies

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are essential in diagnosing various diseases, and MATLAB's interactive graphic user interface (GUI) facilitates the flexible processing of high-density EEG datasets.

The objectives of this thesis are successfully accomplished. Firstly, Electroencephalogram (EEG) details are collected based on a literature review concerning clinical aspects related to brain activities. The signals collected include data from control subjects, general epilepsy subjects, and autism spectrum disorder patients using bipolar and monopolar montages. Secondly, the collected data is analyzed from an engineering perspective to identify the appropriate montage. Each montage is simulated to pinpoint the affected lobes using the EEG dataset. Lastly, the study identifies the appropriate montages for different mental disorders using MATLAB software, successfully running the entire program, and meeting the project's objectives.

This research contributes to the understanding and diagnosis of mental disorders through EEG analysis. The combination of EEG data and MATLAB tools enhances the accuracy and efficiency of identifying brain abnormalities. The findings of this study hold promise for the future development of improved diagnostic methods and personalized treatment plans for individuals with mental health conditions. Overall, this research underscores the significance of EEG in the field of neuroscience and its potential to revolutionize mental healthcare.

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Senior Lecturer at Universiti Tun Hussein Onn Malaysia (UTHM), he holds a Bachelor of Electronics and Communication Engineering from Kongu Engineering College, Tamil Nādu, India (2002). He also has a Master's degree in Process Control and Instrumentation Engineering from Annamalai University, Tamil Nādu, India (2005), and a PhD in Medical Electronics from Anna University, Tamil Nādu, India. His academic journey includes serving as a Lecturer at Velalar College of Engineering and Technology, Tamil Nādu, India (2005-2009), Assistant Professor (2010-2012), Professor, and Head of the Department at Nandha College of Technology, Tamil Nādu, India (2012-2015). He has also worked as an Associate Professor at Kongu Engineering College, Tamil Nādu, India (2015).

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Throughout his career, Dr. Ashok has been involved in inspiring and mentoring numerous students and medical practitioners. His passion for the applications of cyber-physical systems in neural engineering has been instrumental in fostering their interest and providing valuable insights. His teachings and guidance have helped students and professionals gain a deeper understanding of the field.

He has also contributed to consultancy projects, such as Android Application Development for IoT-based RO Plant Controlling and Database Management. These projects demonstrate his practical approach to utilizing technology in solving real-world problems.

With his extensive academic background, industry experience, and research interests, Dr. Ashok Vajravelu brings a wealth of knowledge and expertise to the field of neural engineering. His dedication to teaching, research, and practical applications has made him a respected figure among students and medical practitioners alike, inspiring them to explore the potential of cyber-physical systems in improving healthcare and biomedical technologies.

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ABOUT THE BOOK

This book, entitled "Analysis on EEG Montages to Identify Mental Disorders Using MATLAB" is a comprehensive and enlightening book that delves into the cutting-edge application of EEG montages in the realm of mental disorder detection. The book meticulously explores the integration of MATLAB software, providing readers with a deeper understanding of brainwave data analysis and its significance in deciphering the complexities of neurophysiology. By unveiling distinctive patterns linked to different mental illnesses, the diagnostic potential of EEG is emphasized, promising improved healthcare outcomes. The book's focus on engineering perspectives and interactive graphic user interfaces ensures a reader-friendly approach, making it a valuable resource for researchers, clinicians, and anyone interested in the forefront of mental healthcare advancements.

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