OBTAINING EEG-BASED FEATURES OF MENTAL STATES WITH BRAIN-COMPUTER INTERFACES USING MACHINE LEARNING

2024
MASTER THESIS
COMPUTER ENGINEERING

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Master Thesis

KARABÜK
May 2024

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Ahsan MUMTAZ

ABSTRACT

M. Sc. Thesis

OBTAINING EEG-BASED FEATURES OF MENTAL STATES WITH BRAIN-COMPUTER INTERFACES USING MACHINE LEARNING

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Assist. Prof. Dr. Iman ELAWADY
May 2024, 74 pages

This thesis examines the development of passive brain-computer interfaces that monitor mental states such as focused, unfocused, or drowsy using electroencephalographic (EEG) brain activity imaging and machine learning techniques. The aim of the study is to develop and compare suitable algorithms for accurately detecting and tracking mental states.

A comprehensive step-by-step process is established for processing EEG data in the study. This process encompasses preprocessing, feature extraction, and classification stages of EEG signals. Various time and frequency-based methods are employed in the feature extraction stage to obtain meaningful information from the signal. The extracted features are then fed into classification algorithms.

The thesis compares three different machine learning algorithms – k-Nearest Neighbors (k-NN), Adaptive Decision Tree (ADT) classifier, and Support Vector Machines (SVM) – using the Radial Basis Function (RBF) model. The objective of this comparison is to determine which algorithm provides the highest accuracy in mental state detection.

As a result, experiments and analyses conclude that the SVM algorithm outperforms the other methods in mental state detection. The superior performance of SVM stems from its ability to work effectively on complex and high-dimensional datasets. These findings represent a significant step towards the development and implementation of EEG-based passive brain-computer interfaces.

This thesis contributes to the development of methods that enable continuous and reliable monitoring of individuals' mental states by analyzing EEG signals and utilizing machine learning techniques.

Keywords : Brain computer Interface, BCI, electroencephalographic (EEG), Support Vector Machines (SVM) , Feature extraction of Mental states.

Science Code : 92419

ÖZET

Yüksek Lisans Tezi

MAKİNE ÖĞRENMEYİ KULLANARAK BEYİN-BİLGİSAYAR ARAYÜZLERİ İLE ZİHİNSEL DURUMLARIN EEG TABANLI ÖZELLİKLERİNİN ELDE EDİLMESİ

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Mayıs 2024, 74 sayfa

Bu tez, elektroensefalografik (EEG) beyin aktivitesi görüntüleme ve makine öğrenme teknikleri kullanarak, kişinin odaklanmış, odaklanmamış veya uykulu olma gibi zihinsel dikkat durumlarını izleyen pasif beyin-bilgisayar arayüzlerinin geliştirilmesini incelemektedir. Çalışmanın amacı, zihinsel durumların doğru bir şekilde tespit edilmesi ve izlenmesi için uygun algoritmaların geliştirilmesi ve karşılaştırılmasıdır.

Çalışmada, EEG verilerinin işlenmesi için kapsamlı bir adım dizisi oluşturulmuştur. Bu süreçte, EEG sinyallerinin ön işleme, özellik çıkarımı ve sınıflandırma aşamaları ele alınmıştır. Özellik çıkarımı aşamasında, sinyalden anlamlı bilgilerin elde edilmesi amacıyla çeşitli zaman ve frekans tabanlı yöntemler kullanılmıştır. Elde edilen özellikler, daha sonra sınıflandırma algoritmalarına girdi olarak verilmiştir.

Tezde, Radial Basis Function (RBF) modeli kullanılarak, k-en yakın komşu (k-NN), Adaptif Karar Ağacı (ADT) sınıflandırıcı ve Destek Vektör Makineleri (SVM) olmak üzere üç farklı makine öğrenme algoritması karşılaştırılmıştır. Bu karşılaştırmanın amacı, hangi algoritmanın zihinsel durum tespiti konusunda en yüksek doğruluğu sağladığını belirlemektir.

Sonuç olarak, yapılan deneyler ve analizler neticesinde SVM algoritmasının diğer yöntemlere kıyasla zihinsel durum tespitinde daha yüksek bir performans gösterdiği tespit edilmiştir. SVM'nin üstün performansı, onun karmaşık ve yüksek boyutlu veri setleri üzerinde daha etkili çalışabilme yeteneğinden kaynaklanmaktadır. Bu bulgular, EEG tabanlı pasif beyin-bilgisayar arayüzlerinin geliştirilmesi ve uygulanması için önemli bir adım teşkil etmektedir.

Bu tez, EEG sinyallerinin analiz edilmesi ve makine öğrenme tekniklerinin kullanılmasıyla, bireylerin zihinsel dikkat durumlarının sürekli ve güvenilir bir şekilde izlenmesini sağlayacak yöntemlerin geliştirilmesine katkıda bulunmaktadır.

Anahtar Kelimeler : Beyin Bilgisayar Arayüzü, BCI, Elektroensefalografik (EEG), Destek Vektör Makineleri (SVM), Zihinsel Durumların Özellik Çıkarımı

Bilim Kodu : 92419

ACKNOWLEDGMENT

I only want wisdom and purity. People without willpower are exhausted, defeated, and miserable. As darkness falls, we adore and admire the Supreme Being, Omnipotent, Primordial and Ultimate, Manifest and Hidden, Who gives us many gifts, sustains us, and enlightens our journey. Allah's messenger Muhammad bin Abdullah and his family deserve peace and grace. He gave us his famous Qur'an to correct our ignorance and motivate us to learn. We thank Allah for victory and for giving us the will to finish our tiny attempt. I wish to convey my appreciation to my principal mentor, Assist. Prof. Dr. Iman ELAWADY, who provided guidance and support during the duration of this project. I wish to extend my sincere appreciation to Assist. Prof. Dr. Nehad T.A RAMAHA for his invaluable guidance and pointing out my errors. I would want to express my gratitude to my friends and family for their unwavering support and valuable contributions to my research. I would like to extend my utmost gratitude to my committee for their unwavering support and encouragement. I express my genuine gratitude for the educational possibilities offered by my committee. I greatly appreciate and acknowledge your support during challenging times.

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SYMBOLS ABBREVITIONS INDEX

BCI : Brain-Computer Interfaces

EEG : Electroencephalography

SVM : Support Vector Machines

MEG : Magnetoencephalography

FFT : Fast Fourier Transform

PCA : Principal Component Analysis

EP : Evoked Potential

ERP : Event-Related Potential

IDE : Integrated Development Environment

ML : Machine Learning

STFT : Short-Time Fourier Transform

DFT : Discrete Fourier Transform

RBF : Radial Basis Function

KNN : k-Nearest Neighbors

PART 1

INTRODUCTION

1.1. OVERVIEW

Human interplay, both verbal and non-verbal, is fundamental to our each day lives. It enables us to specific feelings, deliver mind, and interact with our surroundings. However, for people with bodily disabilities due to accidents, ailments, or congenital conditions, conventional method of conversation may be significantly restrained or even not possible. This affords a considerable barrier to their capacity to engage with others and participate completely in society. Brain-Computer Interfaces (BCIs) offer a progressive solution by using establishing a direct communique pathway among the brain and external devices. By leveraging neuroimaging strategies including Electroencephalography (EEG), BCIs permit people to transmit messages, control devices, and engage with their surroundings the usage of neural pastime on my own [11]. This paradigm shift in communication technology holds large promise for reinforcing the great of existence for people with disabilities and unlocking new opportunities for human-computer interaction.

1.2. MOTIVATION

The motivation behind this research lies in the profound impact that BCIs can have on the lives of individuals with severe motor disabilities or communication impairments. By providing a means of communication and control that bypasses traditional neuromuscular pathways, BCIs offer newfound independence and autonomy to those who were previously unable to express themselves or interact with their environment. This not only improves their quality of life but also opens up avenues for personal expression, social interaction, and participation in various activities. Additionally, the advancement of BCI technology has broader implications for fields such as healthcare, assistive technology, gaming, and neurorehabilitation. By addressing the technical challenges and limitations of current BCI systems, this research aims to contribute to the development of more robust, reliable, and user-friendly interfaces that can benefit a wide range of users.

1.3. PROBLEM STATEMENT

Despite the tremendous potential of BCIs, several challenges remain to be addressed. One of the primary challenges is the accurate extraction of relevant information from EEG signals. EEG recordings, while rich in data, are also inherently noisy and subject to various artifacts, which can complicate the interpretation of neural activity [27]. Furthermore, the translation of raw EEG signals into meaningful commands or instructions for external devices requires sophisticated signal processing techniques and machine learning algorithms. Another challenge is the lack of standardized methodologies for assessing the accuracy and performance of BCI systems. Evaluating the effectiveness of different signal processing methods and machine learning models in real-world scenarios is essential for advancing the field and ensuring the practical utility of BCIs for end-users.

1.4. AIM AND OBJECTIVES

The aim of this studies is to increase an effective framework for EEG-based totally statistical feature extraction of mental states with Brain-Computer Interfaces. To achieve this aim, the subsequent objectives could be pursued:

Gain a comprehensive understanding of the underlying principles and programs of Brain-Computer Interfaces (BCIs) and Electroencephalography (EEG).
Investigate the hardware and software program requirements for implementing an EEG-based totally BCI gadget, along with EEG electrode placement, sign acquisition hardware, and software gear for facts processing and evaluation.
Develop robust signal processing strategies for extracting applicable features from EEG alerts, such as strategies for artifact removal, feature extraction, and dimensionality reduction.

Implement machine gaining knowledge of algorithms, such as Support Vector Machines (SVM) [50], for mental state detection and classification based totally on extracted EEG features.
Evaluate the accuracy and overall performance of various device mastering fashions for mental kingdom classification using actual-world EEG statistics accrued from human members.

Explore capacity applications of EEG-based BCI systems in various domain names, including healthcare, assistive technology, gaming, and human-pc interaction.

1.5. CONTRIBUTIONS

This research contributes to the advancement of EEG-based BCI systems by addressing key challenges in signal processing and machine learning. By developing simplified and improved methods for extracting features, artifact reduction, and mental state classification, this work aims to improve the effectiveness, reliability, and user experience of BCIs for individuals with disabilities. Additionally, by evaluating the performance of different machine learning models in real-world scenarios, this research provides valuable insights into the strengths and limitations of current BCI technology and informs future development efforts.

1.6. STRUCTURE OF THE THESIS

The thesis is structured as follows:
Chapter 1 provides an overview of Brain-Computer Interfaces (BCIs) and Electroencephalography (EEG), highlighting their significance, historical development, and applications in various fields.

Chapter 2 explores the hardware and software requirements for implementing an EEG-based BCI system, including EEG electrode placement, signal acquisition hardware, and software tools for data processing and analysis.

Chapter 3 delves into the details of data acquisition and signal processing techniques for feature extraction from EEG signals, including methods for artifact removal, feature extraction, and dimensionality reduction.

Chapter 4 presents the methodology for mental state detection and classification using machine learning algorithms, including Support Vector Machines (SVM), Neural Networks, and Ensemble methods.

Chapter 5 Evaluates the accuracy and performance of different machine learning models for mental state classification using real-world EEG data collected from human participants, including quantitative analysis of classification accuracy, precision, recall, and F1-score.

Finally, **concludes** the thesis by summarizing the key findings, discussing their implications for future research and development, and suggesting directions for further investigation.

PART 2

LITERATURE REVIEW

The use of Brain-Computer Interfaces (BCIs) in conjunction with system mastering for tracking mental states through EEG information is a rapidly advancing field. This literature assessment explores latest advancements in EEG-based totally BCIs, focusing on methods for characteristic extraction and category of mental states, with an emphasis on the brand new research findings.

Electroencephalography (EEG) is a broadly applied non-invasive method for recording brain electrical interest, offering excessive temporal resolution. EEG alerts have been validated to effectively replicate diverse cognitive and emotional states, such as attention, relaxation, and drowsiness, with the aid of analyzing feature patterns in brainwave frequencies [1]. Recent studies have highlighted the capability of EEG in actual-time monitoring of intellectual states, essential for packages in each clinical and non-scientific settings [2].

The extraction of applicable features from uncooked EEG records is essential to the fulfillment of intellectual country monitoring. Commonly extracted features consist of energy spectral density, wavelet coefficients, and Hjorth parameters. Research indicates that specific frequency bands (e.G., delta, theta, alpha, and beta) correlate with exceptional cognitive states. For example, expanded theta pastime is regularly related to drowsiness, at the same time as beta interest is related to focused attention.

Power Spectral Density (PSD) is often used to quantify the electricity distribution of the EEG sign across extraordinary frequency bands. Studies have shown that PSD features can efficiently distinguish among various intellectual states, together with alertness and drowsiness [3]. Wavelet transform affords a time-frequency representation of the EEG signal, making it appropriate for reading non-desk bound alerts like EEG. This approach has been efficiently implemented to extract capabilities indicative of cognitive workload and stress [4].

Machine learning algorithms are essential for classifying EEG information into distinct mental states. Support Vector Machines (SVM), ok-Nearest Neighbor (k-NN), and choice tree classifiers are many of the most generally used techniques.

Support Vector Machines (SVM) are extensively employed in EEG-based totally BCIs because of their capability to address excessive-dimensional data and robustness against overfitting. Recent studies have proven the excessive accuracy of SVMs in classifying mental states. For instance, Zhang et al. (2022) accomplished an accuracy of over 90% in detecting cognitive load using SVMs [5]. The ok-Nearest Neighbor (k-NN) set of rules classifies facts points primarily based on the bulk class amongst their ok nearest neighbors. Although easy, its performance may be stimulated via the choice of k and the gap metric used. Recent programs of ok-NN in EEG-based totally emotion popularity have proven promising results, with accuracies comparable to extra complex fashions [6]. Decision bushes break up statistics into branches based totally on function values, taking pictures complex choice obstacles. While liable to overfitting, recent advances in pruning strategies have advanced their robustness. Decision bushes had been effectively utilized in real-time mental country category systems due to their fast computation instances [7].

Comparative studies have shown that whilst SVMs typically outperform different classifiers in phrases of accuracy, the choice of set of rules can depend on the dataset and computational resources. For example, a examine through Li et al. (2021) evaluating SVM, okay-NN, and selection bushes for EEG-primarily based intellectual nation classification determined that SVMs provided the exceptional universal overall performance, however choice timber supplied faster type times, beneficial for real-time applications [8].

BCIs utilizing EEG information to monitor attention in the course of continuous overall performance obligations are designed to evaluate and decorate cognitive characteristic. These systems require real-time processing and high accuracy.

Modifications to standard EEG headgear, blended with superior machine learning algorithms, have appreciably advanced the accuracy and usability of these systems. A latest have a look at proven that a modified EEG headgear, together with an SVM-primarily based classifier, may want to accurately determine interest states with an accuracy of 92.6% in a continuous overall performance venture [9].

Future research need to focus on enhancing the robustness and generalizability of EEG-based totally BCIs throughout various populations and environments. Exploring hybrid models that combine multiple classifiers or integrate deep learning techniques may want to further beautify category performance. Additionally, growing user-friendly and non-intrusive EEG devices will be critical for vast adoption in diverse applications [10].

Advancements in EEG-based totally BCIs and device getting to know have supplied powerful equipment for tracking mental states. The use of SVMs, ok-NN, and selection tree classifiers has shown promising outcomes in accurately detecting states including focused interest, unfocused attention, and drowsiness. Continued research and development on this area keep awesome capability for applications in healthcare, productivity enhancement, and beyond.

PART 3

BRAIN COMPUTER INTERFACE

3.1. INTRODUCTION OF BCI

(BCIs) Brain-computer interfaces are revolutionary technologies that allow direct communication between the human brain and external devices. These systems bridge the gap between the mind and machines, opening up a world of possibilities for individuals with neurological impairments, enhancing human capabilities, and transforming various aspects of life. BCIs are systems that translate brain signals into commands, allowing users to interact with their surroundings without relying on traditional neuromuscular pathways [11]. They intercept and interpret the electrical activity generated by the brain's neurons, which reflects the user's thoughts, intentions, and motor imagery [12].

3.2. HOW BCI WORKS

Brain-computer interfaces (BCIs) operate by assessing brain activity and converting it into commands applicable for the control of external devices. This procedure encompasses three key steps. Figure. 3.1. illustrates set of steps of standard processing for communication and mobility BCIs. Common components within the set of steps encompass artifact suppression, feature extraction, and signal classification techniques. The outcomes of this process govern the control of communication or mobility aids. [12].

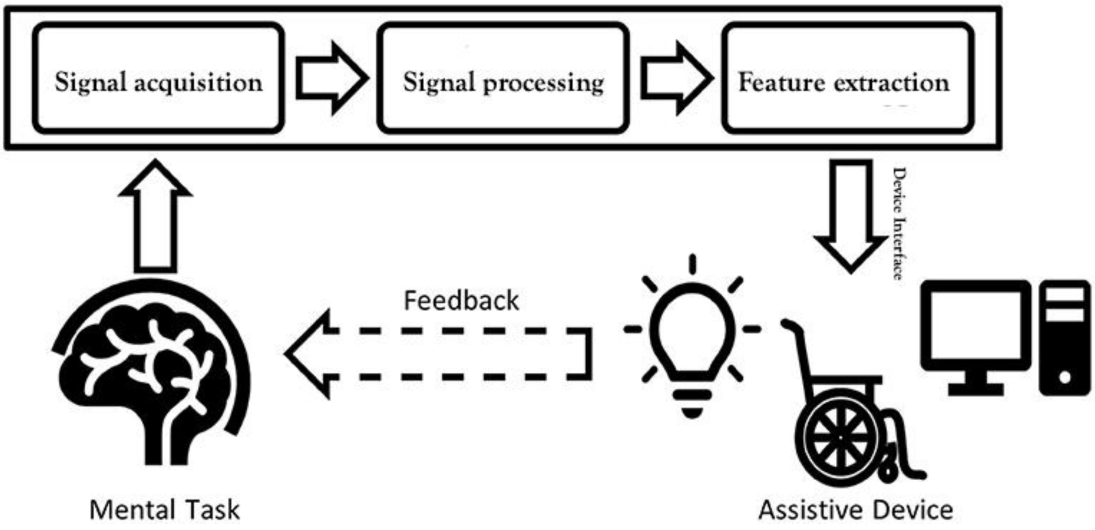

Figure. 3.1. The main steps of BCI [12].

3.2.1. Signal Acquisition

Brain-Computer Interfaces (BCIs) record neural activity using a number of sensors, including electroencephalography (EEG), magnetoencephalography (MEG), and functional magnetic resonance imaging (fMRI). Because it is non-invasive and relatively inexpensive, EEG is the most commonly used sensor in BCIs. EEG sensors are placed on the scalp to measure brain electrical activity. Figure. 3.2. [13].

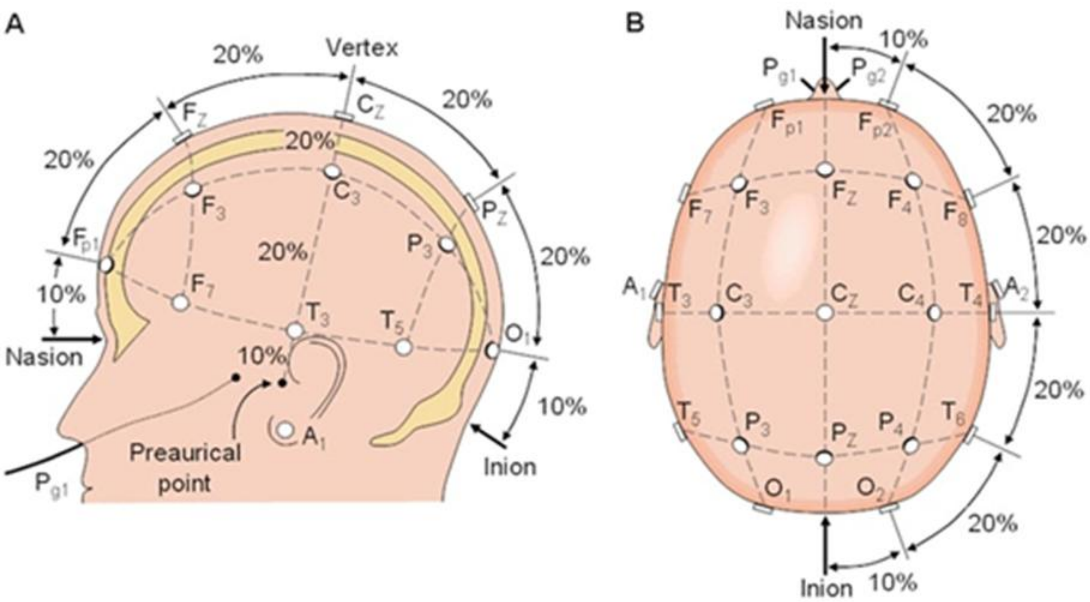

Figure. 3.2. EEG Sensor locations on Scalp [13].

Nowadays, there have been noteworthy advancements in EEG sensor technology, leading to enhancements in signal quality and resolution. A notable illustration is the work of researchers at the University of California, San Francisco [14], who have introduced a novel EEG sensor type characterized by heightened sensitivity and reduced susceptibility to noise compared to conventional EEG sensors.

Another encouraging trend involves the adoption of wearable EEG devices [15]. These devices are typically more compact and comfortable than traditional EEG headsets, rendering them better suited for daily use. An instance is the Emotiv Epoc+, a wearable EEG headset designed for tasks such as mind-controlled video games and various other applications.

3.2.2. Signal Processing

After acquiring the brain signals, the next step involves processing them and extracting relevant features. This process includes signal filtering to eliminate noise and identifying patterns that correlate with distinct brain states or activities.

Noteworthy progress in machine learning has resulted in substantial enhancements in signal processing algorithms for Brain-Computer Interfaces (BCIs). An illustrative example is the work conducted by researchers at the Massachusetts Institute of Technology) [16], who have introduced a groundbreaking algorithm capable of decoding brain signals with unprecedented accuracy. This algorithm is proficient in learning intricate patterns of brain activity associated with Mental states like focus or unfocus etc

3.2.3 Feature Extraction

Species possess distinctive features that distinguish them from one another. An essential aspect of Brain-Computer Interface (BCI) technology involves the capability to identify emotions by analyzing EEG data, facilitating a direct assessment of an individual's "inner" state. Various methods for extracting characteristics have been explored, with insights from neuroscientific research often guiding the selection of appropriate features and electrode placements.

Table. 3.1. illustrates different strategies for feature extraction, encompassing both linear and nonlinear approaches. Linear methods include Fast Fourier Transform (FFT), Wavelet Packet Decomposition (WPD), Eigenvector, Autoregressive (AR), Independent Component Analysis (ICA), Wavelet Transform (WT), and Principal Component Analysis (PCA). On the other hand, examples of nonlinear methods consist of fractal dimension (FD), higher-order spectrum (HOS), recurrence plots, phase space plots, correlation dimension (CD), Hurst exponent (H), largest Lyapunov exponent (LLE), and other entropy measures.

Table 3.1. BCI Extracted Features [17],

Feature Domain	**Data Type**	**Extracted Features**	**Abbreviated features**
Time	HRV Signal	Standard Deviation	SDNN
		RR means Of differences	MNN
		Root Mean Square of the Successive Differences	RMSSD
		Standard Deviation of Successive differences	SDSD
		Percentage of RR Differences	PNN
Frequency	HRV Signal	Estimation of the spectrum, low frequency, very low	PSD, LF, VLF, HF

		frequency, and high frequency bands	
Non - Linear	HRV Signal	Discrete wavelet transform, Point dimension, Detrended fluctuation analysis, Poincare, Hurst, Fractal dimension Correlation Dimension, Sample Entropy, Approximate Entropy	DWT, PD, DFA, POINC, ARE, H, FD, CD, SampEnt, approxEnt
Linear	HRV Signal	Geometric method, Statistical method, Time frequency method	Geometric method, Statistical method, Time frequency method

The features extracted are subsequently converted into commands for the operation of an external device. This translation process is facilitated by machine learning algorithms that undergo training on a dataset comprising brain signals and their corresponding commands.

Recent studies have concentrated on the creation of machine learning algorithms characterized by increased robustness and adaptability to fluctuations in the user's brain activity. A case in point is the work conducted by researchers at the University of California, Berkeley [18], who introduced a novel algorithm capable of learning to interpret brain signals into commands, even in situations where the user's brain activity undergoes changes over time.

3.3. APPLICATIONS OF BCIs

Brain-computer interfaces (BCIs) possess a diverse array of prospective uses, which encompass:

- **Reinstating motor abilities in paralyzed individuals:** Brain-computer interfaces (BCIs) can be employed to govern artificial limbs and wheelchairs, enabling individuals with paralysis to recover lost functionality and self-sufficiency. Hybrid brain-computer interface (BCI) systems are suggested to enhance the systematic efficiency of conventional BCIs by enabling multi-degree control of a physical wheelchair [19].

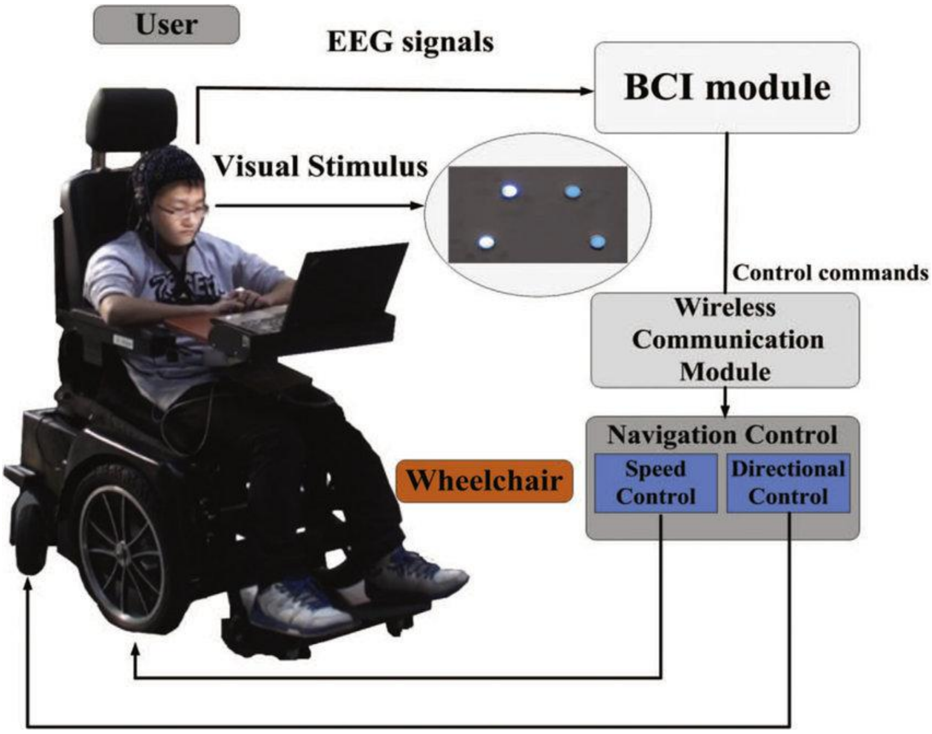

Figure. 3.3. BCI for wheelchair control [19].

- **Communication for people with locked-in syndrome:** Communication for individuals with locked-in syndrome can be facilitated through the use of Brain-Computer Interfaces (BCIs). Locked-in syndrome refers to a state of paralysis and inability to talk or move**.**

- **Controlling prosthetic limbs and exoskeletons:** BCIs can be employed to govern prosthetic limbs and exoskeletons, enabling individuals with disabilities to execute intricate movements and accomplish difficult activities with greater naturalness.
- **Neurorehabilitation for stroke and other neurological disorders:** Brain-computer interfaces (BCIs) can be employed to aid individuals suffering from stroke and other neurological illnesses in regaining lost functionality.
- **Treatment of neurological disorders such as epilepsy and Parkinson's disease:** Neurological illnesses including epilepsy and Parkinson's disease can be treated with BCIs, which offer brain feedback or stimulate targeted brain areas.
- **Enhancement of cognitive performance and decision-making:** BCIs can be utilized to improve cognitive performance and decision-making abilities in those who are in good health.
- **Immersive gaming experiences:** BCIs can create more immersive and interactive gaming experiences by directly connecting the player's brain to the game [20].

Brain-computer interfaces (BCIs) are an emerging area of study that have the capacity to fundamentally transform our methods of engaging with the surrounding environment.

3.4. CHALLENGES AND FUTURE DIRECTIONS

Challenges

BCIs are a rapidly developing field with the potential to revolutionize the way we interact with the world around us.

- **Signal quality and robustness:** BCIs are still susceptible to noise and signal artifacts, which can limit their accuracy and reliability [16].

- **Ethical and social implications:** The use of BCIs raises a number of ethical and social concerns, such as privacy, autonomy, and the potential for misuse [21].
- **User acceptance and adoption:** Widespread adoption of BCIs will depend on factors such as user acceptance, cost, and availability of training and support [22].

Future Directions

- **Development of more advanced signal processing algorithms:** New algorithms are needed to improve the accuracy and robustness of BCIs in the face of noise and signal artifacts [23].
- **Investigation of new BCI paradigms:** Researchers are exploring new ways to use brain signals to control devices and interact with the world around us [24].
- **Development of more user-friendly and accessible BCI systems:** BCIs need to become more user-friendly and accessible in order to be widely adopted by people with disabilities and other user populations [25].

BCIs are a rapidly developing field with the potential to revolutionize the way we interact with the world around us. By addressing the challenges and pursuing the future directions outlined above, BCIs can have a profound impact on the lives of millions of people.

3.5. CONCLUSION OF THE CHAPTER

Brain-computer interfaces (BCIs) represent swiftly advancing technologies poised to reshape our interactions with the world. They hold promise across various applications, from restoring motor function in individuals with paralysis to facilitating communication for those with locked-in syndrome and enhancing cognitive performance. Despite these potentials, there are ongoing challenges, including the improvement of signal quality and robustness, addressing ethical and social considerations, and ensuring widespread user acceptance. Overcoming these challenges and charting future directions can lead to the transformative societal impact of BCIs. In the subsequent chapter, we will delve into the significance of EEG in BCI and its role in extracting features from brain wave.

PART 4

ELECTROENCEPHALOGRAPHY (EEG)

4.1. INTRODUCTION TO EEG

Electroencephalography (EEG) is a non-invasive technique for recording electrical activity of the brain. It is widely used in clinical and research settings to assess brain function and diagnose neurological disorders. EEG recordings are typically obtained by placing electrodes on the scalp, which measure the voltage fluctuations generated by the brain's electrical activity [26] [27]. In order to accurately extract relevant data about specific tasks from EEG signals, modern signal analysis techniques and a close examination of the signals' distinct characteristics are essential. In order to improve our understanding of brain activity, [28]. states that precise identification and analysis of EEG data is crucial. The search results obtained from Google Scholar, PubMed, and Web of Science between 2016 and 2022 demonstrate the substantial interest in EEG as a topic of study, as illustrated in Fig 4.1. By giving a comprehensive explanation of denoising procedures—including mathematical formulations accompanied by pseudocodes—the paper presents a novel addition. Additionally, we outline the most recent advancements in the field of EEG, highlighting current challenges and discussing future directions [29]

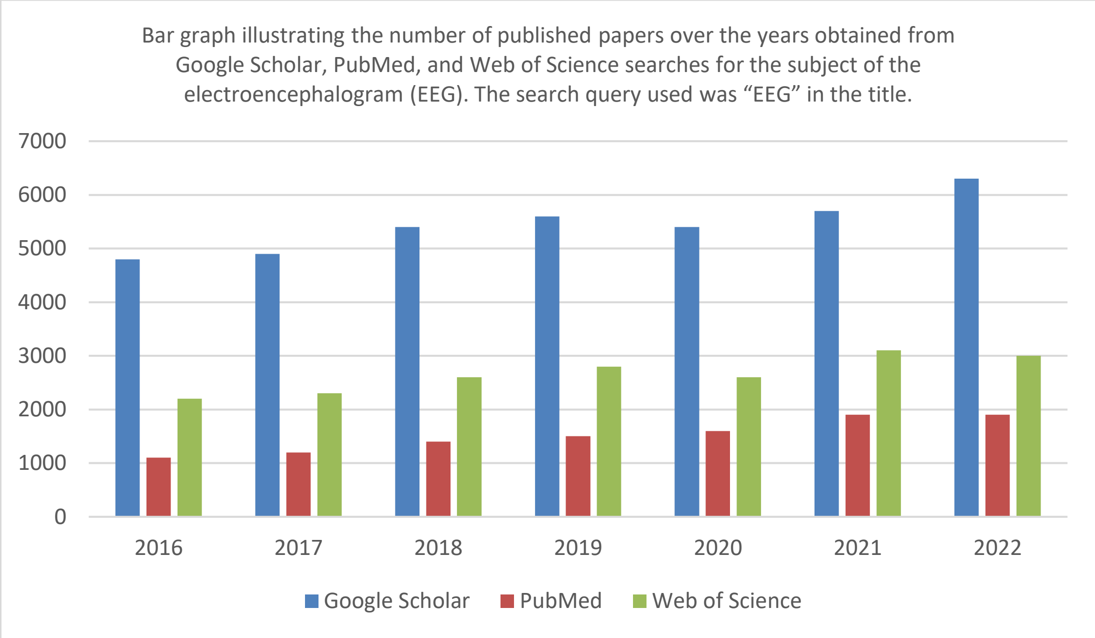

Figure. 4.1. Bar graph illustrating the number of published papers over the years obtained from Google Scholar, PubMed, and Web of Science searches for the subject of the electroencephalogram (EEG) [29]

EEG is used to evaluate a huge variety of mind capabilities, which include:

- **Brain interest:** EEG may be used to degree the general stage of mind pastime, which can be beneficial in diagnosing conditions [30] consisting of epilepsy and coma.
- **Sensory processing:** EEG may be used to have a look at how the brain strategies sensory statistics [31] inclusive of attractions and sounds.
- **Cognitive function:** EEG can be used to evaluate cognitive feature, together with interest, memory, and language processing.
- **Motor function**: EEG can be used to study how the brain controls movement.

4.2. HOW ELECTROENCEPHALOGRAPHY (EEG) WORKS

Electroencephalography (EEG) is a non-invasive technique designed to gauge electric activity inside the brain. It operates on the principle that synchronized firing of a collection of neurons generates a minute electrical signal. Electrodes located at the scalp choose up those voltage fluctuations, typically in the microvolt variety [32]. Subsequently, those indicators are amplified and recorded using an EEG device.

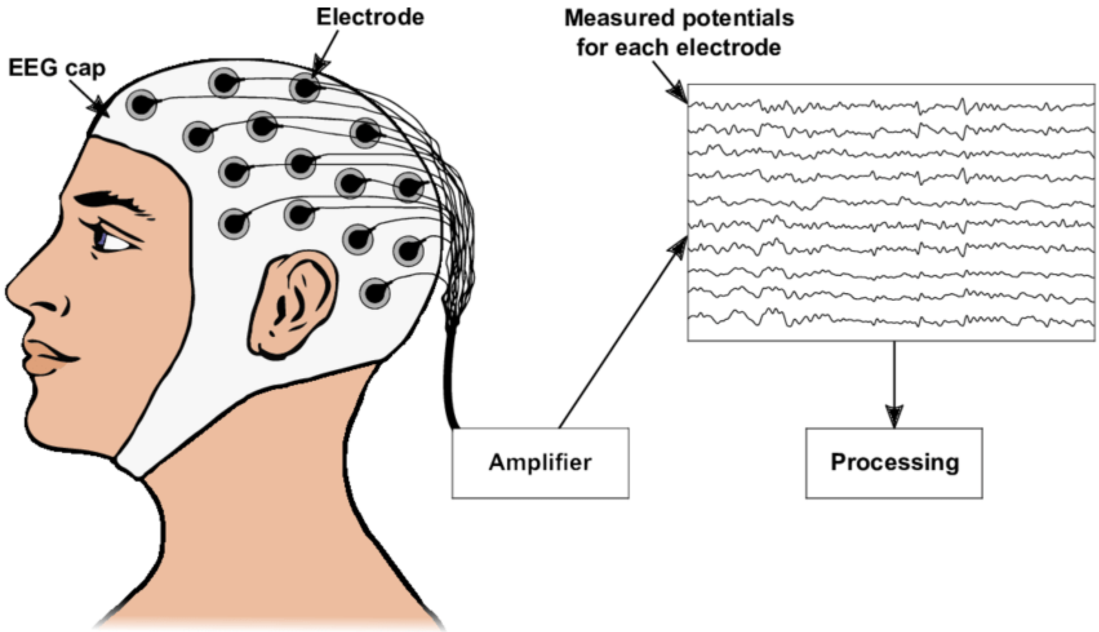

Figure. 4.2. An EEG allows measuring the electrical activity on the scalp using electrodes which are often fixated on an EEG cap [33]

4.2.1. The Brain's Electrical Activity

The mind is a exceptionally complex organ composed of billions of neurons, which can be the primary units of the fearful system. Neurons talk with each different through sending electrical signals thru their axons, lengthy, thin fibers that join neurons to different cells [32]. When a neuron fires, it releases an electrical impulse that travels down its axon, causing the discharge of neurotransmitters at the synapse, the junction among two neurons. These neurotransmitters then bind to receptors on the postsynaptic neuron, triggering the technology of an electrical sign within the postsynaptic neuron. The human brain capabilities as an organic electrochemical laptop, with neurons using chemical reactions to provide electrical activity. The electrochemical properties of neurons are liable for producing our movements, styles, and behavior. When a neuron is stimulated by means of outside or internal stimuli, it transmits electrochemical impulses obtained from the dendrites along the axon to the following neuron, as depicted in Figure. 4.Three. An electroencephalogram (EEG) is a way used to come across the voltage versions of the mind's electrical interest at some stage in a quick time period, normally 20-40 mins. This is done by using putting severa electrodes on the scalp [34].

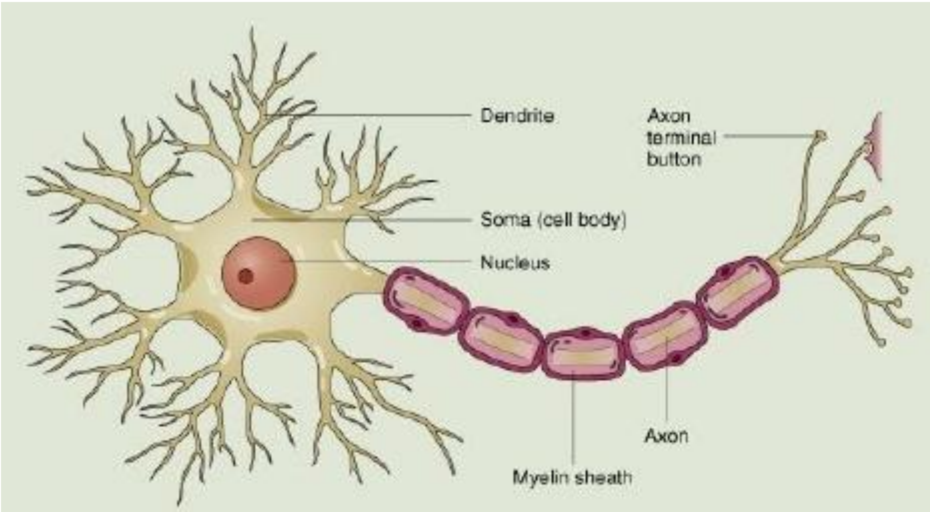

Figure. 4.3. Structure of the neuron [34]

4.2.2. Generating EEG Recordings

EEG electrodes are placed at the scalp to capture the electric hobby of the brain. These electrodes are typically made from silver or gold and are packed with a conductive gel to set up most excellent contact with the pores and skin. A connection is made between the electrodes and an EEG machine, which both amplifies and records the electrical signals identified by the electrodes.

4.2.3. EEG Waves and Brain Activity:

Recordings from EEG typically reveal a series of waves, each characterized by a specific frequency and amplitude. The frequency of an EEG wave is quantified in hertz (Hz), and its amplitude is measured in microvolts (μV). Various types of brain activity generate distinct EEG waves. For instance, alpha waves, linked to relaxed wakefulness, exhibit a frequency of 8-12 Hz, while beta waves, associated with active mental engagement, display a frequency of 12-30 Hz. [35] . Figure. 4.4.

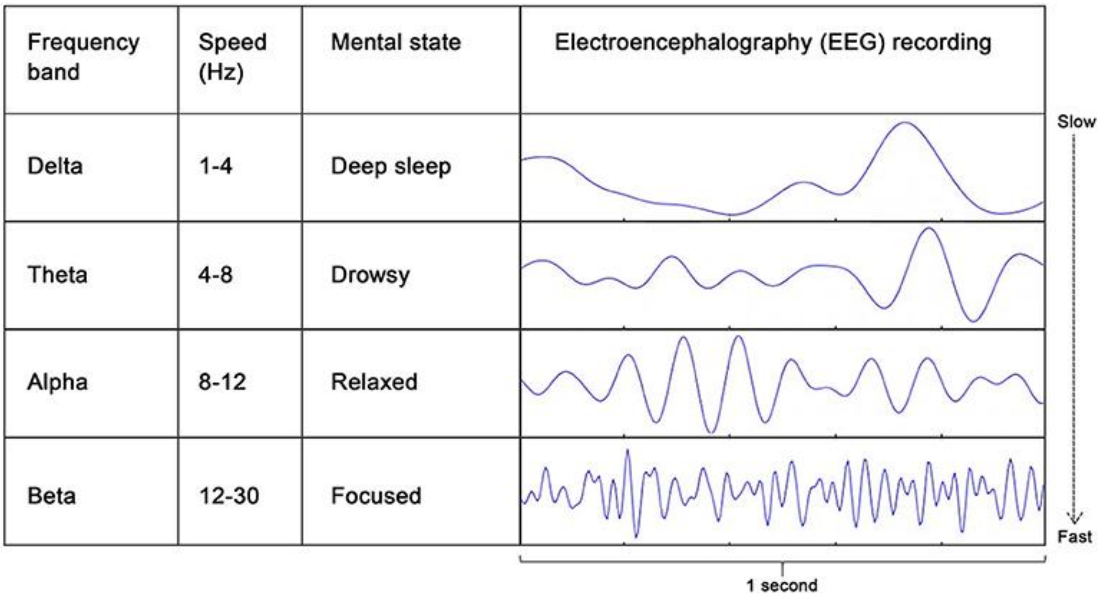

Figure. 4.4. Different EEG waves output and it’s Mental state results [35]

4.3. HISTORY OF EEG

Hans Berger, the father of EEGs, wanted to be an astronomer. Berger quit his mathematics studies at Friedrich Schiller University of Jena after one semester to join the army for a year. After falling off his horse, his distant sister sent him a telegraph, feeling he was in bad shape. Since Berger was kilometers from his sister, he thought this was telepathic communication and was inspired to research psychic experiences' physiological roots. He earned a medical degree from Jena University in 1897 [36].

Berger researched neurology, brain circulation, psychophysiology, and temperature. In 1924 [36], Berger performed the first EEG recording of human brain activity, named ‘Elektrenkephalogramm’, following Richard Caton's animal studies.

Berger recorded intracerebral brain activity in skull defect patients by putting the electrode in the periosteum and inserting silver wires under the scalp at the front and back. By 1927, he could obtain readings from an unbroken skull with more sensitive equipment and created a non-invasive recording method utilizing silver foil electrodes secured to the head by a rubber bandage. He recorded the first human brain electrical activity and championed translating the brain recording technology from animals to humans, which Polish scientist Adolf Beck had used on frogs and English physiologist

Richard Caton had used on rabbits and monkeys. Berger often tested Klaus and Ilse, his children [36]

Berger originally described normal and aberrant brainwaves, including the alpha wave rhythm (Berger's wave) and the quicker beta waves.

Berger initially described “the nature of EEG alterations in brain diseases such as epilepsy”. "The discovery of the EEG was not only a breakthrough in neurophysiology but also that this technology was of outstanding importance for its diagnostic value," he concluded. In 1937, an international forum recognized his discoveries, and by 1938 [37], electroencephalography was widely recognized by scholars, leading to its use in the US, England, and France for diagnostic purposes. Berger was nominated for the 1940 Nobel Prize in Physiology or Medicine but declined owing to the war [37].

4.4. CLINICAL APPLICATIONS OF EEG

EEG serves as a versatile tool with diverse applications in clinical settings, including:

4.4.1. Diagnosing Neurological Disorders

EEG is employed for diagnosing various neurological disorders like epilepsy, dementia, and sleep disorders. By identifying characteristic EEG patterns, clinicians gain valuable insights into underlying brain activity, facilitating informed diagnostic decisions [38].

4.4.2. Monitoring Brain Function

In critical care or cases of head injuries, EEG can monitor brain function. Continuous EEG monitoring provides real-time assessment of brain activity, allowing for early detection of potential complications.

4.4.3. Brain-Computer Interfaces (BCIs)

EEG plays a pivotal role in Brain-Computer Interfaces (BCIs), enabling users to control external devices, such as computers or prosthetics, using their thoughts.

Through the analysis of EEG signals, BCIs interpret users' intentions and translate them into commands for the external device [39].

4.5. ADVANTAGES AND LIMITATIONS OF EEG

EEG presents several advantages as a neuroimaging technique:

4.5.1. Non-Invasive

EEG is a non-invasive procedure, eliminating the need for surgery or substance injections. This characteristic renders it a safe and well-tolerated technique for both clinical and research applications.

4.5.2. High Temporal Resolution

Offering high temporal resolution, EEG permits the real-time measurement of brain activity. This capability facilitates the examination of dynamic brain processes, including alterations in neural activity linked to sensory perception or cognitive tasks.

4.5.3. Cost-Effective

Compared to other neuroimaging methods like fMRI or MEG, EEG is relatively cost-effective. This affordability enhances its accessibility for both clinical and research purposes.

However, alongside its advantages, EEG also has limitations:

4.5.4. Low Spatial Resolution

EEG possesses low spatial resolution, lacking precision in pinpointing the exact source of brain activity. This limitation arises from the skull's electrical conductivity, causing distortion and attenuation of the electrical signals generated by the brain.

4.5.5. Susceptibility to Artifacts

EEG recordings are susceptible to artifacts, signal distortions caused by factors such as eye movements, muscle activity, and external electrical interference. These artifacts pose challenges in accurately interpreting EEG data.

4.6. THE FUTURE OF EEG RESEARCH

Ongoing EEG research is dynamic, with scientists exploring novel techniques and applications for this valuable tool. Some promising areas of investigation include:

Development of New EEG Technologies: Researchers are actively working on developing innovative EEG technologies that offer improved spatial resolution and reduced susceptibility to artifacts. This includes the exploration of dry EEG electrodes, eliminating the need for conductive gel and enhancing comfort and convenience in use.

Integration with Other Brain Imaging Techniques: EEG is undergoing integration with other brain imaging techniques, such as fMRI and MEG, to provide a more comprehensive understanding of brain function. This multimodal neuroimaging approach is generating valuable insights into the intricate neural mechanisms governing brain activity.

Personalized Medicine Applications: Exploration of EEG extends to personalized medicine applications, particularly in tailoring treatment strategies for neurological disorders based on individual EEG patterns. This personalized approach holds promise for enhancing treatment outcomes and overall patient care.

4.7. CONCLUSION OF THE CHAPTER

Electroencephalography (EEG) stands as a crucial non-invasive technique in both clinical and research domains, offering valuable insights into brain function and aiding in the diagnosis of neurological disorders. The chapter provides a comprehensive overview of EEG, detailing its working principles, historical development, clinical applications, advantages, and limitations. The presented information underscores the significance of precise signal analysis techniques in extracting meaningful data from EEG recordings. The documented surge in research interest, as evidenced by the increasing number of published papers over the years, highlights the continued relevance and importance of EEG in scientific inquiry. Furthermore, the discussion on the future of EEG research points towards promising advancements, including the development of new technologies, integration with other imaging techniques, and personalized medicine applications. As EEG continues to evolve, it holds the potential to enhance our understanding of the intricate neural processes governing brain activity and contribute to innovative approaches in diagnostics and personalized treatment strategies for neurological disorders.

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PART 5

WORK ENVIRONMENT

5.1. INTRODUCTION OF THE CHAPTER

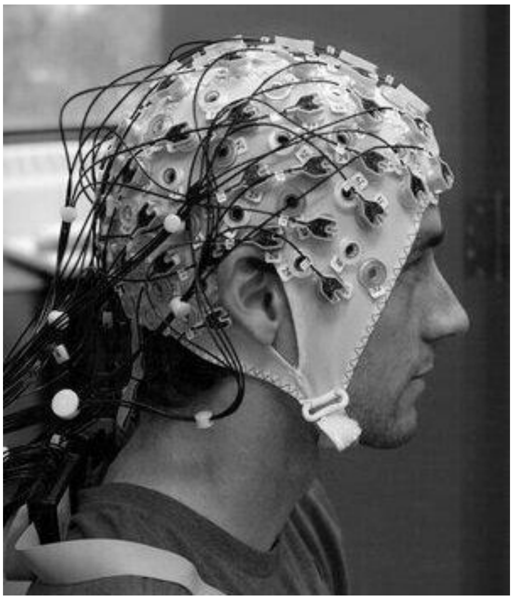
Before initiating the project, it is crucial to define the specifications of our work environment, encompassing both hardware and software components. Kaggle stands out as a prominent global community for data science, providing robust tools and resources to support individuals in achieving their data science goals. All brain signal datasets were sourced from **Kaggle**, and the raw experimental data is accessible on the Kaggle website [40].Subsequently, I processed these datasets to derive meaningful findings, focusing on data intervals of 0-10 minutes for concentration, 10-20 minutes for lack of focus, and 20-30 minutes for drowsiness. The initial two files represent practice data, and for analysis, I will utilize the last 5 files from each participant. Additionally, I will elaborate on the essential components of the datasets.

In this chapter, the discussion will cover various hardware components, including the EMOTIV device and EEG sensors. Software components such as pandas, scipy, the Numpy library, and the programming language Python will also be addressed.

5.2. HARDWARE

5.2.1. EEG Electrodes

EEG electrodes are small, metal discs which are connected to the scalp to document electric activity in the brain. They are utilized in a variety of clinical approaches, such as electroencephalography (EEG), evoked capacity (EP), and occasion-associated capability (ERP) studies. EEG electrodes are commonly product of silver/silver chloride (Ag/AgCl) or gold, and they are packed with a conductive gel or paste to make certain correct contact with the scalp [41].



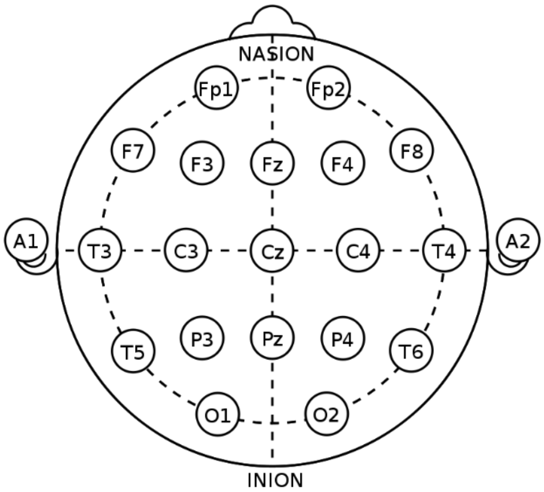


Figure. 5.2. International 10-20 system for EEG [42].

Figure. 5.1. EEG Sensor Placed on scalp

There are two main types of EEG electrodes: dry and wet. Dry electrodes do not require any gel or paste, and they are typically used for short-term recordings. Wet electrodes require gel or paste to ensure good contact with the scalp Figure. 5.1, and they are typically used for longer-term recordings.

EEG electrodes are placed on the scalp according to the International 10-20 system Figure. 5.2. This system is a standardized way of placing electrodes on the scalp that ensures that recordings from different patients can be compared.

EEG electrodes are a safe and effective way to record electrical activity in the brain. They are used in a variety of medical procedures to diagnose and monitor brain disorders.

The **Emotiv EPOC gadget**, worn on the head, records brain waves using Electro Encephalography and transmits data wirelessly. Figure 5.3. provides a perspective of the device. This device can be used for study or fun.

Figure. 5.3. Emotiv EPOC EEG [43].

5.2.2. System Requirements

Below are the minimum system requirements for working on BCI and EEG signal processing:

CPU:

A powerful CPU is essential for real-time BCI processing. A quad-core or octa-core processor is recommended.

RAM:

BCI processing can be memory-intensive, so 8GB of RAM or more is recommended.

Storage:

BCI data can be large, so a large hard drive or SSD is recommended.

Graphics Card:

A dedicated graphics card is not required for BCI processing, but it can be helpful for visualizing EEG data.

Operating System:

Windows, macOS, or Linux can be used for BCI processing.

Table 5.1. Minimum System Requirements

Component	Minimum	Recommended
CPU	Dual-core	Quad-core or octa-core
RAM	4GB	8GB or more
Storage	500GB	1TB or more
Graphics Card	Integrated	Dedicated (optional)
Operating System	Windows, macOS, or Linux	

5.3. SOFTWARE

5.3.1. EEGLab

EEGLAB stands as an open-source toolbox designed for the evaluation of electroencephalography (EEG) facts, created by way of Arnaud Delorme and Scott Makeig. Widely adopted through researchers and clinicians globally, EEGLAB offers a complete set of functions for facts preprocessing, visualization, and analysis. These consist of:

Data Importing and Exporting:
EEGLAB facilitates the import and export of data from various file formats, including EDF, BIDS, and BV.

Data Preprocessing:
EEGLAB provides a range of tools for data preprocessing, encompassing filtering, artifact rejection, and channel interpolation.

Data Visualization:
EEGLAB offers diverse tools for data visualization, such as time-frequency plots, topographic maps, and event-related potentials (ERPs) [42].

Statistical Analysis:

EEGLAB includes various tools for statistical analysis, covering t-tests, ANOVAs, and correlation analysis.

Source reconstruction:

EEGLAB provides a variety of tools for source reconstruction, such as LORETA and sLORETA.

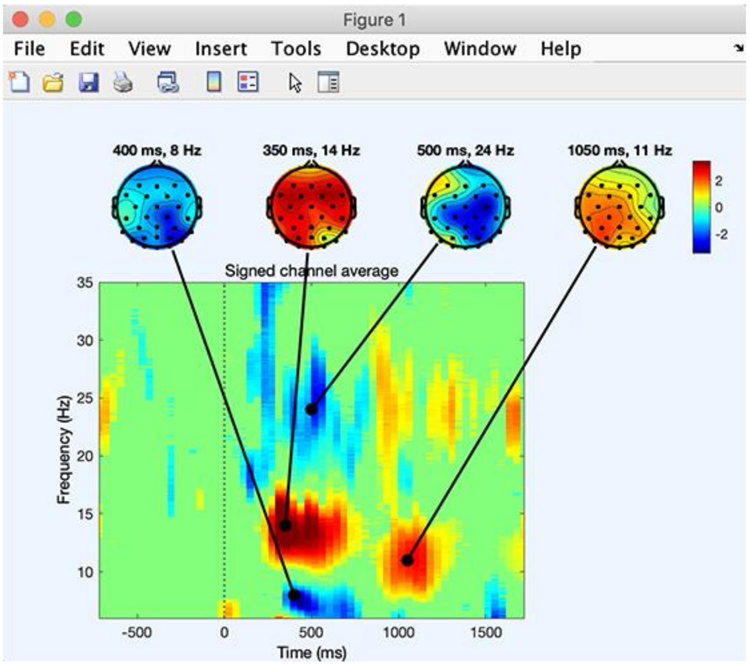


Figure. 5.4. EEGLab Output on different frequencies

5.3.2 PyCharm

PyCharm is an included development environment (IDE) for Python evolved by means of JetBrains. It is a famous IDE for Python development, and it's far utilized by a massive wide variety of builders.

PyCharm provides a wide range of features for Python development, including:

Code completion: PyCharm gives code of completion for Python code, which can help you to write down code greater quick and as it should be.

Code inspection: PyCharm presents code inspection for Python code, which can help you to discover and fix capacity insects on your code.

Refactoring: PyCharm offers refactoring gear for Python code, which let you to enhance the great of your code.

Debugging: PyCharm affords debugging gear for Python code, which permit you to to debug your code.

Testing: PyCharm offers testing tools for Python code, which let you to test your code.

Profiling: PyCharm affords profiling equipment for Python code, which permit you to to discover overall performance bottlenecks for your code.

In addition to these capabilities, PyCharm also affords a number of different features that make it a powerful and versatile IDE for Python improvement, including:

A customizable consumer interface: PyCharm's consumer interface can be customized to fit your man or woman wishes.

A extensive variety of plugins: PyCharm helps a wide range of plugins, which could add extra functionality to the IDE.

Integration with version manage systems: PyCharm may be integrated with popular version manage systems, which include Git and Mercurial**.**

Support for far off improvement: PyCharm can be used to increase Python applications on far flung servers.

PyCharm is available in editions: Community and Professional. The Community Edition is free and open-source, and it offers a wide variety of functions for Python improvement. The Professional Edition is a business product, and it includes additional functions, along with help for scientific computing and web improvement.

5.3.3. Python

Python is a popular programming language for brain-computer interface (BCI) applications due to its simplicity, versatility, and extensive library support. It offers a range of tools and libraries that facilitate various aspects of BCI development, including data acquisition, signal processing, feature extraction, and machine learning.

Data Acquisition

Python offers libraries such as PyBCI and NeuroPy that facilitate seamless interaction with BCI hardware devices. These libraries enable real-time data acquisition from various neuroimaging modalities, including EEG and MEG, handling the intricacies of device communication and data streams effectively [44].

Signal Processing

In the domain of signal processing, Python boasts a diverse ecosystem of libraries, including SciPy, NumPy, and PyBioSignal. These tools are instrumental in tasks such as filtering, artifact removal, and feature extraction from raw neurophysiological data [45].They empower developers to clean, preprocess, and transform acquired signals into a format suitable for in-depth analysis, allowing a focused approach to core BCI algorithms.

Feature Extraction

Feature extraction plays a pivotal role in transforming preprocessed signals into meaningful representations that capture underlying neural activity patterns. Python libraries like MNE-Python and OpenBCI provide robust tools for extracting relevant features, such as power spectral density, event-related potentials, and connectivity measures [46]. These resources empower developers in capturing essential information for further analysis and interpretation.

Machine Learning

Machine learning plays a crucial role in BCI applications, enabling the classification of mental states, control of external devices, and decoding neural signals. Python offers powerful machine learning libraries like scikit-learn, TensorFlow, and PyTorch that provide algorithms for classification, regression, and deep learning [47]. ML plays a crucial role in improving the accuracy and performance of EEG-based BCIs. By effectively extracting meaningful features from EEG signals, selecting appropriate ML algorithms, and continuously adapting to user variations, we can create more robust and reliable BCI systems that can significantly impact various fields, including healthcare, communication, and human-computer interaction.

5.4. CONCLUSION OF THE CHAPTER

This chapter delineates the necessary hardware and software components essential for the development of brain-computer interface (BCI) applications. The hardware prerequisites encompass EEG electrodes and a computer system meeting minimum system requirements. On the software side, the components include EEGLab, PyCharm, and the Python programming language. Each of these tools contributes specific functionalities critical for BCI development: EEGLab provides a comprehensive toolbox for EEG analysis, PyCharm serves as a robust IDE for Python development, and Python offers an extensive library ecosystem for tasks ranging from data acquisition to machine learning.

In the forthcoming chapter, the focus will be on organizing and utilizing unprocessed signals for Signal acquisition and feature extraction. This approach aims to facilitate the examination of outcomes in the BCI development process.

PART 6

METHODOLOGY

6.1. PROPOSED METHODOLOGY

This detailed methodology involves a systematic approach to analyzing EEG signals for the purpose of identifying distinct mental states. It begins with the acquisition of raw EEG data from experiments designed to assess attention levels using a passive EEG BCI. The data is then subjected to pre-processing steps, including signal conditioning with high-pass Butterworth filters to eliminate noise and artifacts while preserving neural information. Feature extraction techniques, such as Short-Time Fourier Transform (STFT), are applied to analyze the frequency content of the EEG signals over time. This provides insights into how neural activity varies across different mental states. Additionally, power spectrum analysis is conducted to examine the distribution of signal power across frequency bands, further characterizing the EEG signals. Data binning is employed to reduce the dimensionality of the data and capture meaningful patterns in the signals. This involves combining adjacent frequency bins into broader frequency bands, facilitating the identification of relevant features for mental state detection.

Finally, machine learning-based classification using Least Squares Support Vector Machines (SVM) is utilized to detect specific mental states based on the extracted features from EEG signals. SVM classifiers are trained to discriminate between different mental states, such as "focused" and "unfocused," using spectral features derived from EEG data. This approach leverages advanced signal processing techniques and machine learning algorithms to enhance the accuracy and reliability of mental state detection, ultimately contributing to the development of more effective Brain-Computer Interface systems.

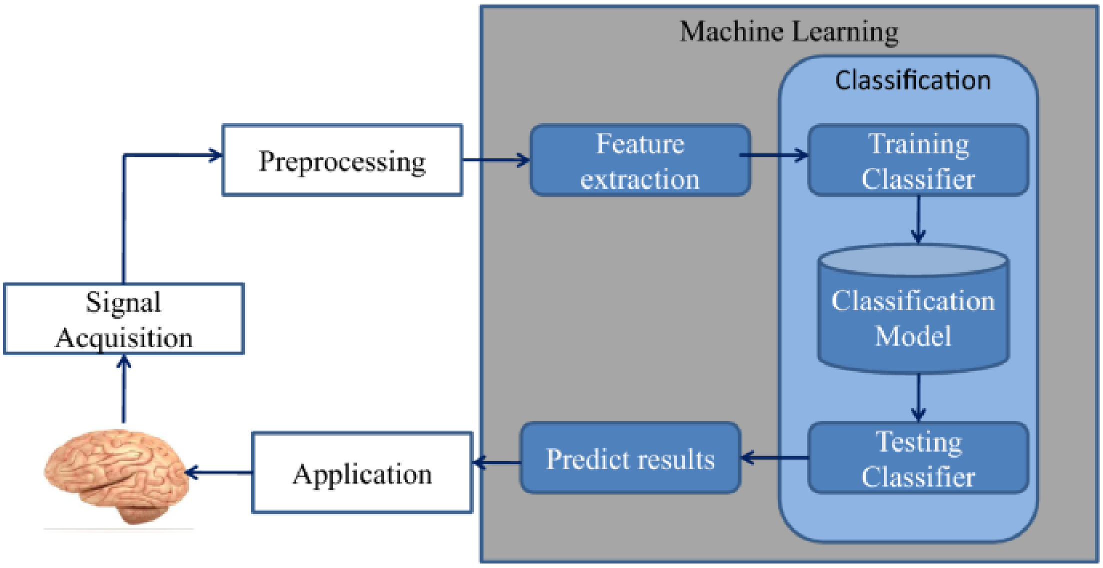


Figure. 6.1. Research methodology [48].

6.2. SIGNAL ACQUISITION:

6.2.1. Raw Data

This compilation consists of 34 experiments (eeg_record1.mat………… eeg_record34.mat) designed to assess the attention levels of individuals using passive EEG BCI (Brain-Computer Interface). Each Matlab file encapsulates the data object obtained from the EMOTIV device after a single experiment. The raw data is stored in the variable o.data, which is an array of dimensions {number-of-samples}x25. Each column o.data(:,i) represents a single data channel. The frequency at which samples are taken is 128 Hz.

We don't know which data are useful I have to plot all the channels Figure. 6.2. There are 14 channels ['AF3', 'F7', 'F3', 'FC5', 'T7', 'P7', 'O1', 'O2', 'P8', 'T8', 'FC6', 'F4', 'F8', 'AF4']

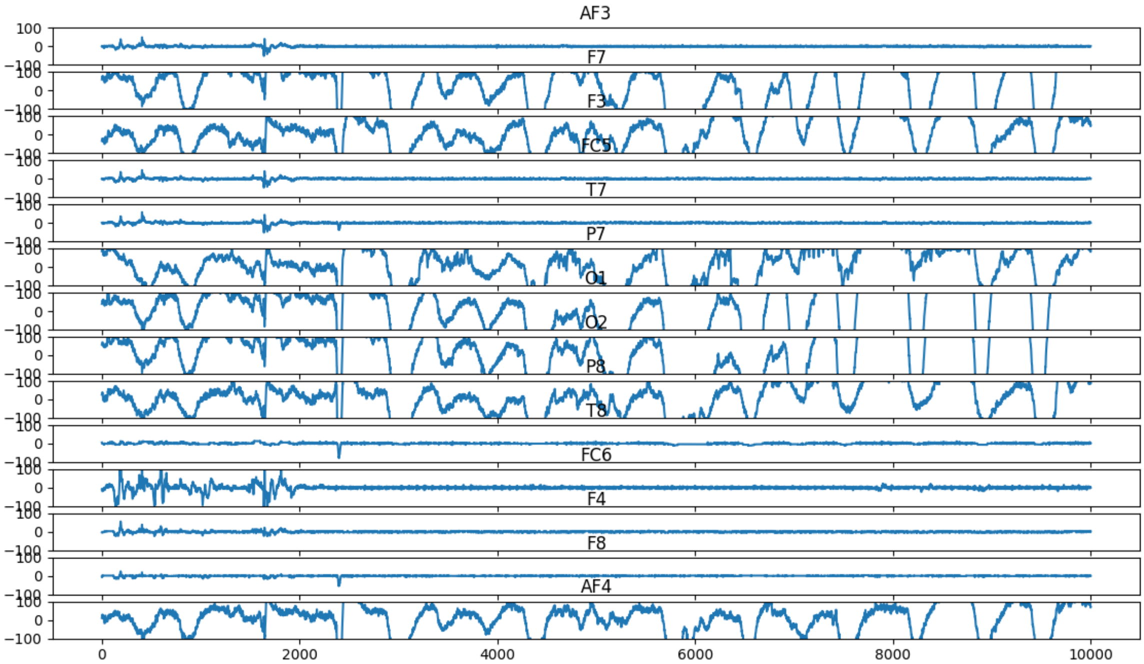


Figure. 6.2. Plot of all 14 channels

6.2.2. Select Useful Channels

Finally, program selects a subset of channels (['F7', 'F3', 'P7', 'O1', 'O2', 'P8', 'AF4']) that appear to have the highest-quality EEG signals based on the plots Figure. 6.3. These channels may be used in subsequent analyses or processing steps.

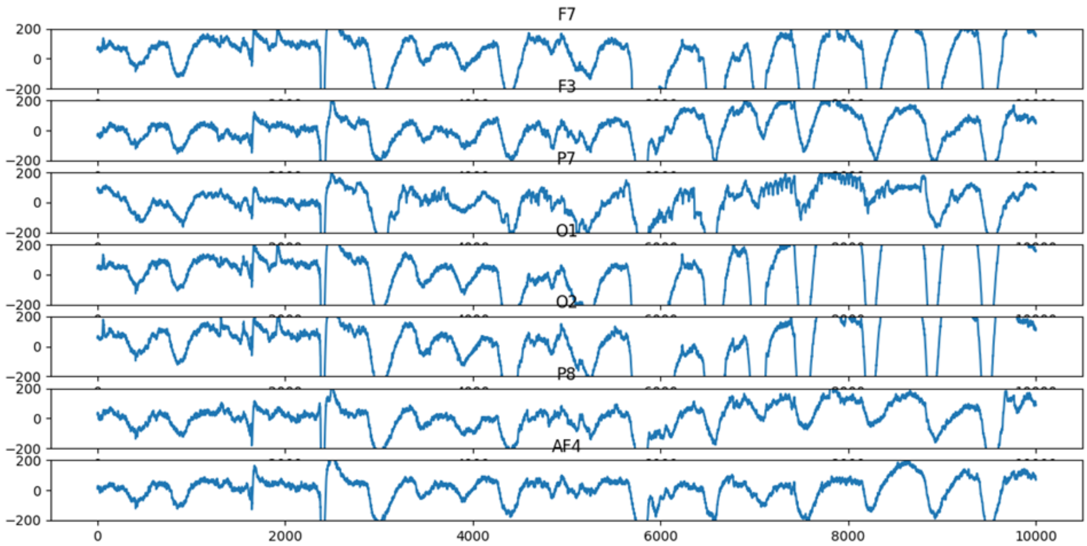


Figure. 6.3. Plot of useful channels

6.2.3. Signal conditioning (filtering)

High-pass Butterworth filters are commonly employed in electroencephalography (EEG) signal processing to eliminate low-frequency artifacts and noise while preserving the vital high-frequency components that carry the underlying neural information [49] [45]. These filters effectively attenuate unwanted signals such as muscle activity, electrode-skin interface artifacts, and DC offset, allowing for a clearer representation of the brain's electrical activity. The cutoff frequency of the high-pass filter is typically set to a value between 0.1 and 1 Hz, depending on the specific application and the desired level of noise reduction [44]. By employing high-pass Butterworth filters, researchers and clinicians can extract meaningful information from EEG signals with greater accuracy, leading to improved understanding of brain function and enhanced diagnostic capabilities.

Therefore, when applying a Highpass filter with a cutoff frequency of 0.16 Hz. All frequencies below 0.16 Hz will be eliminated. The Butterworth high-pass filter has been implemented using the specified cutoff frequency and sampling rate of 128 Hz Figure. 6.4.

```
row, col = data_focus['eeg_record3'].shape
for name in trail_names:
    for i in range(col):
        data_focus[name][:,i]=butter_highpass_filter(data_focus[name][:,i], 0.16, 128, 5)
        data_unfocus[name][:,i]=butter_highpass_filter(data_unfocus[name][:,i], 0.16, 128, 5)
        data_drowsy[name][:,i]=butter_highpass_filter(data_drowsy[name][:,i], 0.16, 128, 5)
        #print(name,data_drowsy[name][:,i].shape)
feature_names = []
freq_range=np.arange(0.5,18.5,0.5)
symb='_'
#useful_channels_names=['F7','F3','P7','O1','O2','P8','AF4']
for index,channel in enumerate(useful_channels_names):
    for freq in freq_range:
        feature_names.append(channel+symb+str(freq))
feature_names
```

Figure. 6.4. A code which set filter of 0.16 Hz cutoff frequency and sampling rate of 128 Hz

The variable "feature_names" seemingly encompasses the names of the features that will be retrieved from the EEG data. The feature name appears to be a combination of the channel name and the frequency range, with an underscore (_) separating them. The frequency ranges are observed to increase by 0.5 Hz from 0.5 Hz to 18.0 Hz.

In Figure. 6.5. red signal represents the raw signal for one of the EEG channels in the 'unfocus' state for the 'eeg_record3' trial. The green signal represents the same channel after it has been filtered using the high-pass filter with a cut-off frequency of 0.16 Hz. The plot shows that the high-pass filter has removed the low-frequency drift in the signal, and the filtered signal has a zero-mean. Therefore, the high-pass filter has validated the elimination of unwanted DC offset from the signal.

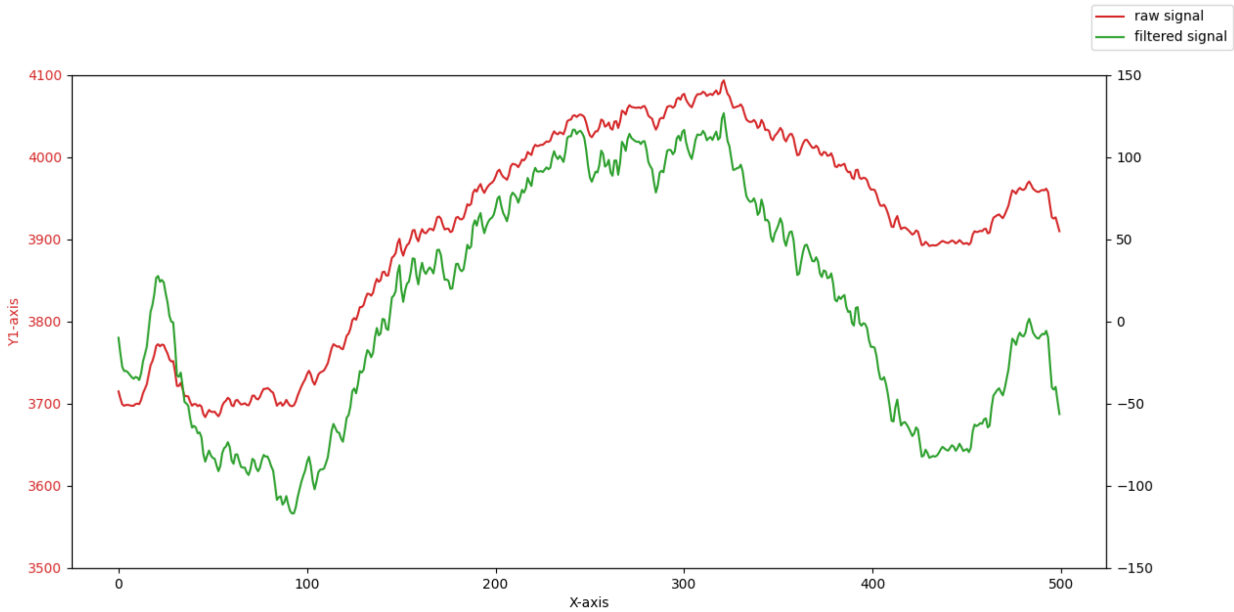


Figure. 6.5. Plot of 'eeg_record3' trial raw and filtered signals

In **Figure. 6.6.** red signal represents the raw signal for one of the EEG channels in the 'unfocus' state for the 'eeg_record3' trial, By using same high-pass filter with a cut-off frequency of 0.16 Hz

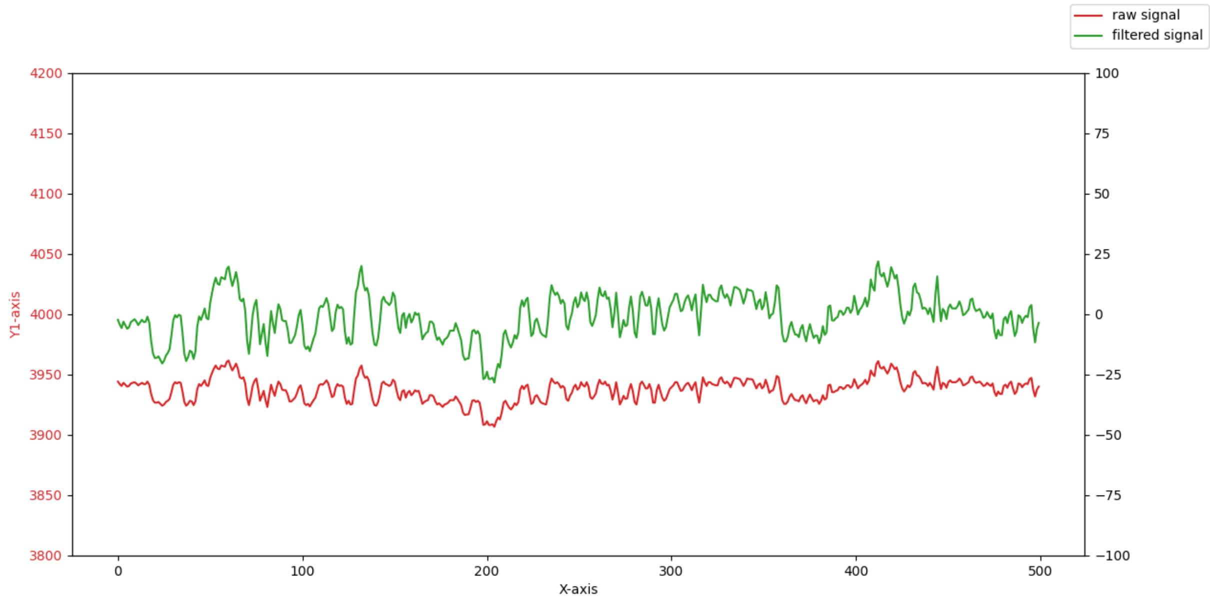


Figure. 6.6. Plot of 'eeg_record33' trial raw and filtered signals

In this way we have calculated 34 plots for all 34 trials.

6.2.4. Short-time Fourier Transform (STFT)

The Short-Time Fourier Transform (STFT) is a powerful tool for analyzing non-stationary signals, like speech, music, and biosignals. It provides a time-frequency representation, revealing how the frequency content of the signal changes over time [50] [51].

The STFT essentially divides a signal into smaller segments and performs a Fourier transform on each segment. This allows us to see how the frequency content evolves over time.

The formula for the STFT X(t,ω) of a signal x(τ) is given [50]:

$$X(t,\omega) \ = \sum_{-\infty}^{\infty} x(\tau) \cdot w(\tau - t) \cdot e - j\omega\tau d\tau \tag{6.1}$$

where w(τ−t) is the window function, and ω is the angular frequency. The spectrogram is defined as the square of the STFT amplitudes. S(t,ω) = $|X_{STFT}(t,\omega)|2$ and quantifies the frequency composition of the EEG signals near a given time point. The raw EEG data was acquired from the Epoc Emotiv headset in 7 channels at a sampling frequency of Fs = 128 Hz. The STFT calculation was performed separately for each channel. STFT was computed using T = 15 second fragments of EEG signals and m = 1024 fast discrete Fourier transform (DFT). The Blackman windowing function was used to make the EEG signal taper at both ends of each fragment. The Blackman windowing function is defined by [39].

$$w(\hat{t}) = \begin{cases} 0.42 - 0.5\cos\frac{2\pi\hat{t}}{M-1} + 0.08\cos\frac{4\pi\hat{t}}{M-1}, 0 \leq \hat{t} < M \\ 0, otherwise \end{cases} \tag{6.2}$$

```
# STFT was then calculated at a time step of 1 s producing a set of time-varying DFT
# amplitudes X STFT (t,ω) at 1s intervals within each input EEG channel.
t_win = np.arange(0, 128)
M = 128
window_blackman = 0.42 - 0.5 * np.cos((2 * np.pi * t_win) / (M - 1)) + 0.08 * np.cos(
    (4 * np.pi * t_win) / (M - 1))  # window_blackman = signal.windows.blackmanharris(128)
```

Figure. 6.7. A code which Calculate STFT

where M is the total number of time points within the window (M = Fs · ΔT = 1920) and \hat{t} = 0,1,…,M−1 is a discrete time-index within the window. STFT was then calculated at a time step of 1 s producing a set of time-varying DFT amplitudes XSTFT(t,ω) at 1 s intervals within each input EEG channel.

After calculating STFT in each EEG channel, the absolute squares of the DFT amplitudes were calculated to construct the time dependent power spectrum (that is, spectrogram) of t signal S(t, ω) in each channel as discussed above. Due to m = 1024 points used in DFT, the obtained spectrum characterized the power distribution in the EEG signal over m/2 + 1 = 513 frequencies ωk = kFs/m = 0.125k Hz, where k changed between 0 and m/2 = 512. These were subsequently binned into 0.5 Hz frequency bands by using average, thus, evaluating an average spectral power in each 0.5 Hz frequency band from 0 to 64 Hz. The frequency range was then restricted to 0–18 Hz so that only 36 frequencies, Ωk = k · 0.5 Hz, k = 1,…,16, were retained in the dataset. The constant component Ω = 0 Hz was discarded. Finally, the binned and frequency restricted spectrograms S(t, Ω) were temporally smoothed by using a 15 s-running average.

The STFT is calculated using a Blackman window of size 128 with 0 overlap Figure.6.7. The STFT is calculated for 1-second windows of data, and the resulting spectrogr`ams are stored in dictionaries with keys 'power_focus', 'power_unfocus', and 'power_drowsy'. These dictionaries have the same keys as the original data dictionary and store the spectrogram for each channel of each trial. The spectrogram is calculated as the squared magnitude of the STFT coefficients.

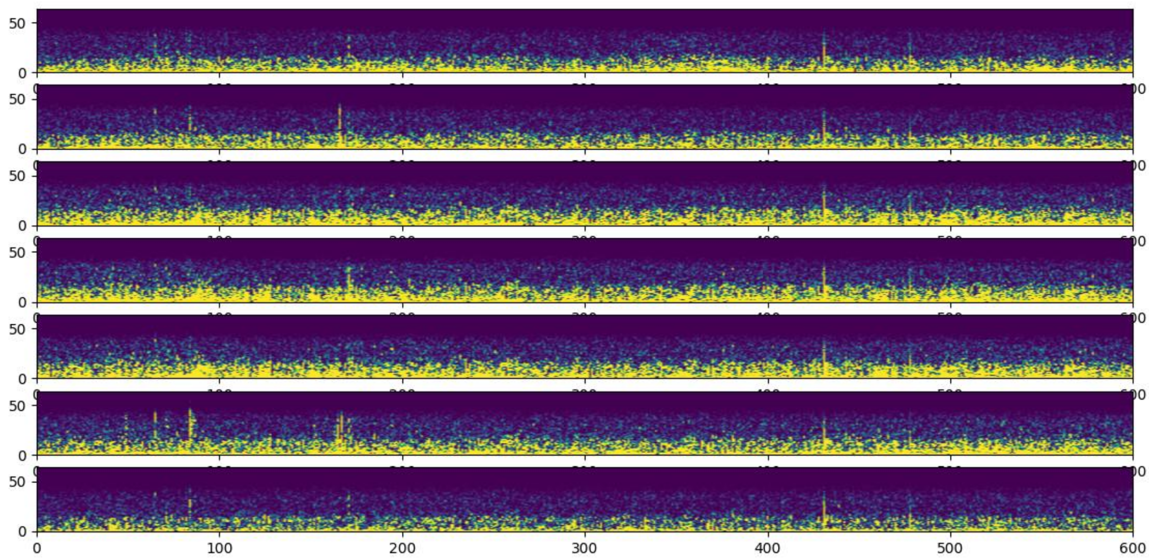


Figure. 6.8. A Pseudocolor plot for a single EEG recording ('eeg_record18') in the focused state for 7 channels

After STFT calculation will get the power values using a pseudocolor plot for a single EEG recording ('eeg_record18', 'eeg_record33') in the focused state Figure. 6.8. & Figure. 6.9. The pcolormesh() function is used to create the plot, with the time and frequency values being the X and Y axes, respectively, and the power values being represented by color. It’s creating a separate plot for each of the 7 channels in the EEG recording.

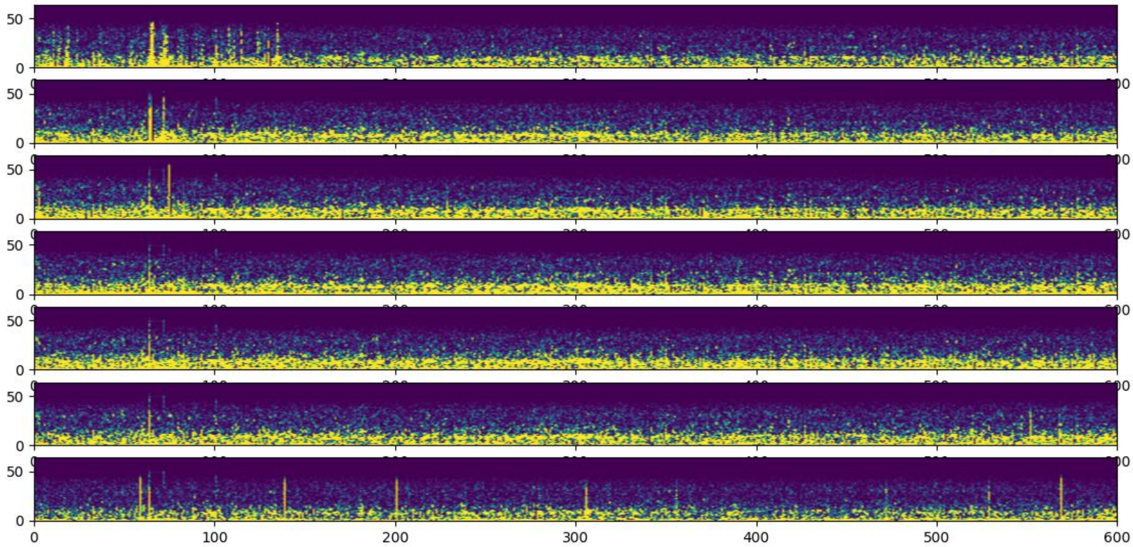


Figure. 6.9. A pseudocolor plot for a single EEG recording ('eeg_record33') in the focused state for 7 channels

In this way got 34 Power values spectrograms of EEG recordings in the focused state, 34 Power values spectrograms of EEG recordings in the unfocused state and 34 Power values spectrograms of EEG recordings in the drowsy state for 7 channels each recording.

6.2.5. Power Spectrum

The power spectrum of a signal is a representation of how the power of the signal is distributed across different frequencies. Here in Figure. 6.10. & Figure. 6.11. we can see Power distribution of two trials on specific time interval

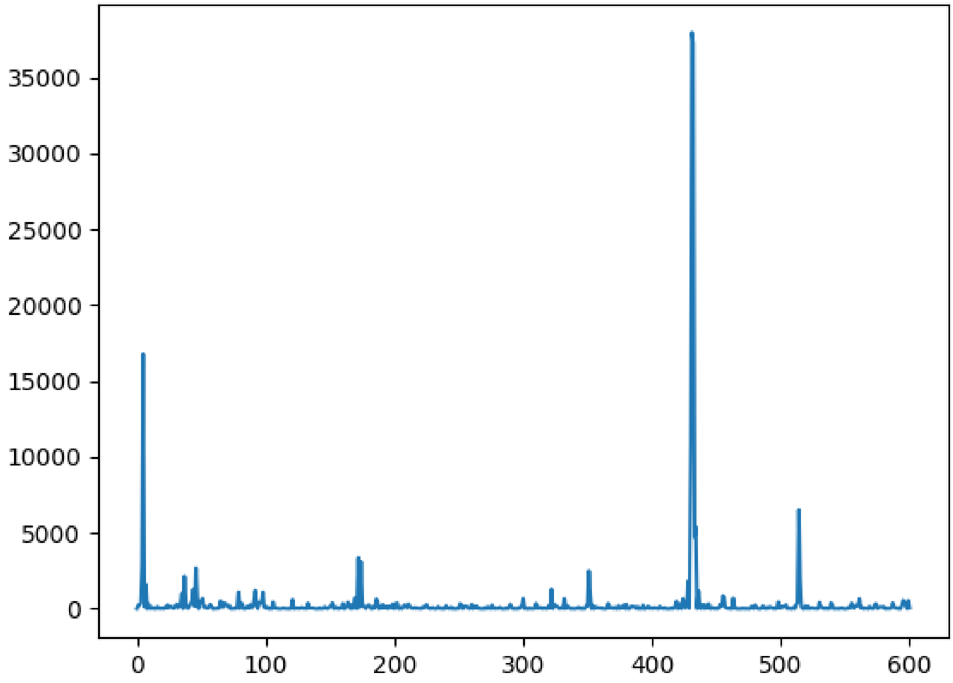


Figure. 6.10. The power spectrum of a specific time interval of eeg_record18 Trial

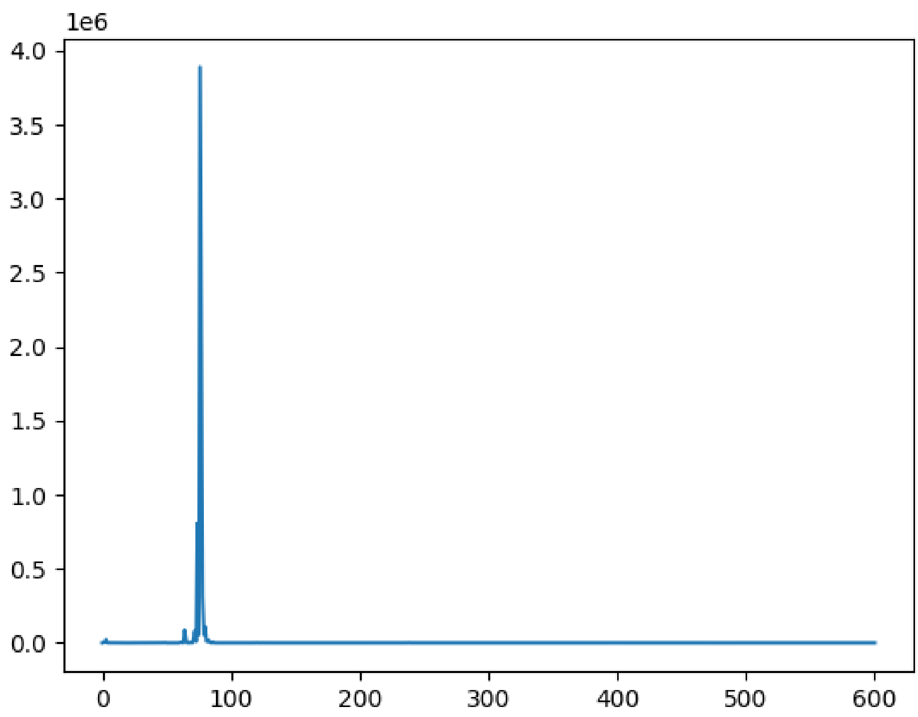


Figure. 6.11. The power spectrum of a specific time interval of eeg_record33 Trial

In this way got 34 Power distribution plots for 7 channels each recording.

6.2.6. Data Binning

The process of combining adjacent frequency bins into broader frequency bands. This is done to reduce the dimensionality of the data and potentially capture more meaningful information about the underlying patterns in the signals. Specifically, we took averages of the power spectrum values within each broader frequency bin.

Here EEG data is processed in several steps, including averaging over 4-second intervals and then further averaging over 15-second running windows

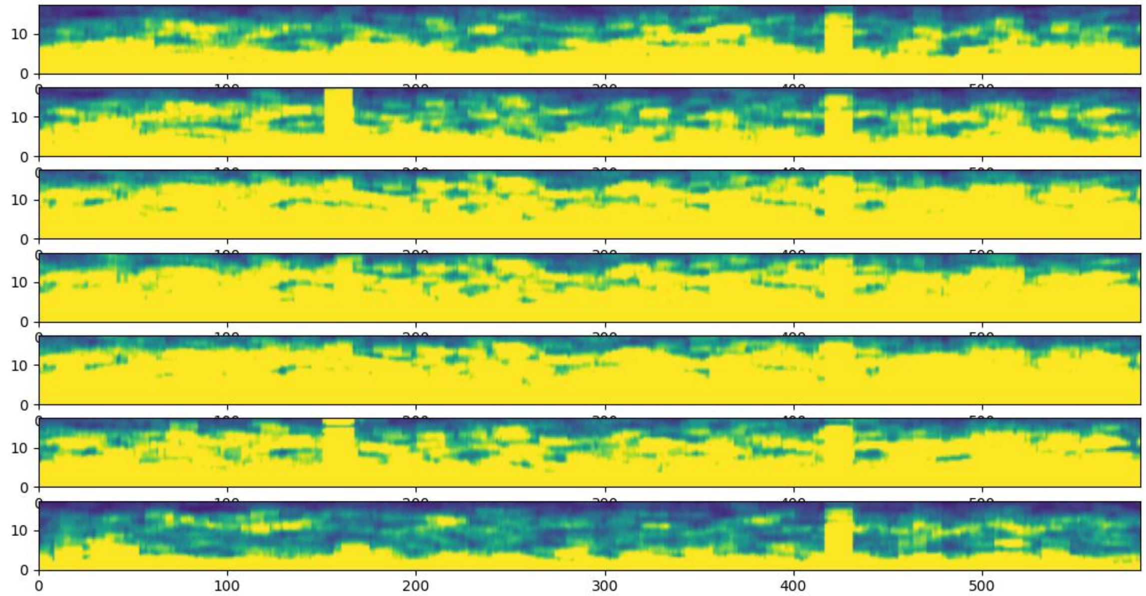


Figure. 6.12. Data bin Avarage over 15 seconds running window of eeg_record18 Trial

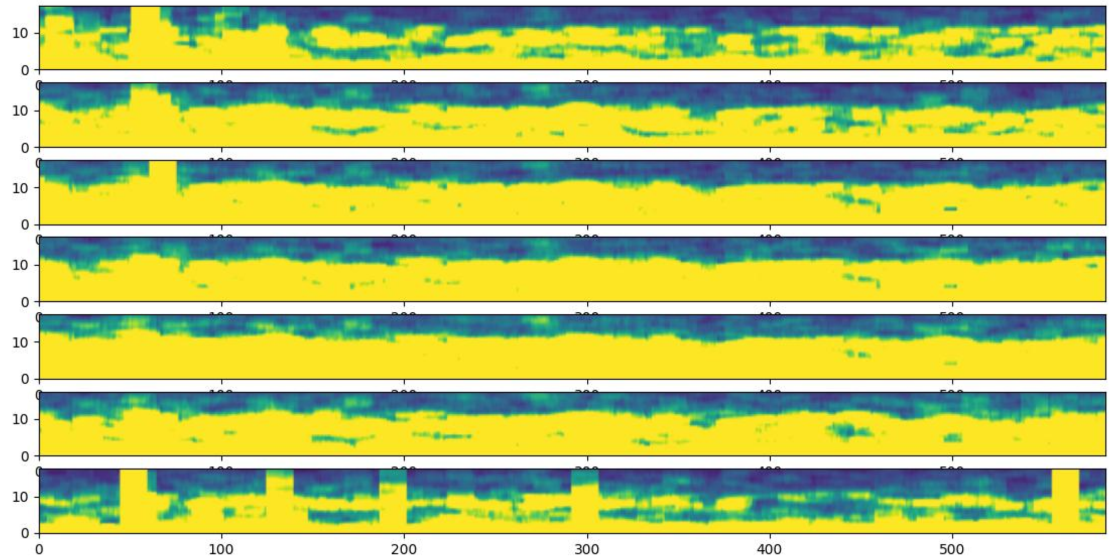


Figure. 6.13. Data bin Avarage over 15 seconds running window of eeg_record33 Trial

6.3. DETECTING MENTAL STATES:

We used the Least Squares Support Vector Machines (SVM) machine learning approach to implement the mental state detector [52] . To create an SVM detector, the time-varying EEG signal's spectra were first reorganized into a feature vector. This was accomplished by combining the power spectra calculated for each time point from all input EEG channels, resulting in a vector with a dimensionality of 252, characterizing the distribution of the EEG signal's power over all EEG channels and frequencies ranging from 0 to 18 Hz at 0.5 Hz steps. Following that, an SVM classifier was trained to detect each mental state individually. A predetermined number of feature vectors were drawn at random from the EEG spectral data to create the training data. Multiple SVM classifiers had to be combined to discriminate between more than two mental states because SVM is a two-class classifier. Over all others, the first SVM classifier was trained to detect the presence of the "focused" state in EEG data. In comparison to the others, a second SVM classifier was trained to detect the presence of the "unfocused" state.

6.3.1. SVM classifier design:

The SVM classifiers were trained using the svmtrain function of the Matlab Statistics Toolbox. The tuning parameters have been left at their default values. The auto-scaling parameter was enabled, and the box constraint (which determines the cost of misclassifications in SVM) was set to one. The linear kernel function and the "least squares" method were used to solve the SVM optimisation problem in this study due to the large size of the training data [53].

SVM is based on the result of a linear convolution of a feature vector representing the temporally-local EEG signal with a vector with weights of W, y = i Wi fi, where fi represents the spectral power features and i represents the index enumerating such features as well as the corresponding weights Wi. The sign and magnitude of the individual weights Wi provide information about the contribution and importance of each feature to the detector's decision process because the feature vector of each time-point is classified as either +1 (present) if y b exceeds a certain threshold b, or as 1 (absent) otherwise. By the construction of the feature vector \overline{f}(t), the weights Wi indicate the frequencies and the electrodes contributing to the discrimination of particular mental states, both in a positive sense when Wi > 0 and negative sense when Wi < 0.

In Figure. 6.14. & Figure. 6.15. we got SVM vectors from power data and visualizing the transformed vectors for eeg_record18 & eeg_record5 recordings under different conditions. The logarithmic transformation will apply to enhance the features for SVM classification

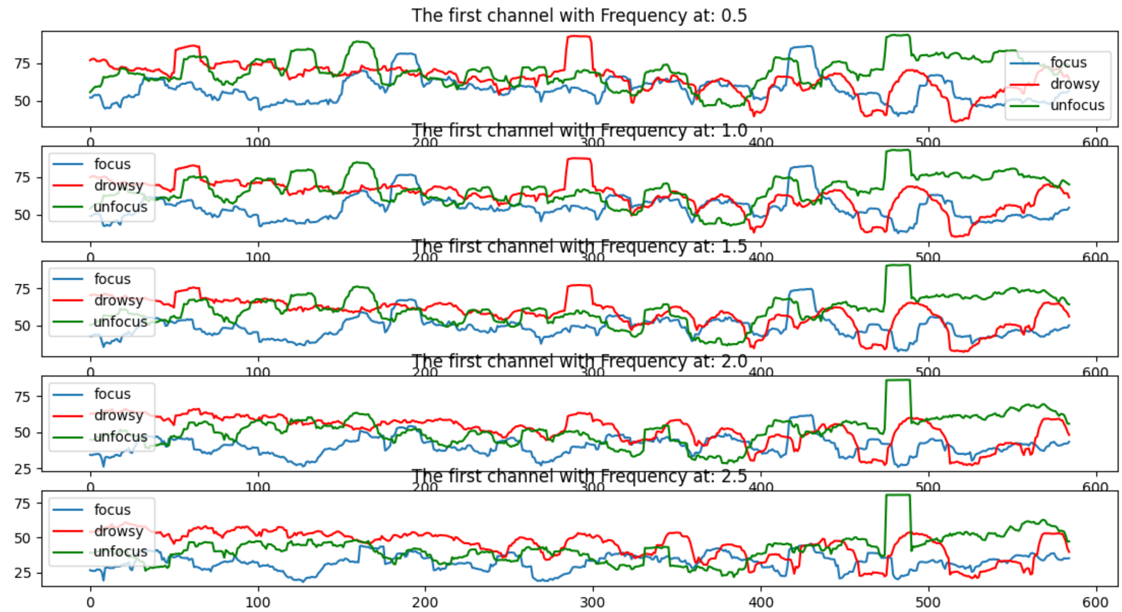


Figure. 6.14. Preparing SVM vectors from power data for eeg_record18

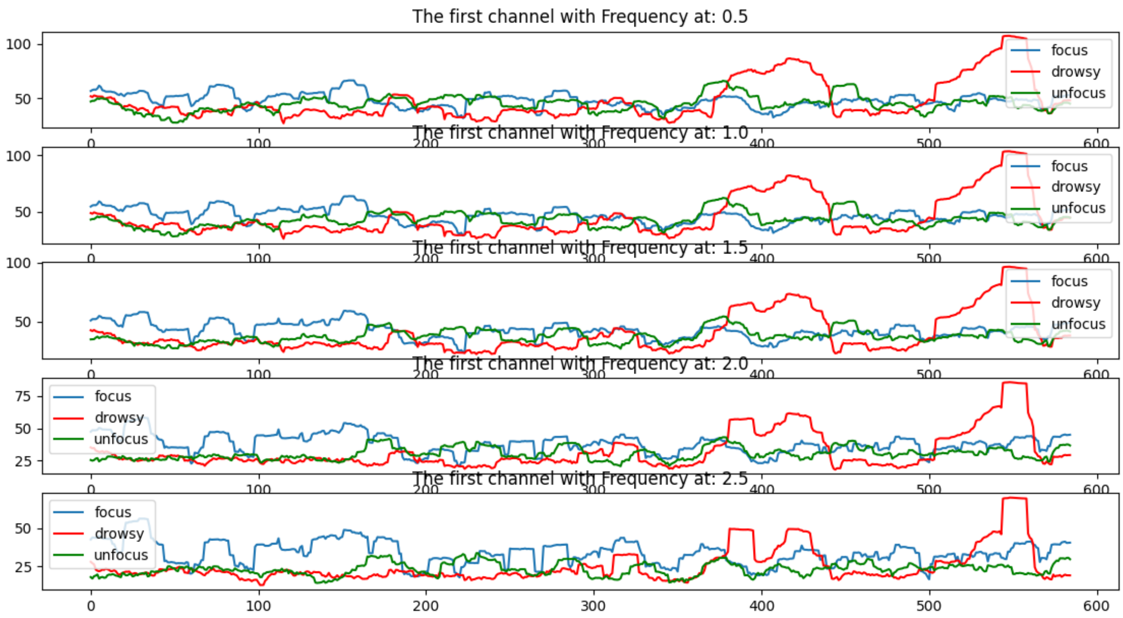


Figure. 6.15. Preparing SVM vectors from power data for eeg_record5

In Figure. 6.16. we have SVM vectors for a specific channel at different time points (every 5th time point within the range of 0 to 25). The peaks in the plot are lowest frequency, and each peak marks the start of the data for that specific channel.

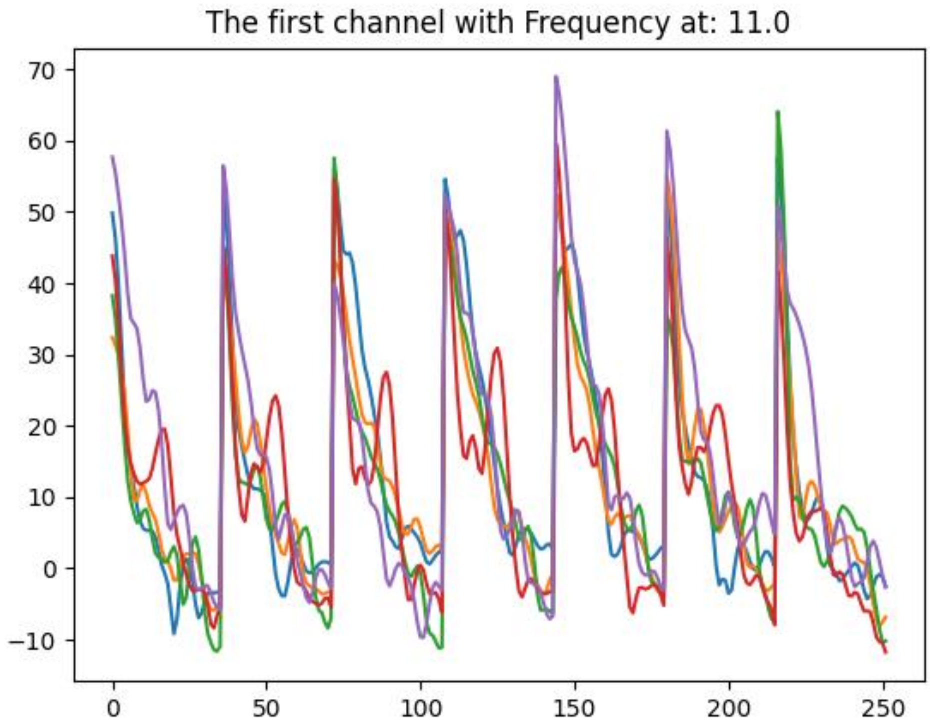


Figure. 6.16. SVM vectors for a specific channel at different time points

The result seems like it's separatable between subjects at 11HZ.

6.4 CONCLUSION OF THE CHAPTER

This chapter 1st plots all 14 channels and subsequently selects a subset of useful channels. Then did Signal conditioning involves applying a high-pass Butterworth filter to eliminate low-frequency artifacts. Short-time Fourier Transform (STFT) is introduced to analyze non-stationary signals, providing a time-frequency representation. Then demonstrates the calculation of STFT and its application to EEG recordings, leading to power values spectrograms. Power spectrum analysis and data binning follow, reducing dimensionality and capturing meaningful information. Mental state detection is implemented using Least Squares Support Vector Machines (SVM) on the reorganized feature vectors derived from power spectra. SVM classifiers are designed, trained, and visualized, showcasing their effectiveness in distinguishing mental states. In next chapter we are going to discuss results and will check our final result with accuracy.

PART 7

RESULTS AND DISCUSSION

7.1. INTRODUCTION OF THE CHAPTER

This chapter will focus on studying and analyzing various outcomes, as well as discussing the distinct impact of training parameters. Preparing and training a Support Vector Machine (SVM) model for mental state classification using EEG data. Additionally, we will endeavor to determine the optimal model parameters. Lastly, we will explore additional enhancements that might enhance the efficiency of the system.

7.2. DATA SPLITTING AND SCALING

Partitioning the data into distinct training and testing sets is a prevalent technique in machine learning to evaluate the efficacy of a model. The primary factors contributing to this are:

7.2.1. Evaluation of the Model:

Training Set: The model undergoes training using the training set, enabling it to acquire knowledge of patterns and relationships present in this specific piece of the data.

Testing Set: The purpose of the testing set is to assess the model's ability to apply its learned knowledge to unfamiliar data. It enables you to simulate the performance of the model on unseen data throughout the training process.

7.2.2 Mitigating Overfitting:

Training and evaluating a model on the same dataset, without dividing it, can lead to the model memorizing the training data instead of learning generic patterns. This phenomenon is referred to as overfitting, in which a model exhibits high performance on the training data but demonstrates poor performance on new, unseen data.

7.2.3. Evaluating Generalization:

The objective of a machine learning model is to exhibit strong generalization capabilities when presented with novel, unfamiliar data. By utilizing a distinct testing set, one can evaluate the model's capacity to extrapolate beyond the training data.

7.2.4. Optimizing Hyperparameters:

When optimizing the hyperparameters of a model, such as modifying parameters that are not learned during training, it is beneficial to have a distinct validation set. This set is utilized for evaluating various hyperparameter setups, and the testing set remains unaltered until the final assessment.

7.2.5. Preventing the unauthorized disclosure of data:

Assessing a model using the identical data it was trained on can unintentionally lead to data leakage, wherein information from the testing set influences the training process.

The process of categorization typically entails the division of data into distinct training and testing sets. Each instance in the training set includes a single "target value" (i.e., the class labels) and several "Attributes" refer to the characteristics or variables that are noticed or measured. The objective of Support Vector Machines (SVM) is to generate a model that can accurately predict the target values of the test data, only based on the properties of the test data [54].

Typical divisions involve ratios such as 80/20 or 70/30, where 80% or 70% of the data is allocated for training and the remaining 20% or 30% is allocated for testing. The precise division ratio is contingent upon variables such as the magnitude of the dataset and the particular demands of the problem.

7.3. SVM MODEL TRAINING:

I partitioned the EEG signal trials that were deemed helpful into five subjects, I will concatenate 5 files of each participant with 3 states. And Intend to employ various models to assess accuracy.

Subj1_files={‘eeg_record3’,’eeg_record4’,’eeg_record5’,’eeg_record6’,’eeg_record7’}

subj2_files={‘eeg_record10’,’eeg_record11’,’eeg_record12’,’eeg_record13’,’eeg_record14’}

subj3_files={‘eeg_record17’,’eeg_record18’,’eeg_record19’,’eeg_record20’,’eeg_record21’}

subj4_files={‘eeg_record24’,’eeg_record25’,’eeg_record26’,’eeg_record27’}

subj5_files={‘eeg_record31’,’eeg_record32’,’eeg_record33’,’eeg_record34’} .

7.3.1. Score of SVM Model:

The efficacy of the mental state classifier based on Support Vector Machines (SVM) is assessed using the accuracy (1), precision (2), and recall (3) parameters, while the F1 score (4) is the harmonic mean of the precision and recall parameters.

$$1.\ \text{Acc.} = \frac{\text{correct predictions result in the}}{\text{whole number of results}} * 100\% \qquad (7.1)$$

$$1.\quad \text{Precision} \ = \frac{TP}{FP+TP} \qquad (7.2)$$

$$2.\quad \text{Recall} \ = \frac{TP}{TP+FN} \qquad (7.3)$$

3. $\mathrm{F1} = \frac{2(\text{Precision} * \text{recall})}{\text{Precision} + recall}$ (7.4)

Figure. 7.1. depicts an enhanced efficacy analysis, showcasing the comparative performance of the mental state classifier utilizing Support Vector Machines (SVM) across a cohort of five subjects.

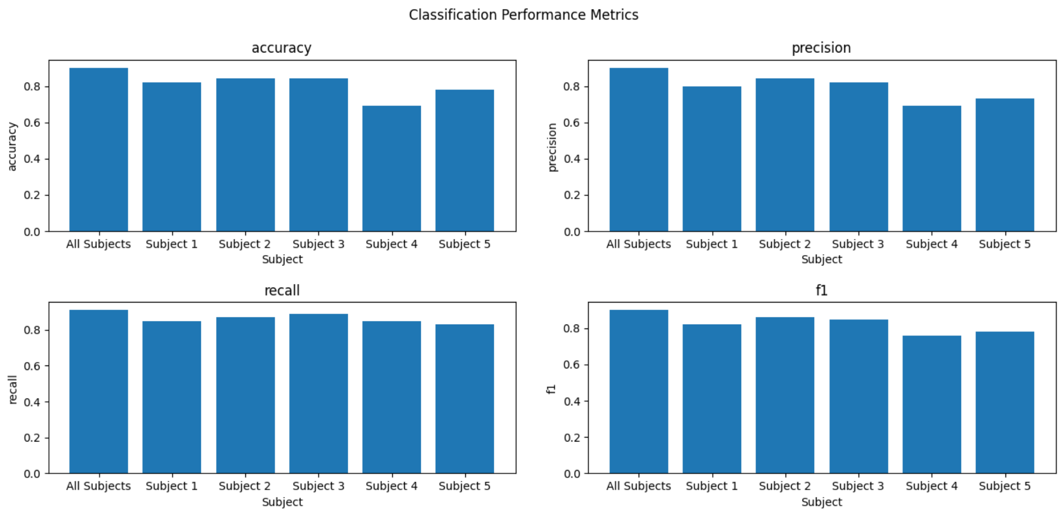


Figure. 7.1. Performance comparison of the 5 Subjects and all Subjects

Table 7.1 shows how well the SVM-based mental state classifier worked with both subject-specific and common-subject scenarios. The table show feature matrix (shape) and gives target labels.

Table 7.1. The feature vectors results from SVM results for focus, unfocus, and sleepy into a feature matrix (shape) and gives target labels.

Subjects	**Length of target**	**Shape**
Subject1	8775	(8775, 252)
Subject2	8775	(8775, 252)
Subject3	8775	(8775, 252)
Subject4	7020	(7020, 252)
Subject5	7020	(7020, 252)
All subjects	40365	(40365, 252)

7.3.2. Principal Component Analysis (PCA):

PCA is a dimensionality reduction technique that transforms the original features into a new set of uncorrelated features called principal components. So I did calculate the variance ratio for each principal component [55] This ratio indicates the proportion of the dataset's total variance captured by each component.

$$Variance\ Ratio\ = \frac{\text{Explained variance}}{\text{Sum of Explained variance}} \tag{7.5}$$

In Figure. 7.2. you can see Heatmap correlation matrix for the scaled training data.

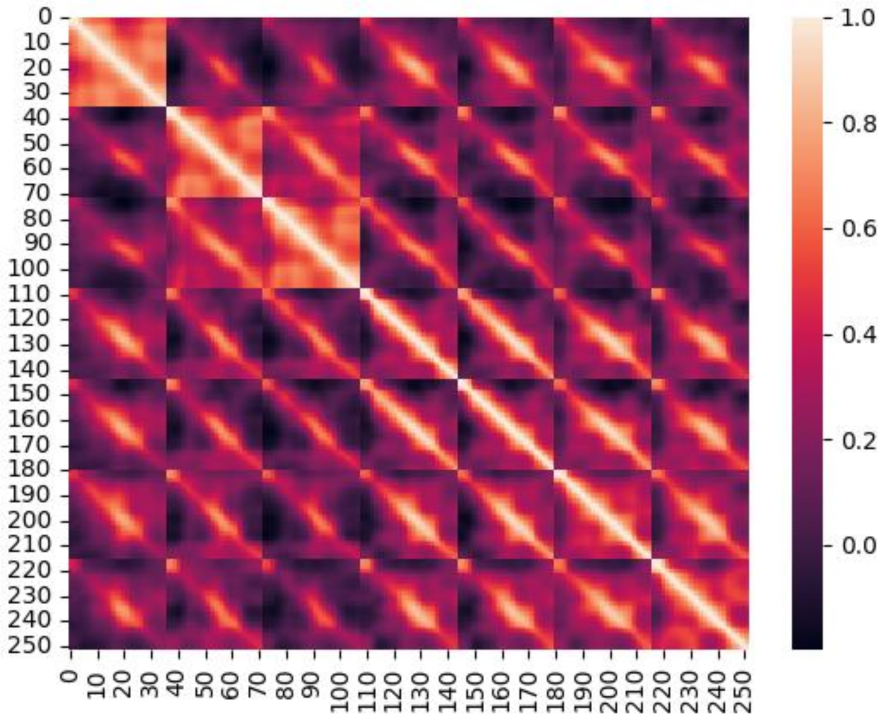


Figure. 7.2. Heatmap of calculated correlation matrix of scaled training data

Figure. 7.3. showing the DataFrame of the loadings of each feature on the principal components. Here plot of first and third principal components, highlighting features with loadings greater than 0.085

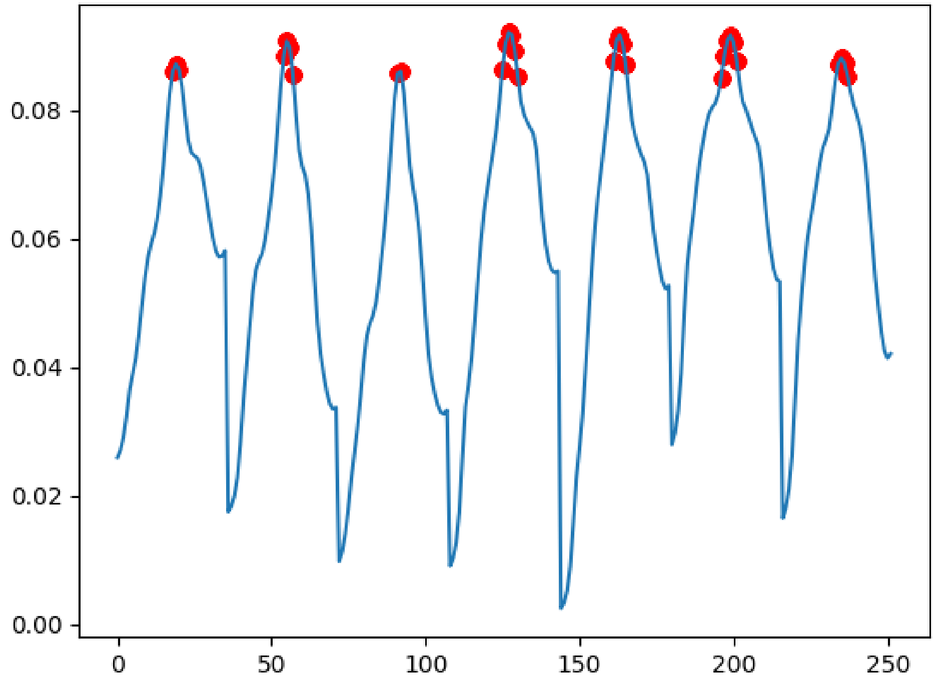


Figure. 7.3. Highlighting features of principle component with loadings greater than 0.085

7.3.3. Radial Basis Function (RBF):

The radial basis function (RBF) is commonly used as a kernel function in support vector machines (SVMs) for various machine learning tasks, particularly in classification and regression. The RBF kernel is defined as [39]:

$$K\ (x, x') = exp(-\ \frac{\|x-x'\|^2}{2\sigma^2}) \tag{7.6}$$

Here, x and x′are input vectors, $\|x - x'\|$is the Euclidean distance between them, and σ is a parameter that controls the width of the Gaussian kernel.

The RBF kernel allows the SVM to capture intricate dependencies and variations. Its flexibility and expressiveness enable the SVM to adapt to various data distributions without explicitly calculating the transformation to a higher-dimensional space. The RBF kernel's parameter (σ) allows fine-tuning of the decision boundary's smoothness, providing control over the model's behavior. Empirically successful in machine learning applications, especially when dealing with high-dimensional and complex data like EEG recordings, the RBF kernel serves as a suitable choice for exploring nuanced patterns in mental state detection [56].

7.3.4. SVM Linear Model :

A linear kernel Support Vector Machine (SVM) is a machine learning model utilized for classification and regression problems. The objective of the linear SVM algorithm is to identify an optimal hyperplane that effectively partitions the input data into distinct classes. The "support vectors" refer to the data points that are in closest proximity to the decision boundary. The optimal hyperplane is designed to optimize the distance between these support vectors, resulting in a wider margin.

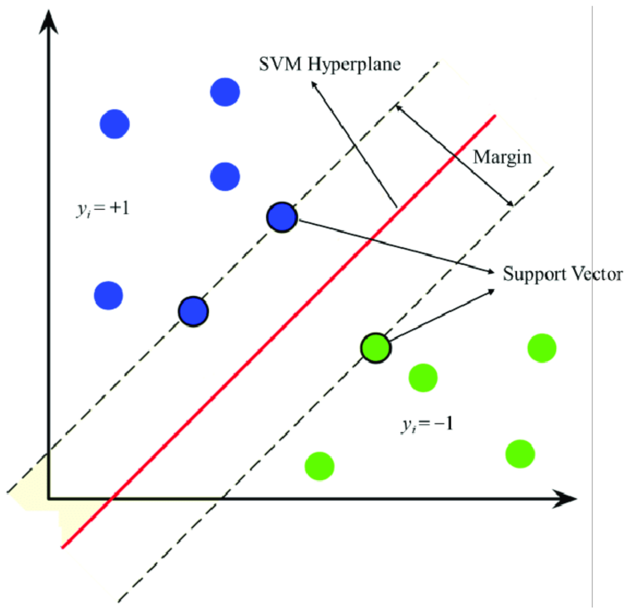


Figure. 7.4. linear SVM Classifier separating the two classes [56]

Concisely:

- SVM stands for Support Vector Machine.
- The linear kernel assumes a decision boundary that is linear.
- Categorization: The task involves the allocation of input data points to pre-established classifications.

- Optimal hyperplane: The decision boundary that optimizes the separation between classes by maximizing the margin.
- Support vectors are the data points that are located closest to the decision border.

The linear Support Vector Machine (SVM) is highly efficient when dealing with datasets that may be easily separated by a straight line, known as linearly separable datasets. Its widespread usage stems from its simplicity and effectiveness in solving binary classification problems.

5.3.5. KNN Model:

KNN, also known as k-Nearest Neighbors, is a straightforward and intuitive machine learning method utilized for problems including classification and regression. The K-nearest neighbors (KNN) algorithm classifies an object based on the majority vote of its k closest neighbors. The value of k is determined by the user [57]. The algorithm categorizes a data point by assigning it to the class that is most frequently represented among its k closest neighbors in the feature space. KNN is a non-parametric and lazy learning method, which implies that it does not make any assumptions about the distribution of the underlying data and does not construct a model during the training phase. Instead, it stores the training dataset in memory and generates predictions during runtime by evaluating the similarity between incoming data points and the old ones. KNN is very beneficial when working with datasets that are small to moderately sized and does not necessitate lengthy training time [58]. Nevertheless, the computational cost might be substantial when dealing with extensive datasets or feature spaces with a high number of dimensions.

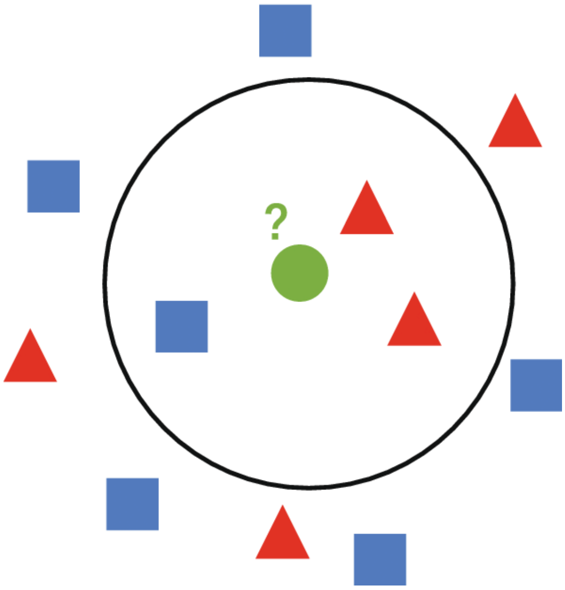


Figure. 7.5. k-Nearest Neighbors model

So, in our program K-Nearest Neighbors (KNN) classifier is implemented using the scikit-learn library. The model is trained and evaluated on both original scaled features and PCA-transformed features. So it's considering 3 nearest neighbors for making predictions. Initially, the KNN model is trained using the scaled training data, and its accuracy scores on both the training and test datasets are calculated. Then, the model is trained using the first 30 principal components of the training data, and again, its accuracy scores on the training and test datasets are computed. This approach allows for comparing the performance of the KNN model when using different feature representations.

7.3.6. Decision Tree Classifier Model:

A Decision Tree Classifier is a machine learning technique that uses a recursive process to divide the dataset into smaller groups depending on the most important feature at each step. The algorithm creates a hierarchical structure resembling a tree. Each internal node corresponds to a decision made using a certain feature. Each branch represents one of the possible outcomes of that decision. Finally, each leaf node represents the ultimate class label. Decision trees possess the quality of interpretability and are capable of handling both classification and regression tasks. These models have the ability to accurately represent intricate connections within the data, but there is a potential for overfitting, particularly when using deep trees. Pruning methods are frequently utilized to prevent overfitting.

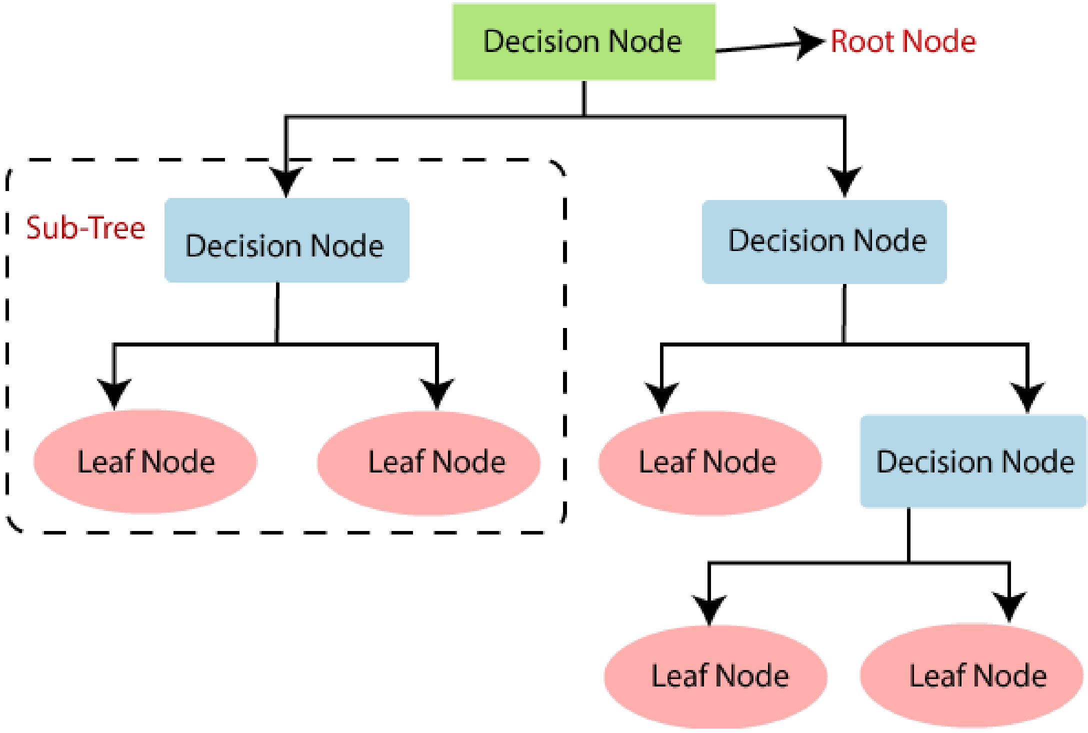


Figure. 7.6. Decision Tree Algorithm in Machine Learning

We used scikit-learn library, it imports tools from scikit-learn to create the model. Then creates an instance of the Decision Tree Classifier with a maximum depth of 16. This controls the complexity of the tree, preventing overly deep trees that might overfit the training data. The model is trained on scaled features and corresponding target labels. Finally, the model checks how well the model performs on both the training data it learned from and unseen test data to see if it can generalize effectively to new situations.

Table. 7.2. The accuracy outcomes of the attention state for various models

MODELS	**Training data score**	**Test data score**
SVM Linear Model	74.6%	73.3%
SVM RBF Model	94.6%	93.3%

SVM RBF Model PCA	91.7%	90.6%
KNN Model	99.8%	99.2%
KNN Model PCA	99.7%	98.7%
Decision Trees	97.8%	84.6%

In this study, we employed several machine learning models, including Support Vector Machines (SVMs) and Random Forests, to analyze the data. We evaluated their performance using established metrics like accuracy (1), precision (2), and recall (3). Accuracy measures the overall model correctness. Precision focuses on the proportion of true positives among the model's predictions. Recall emphasizes the ability to identify all actual positive cases. Furthermore, the F1 score (4) combines precision and recall to provide a comprehensive view.

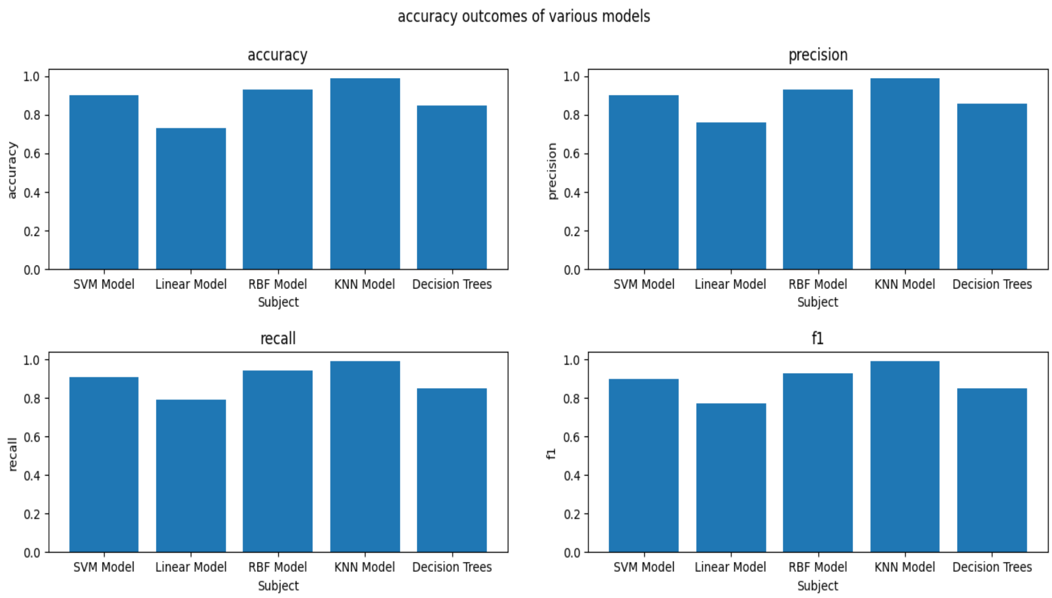


Figure. 7.7. Accuracy, precision, recall and F1 score outcomes of various Models

7.4. RANDOM FOREST CLASSIFIER:

The Random Forest Classifier is an ensemble learning technique that constructs numerous decision trees throughout the training process and produces the most often occurring class (for classification) or the average prediction (for regression) from the individual trees. Boosting is a technique that enhances the decision tree algorithm by aggregating the results of numerous weak learners (individual trees) to achieve more accurate and reliable predictions. It effectively addresses the issue of over-fitting and improves predictive accuracy.

It helps in selecting the optimal depth for the Random Forest Classifier by plotting the training and testing accuracy scores for different depth values. The plot assists in understanding how the model's performance changes with varying depths and guides the selection of an appropriate hyperparameter value for the Random Forest model.

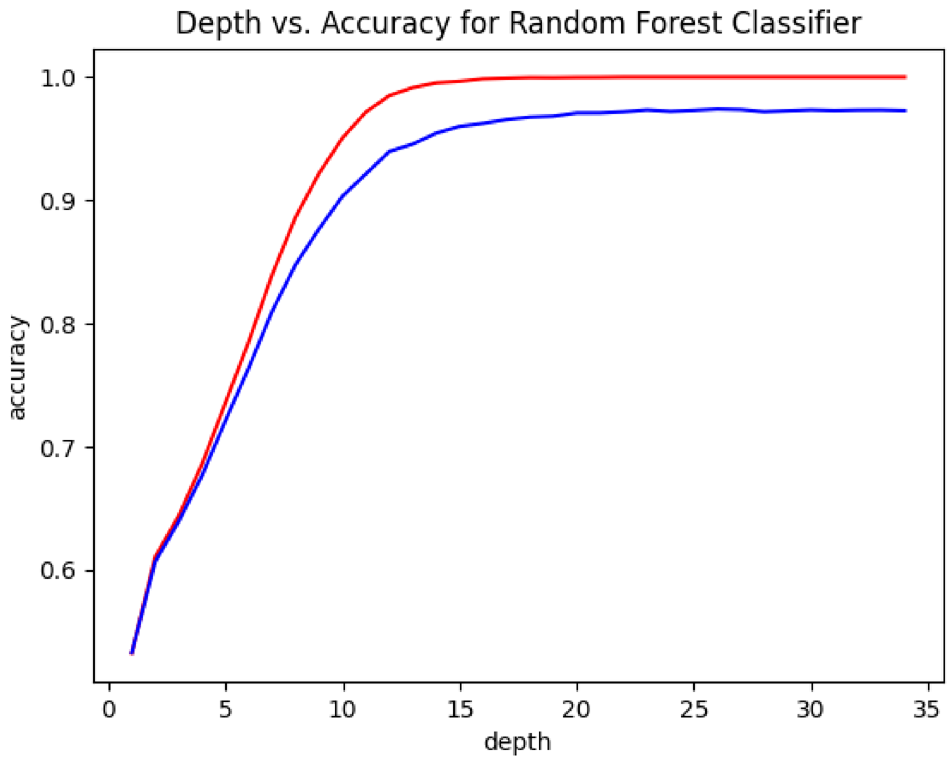


Figure. 7.8. Random Forest Classifier training and testing accuracy scores for different depths of trees

7.5. DISCUSSION

This study aimed to address the issue of identifying mental states in human participants by analyzing EEG data. Past research has examined the issue of distinguishing between drowsy and attentive states by analyzing EEG data, specifically in the context of car driving. In contrast to previous investigations, the current study focused on distinguishing between the cognitive states involved in passive observation or supervision tasks. The lack of active engagement in the work resulted in significant disparities in this context. There were also three other cognitive states identified: concentrated, drowsy, and unfocused or detached. The latter condition occurs when participants are not actively dozing but, as a result of a lack of attention, lose the ability to respond to events. Despite its significant potential for process control and its increased level of intrigue and difficulty in detection, the latter state has not been studied in previous research. This is because a "detached" mental state may not be evident through any overt signs or indicators, whether visual or otherwise. Within that framework, the latter is denoted as a distinct state, namely a pristine mental state. The techniques suggested in the research for differentiating this "unadulterated" mental state can be more widely utilized to differentiate subjective states in various tasks and circumstances, in addition to discerning between separate categories of states.

Prior research has mostly focused on the fatigue of car drivers, as well as the stress levels of those who work in mentally demanding occupations. In that case, in addition to EEG monitoring, other techniques such as video and movement monitoring were used. Despite their historical success, many of these strategies are difficult to adapt to different situations. Video- and movement-based alertness monitoring has a unique problem when individuals are inactive or passive. Passive BCI based on EEG is a viable solution to this problem because it provides a simple and transferable technology for monitoring people's state of mind. EEG signals provide a direct connection to brain neural activity and allow for direct monitoring of neural patterns associated with various mental states. This method avoids the limitations of existing methods for monitoring mental conditions that rely on physical, visual, or physiological cues.

We collected an original EEG dataset for this study to investigate the issue of detecting and monitoring mental states. The dataset focuses on the level of participation of participants during a passive observation job. To detect changes in attentional mental states, a method based on Support Vector Machines (SVM) was presented. The Support Vector Machine (SVM) detector was trained using EEG data samples collected from participants during specific mental states. The detection was carried out using a collection of machine learning Support Vector Machine (SVM) classifiers that were combined using an XOR aggregation of the results of numerous state-specific classifiers. The created detector proved to be both effective and beneficial in differentiating between focused, unfocused, and drowsy mental attention states using EEG data.

Table 7.3 chronologically summarizes previous research findings on identifying mental attention states. According to the data in Table 5.3, our study outperformed the majority of previous investigations. Examining the studies that produced similar results, it is clear that they either included additional data to corroborate the EEG signal or simply classified attention into two distinct stages.

Table 7.3 Comparing different studies that tried to predict people's attention states

Dataset	**Mental states predicted**	**Method**	**Accuracy (%)**	**Reference**
EEG	3 different attention levels	KNN	57.00	[59]
EEG	2 states (i.e. attentive or inattentive)	SVM	76.82	[60]
EEG and respiration data	6 levels (i.e. awake, slightly drowsy, moderately drowsy, extreme drowsy, sleep, deep sleep)	SVM	98.60	[61]
EEG	3 levels (i.e. attention, no attention and rest)	SVM	76.19 −85.24	[62]

EEG	2 states (i.e. driving or math task)	SVM	84.6 ± 5.8–86.2 ± 5.4	[63]
EEG	2 states (i.e. attentive or inattentive)	SVM	77.00–83.00	[64]
EEG	3 states (i.e. fatigue, frustration, attention)	SVM	71.6–84.8	[65]
EEG	2 states (i.e. attentive or inattentive)	SVM	92.80	[66]
EEG engagement index	2 states (i.e. attentive or inattentive)	SVM	93.33 ± 8.16	[67]
Only EEG	3 diff. attention levels	SVM	92.6(best) 91.3 (avg.)	[40]

Our research revealed that training the mental state detectors separately for each person is crucial. We noticed that a general mental state detector had notably inferior performance compared to the detectors tailored to specific individuals, resulting in a decrease of 20-30% in detection accuracy for the three indicated mental states.

7.6. CONCLUSIONS OF THE CHAPTER

The final chapter of this thesis provides a comprehensive exploration of the application of Support Vector Machine (SVM) models for mental state classification using EEG data. The chapter begins by elucidating the importance of data splitting and scaling in machine learning, emphasizing the mitigation of overfitting, evaluation of generalization, and optimization of hyperparameters. The subsequent sections detail the SVM model training process, showcasing the impressive accuracy achieved for subject-specific and common-subject paradigms. The inclusion of Principal

Component Analysis (PCA) further enhances the understanding of the feature space, allowing for a nuanced exploration of patterns in mental state detection. Additionally, the chapter introduces the Radial Basis Function (RBF) kernel, highlighting its adaptability to complex data distributions such as EEG recordings. The comparison of various models, including SVM linear and RBF models, KNN, Decision Trees, and Random Forest Classifier, presents a diverse array of approaches for mental state detection. The discussion section synthesizes the key findings, emphasizing the novel contribution of detecting a "detached" mental state and the importance of tailoring mental state detectors to individual subjects. The study's success in outperforming prior investigations is underscored, particularly in the context of training detectors separately for each person, which significantly enhances accuracy. Overall, this research provides valuable insights into the nuanced aspects of mental state classification, paving the way for broader applications in diverse tasks and situations.

CONCLUSION:

This study involved the creation of a passive EEG BCI (brain-computer interface) to observe and track specific mental states in humans. We acquired electroencephalogram (EEG) records from subjects engaged in a passive supervision task. We effectively accomplished accurate identification of three distinct cognitive attention states, namely focus, unfocus, and drowsiness, in individuals who were not actively involved in a task. The study reported discriminating accuracy for engaged, disengaged, and drowsing states. We ensure that our signals provide high-quality output after filtering by first dividing them into smaller segments for the Fourier transform, and then merging nearby frequency bins into wider frequency bands. This allows us to achieve best results. The training produced a best accuracy score of 92.6% while the testing achieved a best accuracy score of 92.2%. These findings have significant ramifications for driver security applications.

The work employed an SVM-based EEG BCI approach that enables the utilization of a pre-trained machine learning model. This model may be applied to many scenarios, such as identifying different mental states and diverse settings. Examining the specifications of developed mental state detectors can offer fresh perspectives on how such states are represented in EEG signals. Support Vector Machine (SVM) models for mental state classification utilizing EEG data are thoroughly examined. It emphasizes data splitting and scaling in machine learning to reduce overfitting, evaluate generalization, and optimize hyperparameters. The following sections describe SVM model training and demonstrate subject-specific and common-subject paradigm accuracy.

Principal Component Analysis (PCA) boosts feature space knowledge, enabling subtle mental state detection pattern investigation. The chapter also presents the Radial Basis Function (RBF) kernel, which works well with complicated data distributions like

EEG recordings. The comparison of SVM linear and RBF models, KNN, Decision Trees, and Random Forest Classifier shows a variety of mental state detection methods. The discussion section highlights the innovative contribution of identifying a "detached" mental state and the usefulness of subject-specific mental state detectors. The study outperformed previous studies, especially in training detectors for each person, which improves accuracy. This research illuminates mental state classification's nuances, enabling its use in a variety of tasks and settings.

FUTURE WORK

This study represents a significant leap forward in passive EEG BCI technology, demonstrating its potential to accurately track human mental states without requiring active engagement. By differentiating three distinct attention states with up to 92.6% accuracy, it paves the way for practical applications in driver safety, where early detection of drowsiness or disengagement could prevent accidents. Subsequently, I intend to develop a program capable of identifying states beyond three. Furthermore, this research will pave the way for others to investigate the mental states of animals. The study's use of pre-trained SVM models and subject-specific detectors further enhances its versatility and accuracy, highlighting the nuanced complexities of mental state classification in EEG signals. Overall, this research opens doors for utilizing passive EEG BCI in diverse settings, from healthcare to education, and offers valuable insights for future studies aimed at decoding the intricate language of the human brain and in future animal brain.

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RESUME

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