VIVEKANAND EDUCATION SOCIETY'S INSTITUTE OF TECHNOLOGY

An Autonomous Institute Affiliated to University of Mumbai

Department of Computer Engineering

Project Report on

Cognitive Assessment using EEG Data: Developing a Brain-Computer Interface for Cognitive Function Evaluation

In partial fulfillment of the Fourth Year, Bachelor of Engineering (B.E.) Degree in Computer Engineering at the University of Mumbai

Academic Year 2023-24

Submitted by

Siddhant Kodolkar (D17 - C, Roll no - 28)

Sachin Choudhary (D17 - C, Roll no - 15)

Harsh Karira (D17 - C, Roll no - 24)

Sahil Madhyan (D17 - C, Roll no - 33)

Project Mentor

Prof. Indu Dokare

(2023-24)

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Certificate

This is to certify that **Sachin Choudhary(D17C, 15), Harsh Karira(D17C, 24), Siddhant Kodolkar(D17C, 28), Sahil Madhyan(D17C, 33)** of Fourth Year Computer Engineering studying under the University of Mumbai have satisfactorily completed the project on "**Cognitive Assessment Using EEG Data: Developing a Brain-Computer Interface for Evaluating Cognitive Function**" as a part of their coursework of PROJECT-II for Semester-VIII under the guidance of their mentor **Prof. Indu Dokare** in the year 2023-24.

This project report entitled **Cognitive Assessment Using EEG Data: Developing a Brain-Computer Interface for Evaluating Cognitive Function** by **Sachin Choudhary, Harsh Karira, Siddhant Kodolkar, Sahil Madhyan** is approved for the degree of **B.E. Computer Engineering.**

Programme Outcomes	Grade
PO1, PO2, PO3, PO4, PO5, PO6, PO7, PO8, PO9, PO10, PO11, PO12, PSO1, PSO2	

Date: 12/04/2024

Project Guide:

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Project Report Approval
For
B. E (Computer Engineering)

This thesis/dissertation/project report entitled **Cognitive Assessment Using EEG Data: Developing a Brain-Computer Interface for Evaluating Cognitive Function** by **Sachin Choudhary, Harsh Karira, Siddhant Kodolkar, Sahil Madhyan** is approved for the degree of **B.E. Computer Engineering.**

Internal Examiner

External Examiner

Head of the Department

Principal

Date: 12/04/2024

Place: Mumbai

Declaration

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Sachin Choudhary (15)	Harsh Karira (24)
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Siddhant Kodolkar (28)	Sahil Madhyan (33)

Date: 12/04/2024

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We wish to express our profound thanks to all those who helped us in gathering information about the project. Our families too have provided moral support and encouragement several times.

Computer Engineering Department

COURSE OUTCOMES FOR B.E PROJECT

Learners will be to,

Course Outcome	Description of the Course Outcome
CO 1	Able to apply the relevant engineering concepts, knowledge and skills towards the project.
CO2	Able to identify, formulate and interpret the various relevant research papers and to determine the problem.
CO 3	Able to apply the engineering concepts towards designing solutions for the problem.
CO 4	Able to interpret the data and datasets to be utilised.
CO 5	Able to create, select and apply appropriate technologies, techniques, resources and tools for the project.
CO 6	Able to apply ethical, professional policies and principles towards societal, environmental, safety and cultural benefit.
CO 7	Able to function effectively as an individual, and as a member of a team, allocating roles with clear lines of responsibility and accountability.
CO 8	Able to write effective reports, design documents and make effective presentations.
CO 9	Able to apply engineering and management principles to the project as a team member.
CO 10	Able to apply the project domain knowledge to sharpen one's competency.
CO 11	Able to develop a professional, presentational, balanced and structured approach towards project development.
CO 12	Able to adopt skills, languages, environment and platforms for creating innovative solutions for the project.

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Abstract

Electroencephalography (EEG) is a non-invasive technique for monitoring brain activity in real time, offering insights into cognitive processes such as attention, memory, and problem-solving. Despite its potential, EEG-based cognitive assessment faces challenges in terms of accuracy, real-time processing, and user accessibility. This paper presents a comprehensive methodology for developing a brain-computer interface (BCI) for cognitive function evaluation using EEG data, addressing these challenges and advancing the state-of-the-art in cognitive assessment.

In this study, we propose novel attention indexes based on the power spectral density ratios of theta, alpha, and beta frequency bands extracted from EEG signals. These attention indexes serve as informative features for our BCI model, enabling us to capture and quantify attention spans in real time with improved accuracy and efficiency compared to traditional methods.

Furthermore, we evaluate the efficacy of four machine learning algorithms—Random Forest, Gradient Boosting, K-Nearest Neighbors (KNN), and Decision Tree—in predicting attention spans from EEG features. The accuracy results reported in Table 6.2.1 demonstrate the superior performance of Random Forest, achieving an accuracy of 0.97159, highlighting the effectiveness of our proposed methodology.

Additionally, we have developed a user-friendly website interface where patients' EEG data results are uploaded, processed, and visualised in real time. The system extracts PSD values from the uploaded data, utilises our trained machine learning model to calculate cognitive function evaluation results, and provides personalised recommendations to users. This real-time interaction and visualisation of results enhance user experience and facilitate quick access to valuable insights, contributing to improved cognitive assessment and intervention strategies.

The novelty of our approach lies in the integration of advanced EEG analysis techniques with machine learning methodologies, resulting in a robust BCI system with practical applications in education, healthcare, and human-computer interaction. The impact of this research extends to personalised interventions, early detection of cognitive disorders, and advancements in neurotechnology, paving the way for future research in cognitive neuroscience and EEG-based investigations. Future directions include exploring additional EEG features, integrating multimodal data sources, and expanding the application of our BCI model to diverse user populations and scenarios.

By combining technical innovation with user-centric design principles, this research sets a new standard for EEG-based cognitive assessment, offering a pathway to personalised interventions and enhanced cognitive performance across various domains.

Chapter 1: Introduction

1.1 Introduction

The human brain, often regarded as the most complex organ in the known universe, continues to captivate researchers and scholars alike with its intricate workings and remarkable capabilities. At the forefront of neuroscience, the study of brain function has evolved significantly, propelled by technological advancements that enable us to delve into the realm of brain activity with unprecedented detail and precision [1]. Among these techniques, electroencephalography (EEG) stands out as a cornerstone of non-invasive brain monitoring, offering insights into the dynamic interplay of neural networks that underlie cognitive processes [2].

Cognitive function, the cornerstone of human cognition, encompasses a vast array of mental faculties, including perception, attention, memory, language, and executive functions like problem-solving and decision-making. Understanding these cognitive processes and their neural substrates is not only a scientific pursuit but also holds profound implications for fields ranging from education and healthcare to artificial intelligence and human-computer interaction [3].

The genesis of this research endeavour lies in the intersection of two dynamic domains: EEG analysis and cognitive function assessment. EEG, by measuring the electrical activity generated by neuronal firing in the brain, provides a window into cognitive processes in real-time [4]. This research seeks to bridge the gap between EEG data and cognitive insights, leveraging advanced analytical techniques to extract meaningful information from the complex neural signals captured by EEG [5].

The overarching goal of this project is multifaceted. Firstly, we aim to evaluate the efficacy of state-of-the-art software tools in processing and interpreting EEG signals [6]. These tools, equipped with machine learning algorithms and signal processing techniques, hold the promise of unlocking hidden patterns and associations within EEG data, leading to a deeper understanding of cognitive function.

Secondly, our exploration extends beyond mere data analysis to consider the practical implications of EEG-based cognitive assessment. We delve into the potential applications of EEG in educational settings, where personalised learning strategies informed by real-time brain activity could revolutionise pedagogy [7]. Similarly, in clinical contexts, EEG-based biomarkers hold promise for early detection and intervention in cognitive disorders and neurological conditions.

Drawing inspiration from seminal works in EEG research, such as the foundational studies by Hans Berger and the contemporary advancements in neuroimaging techniques, we embark on a journey to unravel the mysteries of brain activity and cognition [8]. From the pioneering discoveries of brain wave patterns to the intricate dynamics of neural networks underlying higher cognitive functions, our exploration traverses the spectrum of neuroscience.

Furthermore, this research endeavour is not confined to academic curiosity; it has tangible implications for societal well-being. By elucidating the intricate relationship between EEG data and cognitive function, we aim to contribute to the development of innovative technologies and interventions that enhance human cognition, promote brain health, and empower individuals to unlock their full cognitive potential [9].

In summary, this introduction lays the foundation for a comprehensive exploration of EEG analysis for cognitive function assessment. By synthesising knowledge from neuroscience, data science, and cognitive psychology, we aspire to unravel the complexities of the human mind and pave the way for transformative advancements in brain research and cognitive enhancement.

1.2 Motivation

The motivation behind this project is rooted in the critical importance of understanding and assessing cognitive abilities in individuals. Cognitive abilities are fundamental to our daily lives, influencing our capacity to learn, remember, pay attention, and process information efficiently. Detecting cognitive deficits early on is crucial, as these deficits can significantly impact an individual's quality of life, their ability to perform daily tasks, and their overall well-being.

1.3 Problem Definition

In this research endeavour, we explore the methodologies and procedures employed for the analysis of EEG data and their associations with cognitive function. Our primary objective is to evaluate the efficacy of software tools in processing and interpreting EEG signals, thereby enabling the extraction of meaningful information related to cognitive processes. Moreover, our investigation extends to considering the potential ramifications, both in clinical and practical terms, of integrating EEG-based cognitive assessment into educational and cognitive rehabilitation settings.

1.4 Existing Systems

The existing system for assessing cognitive abilities primarily relies on traditional cognitive testing methods, which often involve paper-and-pencil tests or computerised assessments. These methods, while valuable, have certain limitations, including subjectivity in scoring and a potential lack of sensitivity to subtle cognitive deficits. They may also be time-consuming and require specialised training to administer accurately. Moreover, in educational and cognitive rehabilitation settings, the existing systems typically lack real-time feedback and personalised recommendations for improving cognitive functions. As a result, there is a growing need for more objective, efficient, and technology-driven approaches to cognitive assessment and enhancement, which the proposed software application aims to address by leveraging EEG data and advanced machine learning techniques.

1.5 Lacuna of the existing systems

Traditional cognitive tests are frequently criticised for being time-consuming, both in administration and scoring, which limits their usefulness, particularly in contexts that require quick assessments. Furthermore, these traditional methods usually fail to provide full statistics and understandable representations of Electroencephalogram (EEG) data, resulting in inaccurate inference and diagnostic delays. This shortcoming prevents healthcare workers and researchers from correctly reading EEG signals and using them for timely and accurate cognitive tests. As a result, there is an urgent need for the development of streamlined assessment methods that not only save time but also provide robust statistical analyses and intuitive visual representations of EEG data, allowing for timely and informed decision-making in clinical and research settings.

1.6 Relevance of the Project

This project is highly relevant due to its potential to advance cognitive assessment methods significantly. By exploring the use of EEG data for cognitive evaluation, it addresses the need for more accurate and objective assessments of cognitive abilities. This relevance extends to early detection of cognitive deficits, which is critical for timely intervention and support. Additionally, the project has implications for education, offering insights into tailored teaching methods, and for cognitive rehabilitation, potentially providing more precise tracking of progress. It also holds promise in clinical settings for better diagnosis and treatment planning. Finally, the project contributes to scientific advancement by deepening our understanding of EEG data's relationship with cognitive function, fostering future research and innovation in this area.

Chapter 2: Literature Survey

A. Brief Overview of Literature Survey

The literature survey encompasses a range of studies exploring the applications and implications of EEG technology in various domains of neuroscience and cognitive research. Aldayel's work focuses on leveraging EEG data to predict students' attention levels in online learning, contributing to personalised and sustainable educational practices. K. van der Hiele et al.'s study delves into EEG correlates in cognitive decline, offering valuable insights into biomarkers for early detection and personalised management of neurodegenerative disorders. Richard W. Homan's paper sheds light on the importance of the 10-20 electrode system in EEG methodology, enhancing brain activity localization for diagnostic and research purposes. Klimesch's review discusses EEG oscillations' significance in cognitive states and memory processes, providing biomarkers for assessing cognitive function and potential clinical applications. Priyanka A. Abhang et al.'s chapter outlines EEG recording basics, aiding researchers and practitioners in utilising EEG technology effectively for emotion recognition and cognitive research. Jaime et al.'s case study utilises EEG signals to measure attention in individuals with Autism Spectrum Disorder (ASD), contributing to targeted interventions and support strategies. Vilou et al.'s research explores EEG-neurofeedback as a therapeutic approach for cognitive deficits in various neurological disorders, emphasising potential benefits for cognitive rehabilitation and quality of life improvement. Finally, Ismail and Karwowski's systematic review reviews EEG indices' applications in quantifying human cognitive performance, highlighting diverse methodologies and trends in EEG-based cognitive assessment for future research and advancements.

2.1 Research Papers Referred

1. **Aldayel, M. (2021). Predict Students' Attention in Online Learning Using EEG Data. Sustainability, 14(11), 6553. https://doi.org/10.3390/su14116553**

   a. Abstract of the research paper: The paper by Aldayel (2021) delves into the utilisation of Electroencephalography (EEG) data for predicting students' attention levels in online learning settings. With the increasing prevalence of online education, understanding and enhancing students' attention is crucial for effective learning outcomes. The study adopts EEG technology to capture brainwave patterns, which are then analysed using machine learning algorithms to predict attention states. Through a series of experiments and data analysis, the research demonstrates the feasibility and effectiveness of EEG-based attention prediction in online learning environments. The findings highlight the potential of integrating EEG technology into educational practices to optimise attention and engagement, contributing to sustainable and efficient online learning experiences.

b. **Inference drawn:** The study by Aldayel (2021) presents a significant advancement in educational technology by utilising EEG data to predict students' attention levels in online learning environments. By integrating EEG technology with machine learning algorithms, the research demonstrates the feasibility of real-time attention monitoring, paving the way for personalised learning experiences. The inference extends to the potential impact on instructional design, where adaptive content delivery based on students' attention states can lead to improved learning outcomes. This innovative approach aligns with sustainable educational practices by optimising resource utilisation and enhancing overall engagement in online learning settings.

2. **K. van der Hiele, A.A. Vein, R.H.A.M. Reijntjes, R.G.J. Westendorp, E.L.E.M. Bollen, M.A. van Buchem, J.G. van Dijk, H.A.M. Middelkoop, EEG correlates in the spectrum of cognitive decline, Clinical Neurophysiology, Volume 118, Issue 9,2007, Pages 1931-1939, ISSN 1388-2457**

   a. **Abstract of the research paper:** K. van der Hiele et al. (2007) conducted a comprehensive study aiming to uncover Electroencephalography (EEG) correlates across the spectrum of cognitive decline, encompassing normal ageing, mild cognitive impairment (MCI), and Alzheimer's disease (AD). The research involved a thorough analysis of EEG data from individuals representing different cognitive states, utilising advanced signal processing techniques and statistical analyses. By comparing EEG patterns across these groups, the study sought to identify distinctive neural signatures associated with cognitive impairment and disease progression. The findings revealed distinct EEG features characteristic of each cognitive state, highlighting differences in brain activity and connectivity patterns. Specifically, individuals with MCI exhibited subtle alterations in EEG rhythms compared to healthy ageing individuals, while those with AD showed further disruptions in neural oscillations and connectivity. These EEG correlates provided valuable insights into the underlying neurophysiological mechanisms of cognitive decline, offering potential biomarkers for early detection and monitoring of neurodegenerative disorders. Furthermore, the study explored the prognostic value of EEG markers in predicting cognitive decline progression and disease outcomes. The integration of EEG data with clinical assessments enhanced diagnostic accuracy and prognostic capabilities, enabling more targeted interventions and personalised treatment strategies for individuals at different stages of cognitive impairment. Overall, the research contributes significantly to advancing our understanding of EEG correlates in cognitive decline and informs the development of innovative approaches for neurodegenerative disease management.

b. **Inference drawn:** The research by K. van der Hiele et al. (2007) represents a significant advancement in understanding EEG correlates in the spectrum of cognitive decline. The study's detailed analysis of EEG data across various cognitive states, including normal ageing, mild cognitive impairment, and Alzheimer's disease, contributes significantly to the field of neurodegenerative research. By identifying distinct EEG patterns associated with different stages of cognitive impairment, the study not only enhances diagnostic accuracy but also provides valuable insights into the underlying neurobiology of cognitive decline. These findings have profound implications for early detection, prognosis, and personalised management strategies for individuals at risk of neurodegenerative disorders, ultimately leading to improved patient outcomes and quality of life.

3. **Richard W. Homan (1988) The 10-20 Electrode System and Cerebral Location, American Journal of EEG Technology, 28:4, 269-279, DOI: 10.1080/00029238.1988.11080272.**

   a. **Abstract of the research paper:** In his paper "The 10-20 Electrode System and Cerebral Location" (1988), Richard W. Homan provides an in-depth analysis of the 10-20 electrode system commonly used in electroencephalography (EEG) and its significance in determining cerebral location. The 10-20 system is a standardised method for electrode placement on the scalp, with electrodes spaced at specific intervals based on percentages of the head circumference and distance between anatomical landmarks. Homan discusses the rationale behind this electrode system and how it allows for consistent and accurate recording of electrical activity from different regions of the brain. The paper explores the relationship between electrode positions on the scalp and their corresponding cortical areas within the brain. Homan elucidates how the 10-20 system facilitates the localization of brain activity by ensuring that electrodes are placed over specific brain regions known for their functional significance. This understanding is crucial for interpreting EEG signals and mapping brain activity in clinical contexts, such as diagnosing neurological disorders or monitoring brain function during various tasks or states. Additionally, Homan discusses variations and modifications of the 10-20 system, including extensions to cover more electrode positions for enhanced spatial resolution. These advancements contribute to improving the accuracy and reliability of EEG-based assessments of cerebral function, making the 10-20 system a fundamental tool in neuroscience research and clinical neurophysiology.

b. **Inference drawn:** Richard W. Homan's paper on the 10-20 electrode system and cerebral location underscores its critical role in EEG methodology for accurate brain activity localization. This knowledge is vital for diagnosing neurological disorders and advancing neuroscientific research. The 10-20 system's variations and extensions further enhance spatial resolution, benefiting neuroimaging studies and cognitive neuroscience.

4. **Klimesch W. EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. Brain Res Brain Res Rev. 1999 Apr;29(2-3):169-95. doi: 10.1016/s0165-0173(98)00056-3. PMID: 10209231.**

   a. **Abstract of the research paper:** In the paper, the author conducts an extensive review and analysis of research related to EEG alpha and theta oscillations in the context of cognitive and memory performance. The study explores how these brainwave patterns, specifically alpha (8-13 Hz) and theta (4-7 Hz) oscillations, are associated with different cognitive processes and memory functions. Klimesch discusses the role of alpha oscillations in attentional processes, with higher alpha power indicating a more relaxed or inactive state, while lower alpha power is linked to focused attention. Additionally, the paper delves into the relationship between theta oscillations and memory functions, highlighting that increased theta power is often observed during memory encoding and retrieval tasks. The review and analysis synthesise findings from various studies to elucidate how alpha and theta oscillations serve as neural markers for cognitive states and memory performance. The paper also discusses methodological considerations and future research directions to further understand the complex interplay between EEG oscillations and cognitive processes.

   b. **Inference drawn:** Klimesch's analysis of EEG alpha and theta oscillations reveals their importance in cognitive states and memory processes. Alpha power decreases during focused attention, while theta power increases during memory tasks. These patterns serve as valuable biomarkers for assessing attention, memory, and cognitive function, with potential applications in clinical diagnosis and interventions. Further research into alpha-theta dynamics promises deeper insights into brain-behaviour relationships and cognitive enhancement strategies.

5. **Priyanka A. Abhang, Bharti W. Gawali, Suresh C. Mehrotra, Chapter 2 - Technological Basics of EEG Recording and Operation of Apparatus, Editor(s): Priyanka A. Abhang, Bharti W. Gawali, Suresh C. Mehrotra, Introduction to EEG- and Speech-Based Emotion Recognition, Academic Press, 2016, Pages 19-50, ISBN 9780128044902, https://doi.org/10.1016/B978-0-12-804490-2.00002-6.**

    a. **Abstract of the research paper:** In Chapter 2 of "Introduction to EEG- and Speech-Based Emotion Recognition" by Priyanka A. Abhang, Bharti W. Gawali, and Suresh C. Mehrotra (2016), the authors provide a comprehensive overview of the technological basics of EEG recording and the operation of EEG apparatus. The chapter covers essential concepts such as electrode placement, signal acquisition, amplification, filtering, and artefact removal techniques in EEG recording. It also discusses different types of EEG systems, including portable and wireless devices, and their applications in neuroscience research, clinical diagnostics, and cognitive studies. The chapter aims to familiarise readers with the technical aspects of EEG recording, enabling a better understanding of EEG-based emotion recognition and related research domains.

    b. **Inference drawn:** The chapter on EEG recording basics is a foundational resource for researchers and practitioners, emphasising electrode placement precision, signal quality, and artefact reduction methods. It discusses different EEG system types and their applications, bridging technical knowledge with practical use in emotion recognition and cognitive research. This chapter serves as a crucial guide for understanding and utilising EEG technology effectively in diverse scientific and clinical contexts.

6. **Jaime, J., Roberto, O., Efrén, E., & Manuel, G. (2022). Attention Measurement of an Autism Spectrum Disorder User Using EEG Signals: A Case Study. Mathematical and Computational Applications, 27(2), 21. https://doi.org/10.3390/mca27020021**

    a. **Abstract of the research paper:** Autism Spectrum Disorder (ASD) is a neurological condition characterised by challenges in social interaction, communication skills (both verbal and non-verbal), and repetitive behaviours. Individuals with ASD often experience varying levels of attention due to heightened sensitivity and difficulty processing extensive environmental stimuli. Attention is a cognitive process enabling us to focus on relevant stimuli while disregarding irrelevant ones, guiding appropriate actions. This paper introduces a methodology employing electroencephalographic (EEG) signals to measure attention in a 13-year-old boy diagnosed with ASD. EEG signals are captured using an Epoc+

Brain–Computer Interface (BCI) through the Emotiv Pro platform during various learning tasks, with signal processing conducted using Matlab 2019a. Specifically, electrodes F3, F4, P7, and P8 are utilised, and features such as Theta Relative Power (TRP), Alpha Relative Power (ARP), Beta Relative Power (BRP), Theta–Beta Ratio (TBR), Theta–Alpha Ratio (TAR), and Theta/(Alpha+Beta) are calculated to assess attention and neurofeedback. Multiple machine learning (ML) models are trained and evaluated using these features, with the multi-layer perceptron neural network model (MLP-NN) demonstrating superior performance metrics, including an AUC of 0.9299, Cohen's Kappa coefficient of 0.8597, Matthews correlation coefficient of 0.8602, and Hamming loss of 0.0701. These results facilitate the development of tailored learning environments for individuals with ASD, providing quantifiable progress data to guide educators and therapists in reinforcing positive outcomes.

b. **Inference drawn:** The case study by Jaime et al. (2022) showcases the application of EEG signals in measuring attention in individuals with Autism Spectrum Disorder (ASD). The research contributes to understanding attentional patterns and fluctuations in ASD users, highlighting the potential of EEG technology for objective assessment and monitoring of attention-related challenges in this population. Such insights are valuable for developing targeted interventions and support strategies tailored to the attentional needs of individuals with ASD, ultimately improving their quality of life and cognitive functioning.

7. **I. Vilou, A. Varka, D. Parisis, T. Afrantou, and P. Ioannidis, "EEG-Neurofeedback as a Potential Therapeutic Approach for Cognitive Deficits in Patients with Dementia, Multiple Sclerosis, Stroke and Traumatic Brain Injury," Life, vol. 13, no. 2, p. 365, Jan. 2023**

   a. **Abstract of the research paper:** Memory deficits are common in patients with dementia such as Alzheimer's disease, as well as in patients with other neurological and psychiatric diseases such as cerebral palsy, multiple sclerosis, ischemic stroke, and schizophrenia. Memory loss affects patients' ability to function and thus their quality of life. Non-invasive brain training techniques, such as EEG neurofeedback, are used to correct cognitive deficits and behavioural changes in dementia and other neurological diseases by training patients to change their brain activity through operant activity. In this review, we analyse different EEG neurofeedback protocols for memory recovery in patients with dementia, multiple sclerosis, stroke and traumatic brain injury. Research results show the effectiveness of the EEG-NFB method in improving at least one cognitive area, regardless of the number of sessions or the type of protocol used. In future research, it is important to address the methodological weaknesses of the implementation of the method, its long-term effects, and ethical issues.

b. **Inference drawn:** The research by Vilou et al. (2023) examines the use of EEG-neurofeedback as a promising therapeutic strategy for managing cognitive deficits in individuals with various neurological disorders, including dementia, multiple sclerosis, stroke, and traumatic brain injury. This approach holds the potential for enhancing cognitive function and quality of life in affected patients, offering a novel avenue for addressing cognitive impairments beyond traditional treatments. Further studies and clinical trials are warranted to validate the effectiveness and long-term benefits of EEG-neurofeedback in cognitive rehabilitation for these patient populations.

8. **Ismail, L.E.; Karwowski, W. Applications of EEG indices for the quantification of human cognitive performance: A systematic review and bibliometric analysis. PLoS ONE 2020, 15, e0242857.**

    a. **Abstract of the research paper:** In their paper, Ismail and Karwowski (2020) conduct a thorough systematic review and bibliometric analysis to investigate the diverse applications of EEG indices in quantifying human cognitive performance. The study explores the extensive body of literature encompassing EEG-based metrics utilised across various cognitive domains, including attention, memory, executive functions, and emotional processing. The review delves into the methodological approaches, experimental paradigms, and technological advancements employed in EEG-based cognitive assessment. Furthermore, the paper synthesises the findings from numerous studies to elucidate the efficacy, reliability, and validity of EEG indices in measuring cognitive functions. It discusses the utility of EEG metrics such as event-related potentials (ERPs), spectral power analysis, connectivity measures, and neurofeedback techniques in capturing subtle changes in cognitive performance. The systematic review also identifies emerging trends, gaps, and future directions in EEG-based cognitive assessment, highlighting the potential for integrating EEG indices into clinical practice, cognitive rehabilitation programs, and neuroscientific research. The comprehensive analysis provides a nuanced understanding of the strengths and limitations of EEG-based cognitive quantification methods, paving the way for advancements in cognitive neuroscience, neuropsychology, and brain-computer interface technology.

b. **Inference drawn:** The research by Ismail and Karwowski (2020) offers a comprehensive overview of EEG indices' utilisation for evaluating human cognitive performance. Through a systematic review and bibliometric analysis, the paper synthesises existing literature, highlighting the diverse applications of EEG-based metrics in assessing cognitive functions across different domains. This review provides valuable insights into the state-of-the-art methodologies and trends in EEG-based cognitive assessment, paving the way for future research directions and advancements in cognitive neuroscience and neuropsychology.

2.2 Patent Search

1. **Determining cognitive load of a subject from electroencephalography (EEG) signals (EP3011895A1)**

   Inventor: SINHARAY ARIJIT [IN]

   A technique and system for evaluating a subject's cognitive load based on electroencephalography (EEG) data are disclosed. EEG signals are received from channels linked with the left frontal lobe. EEG signals are related with a person executing a cognitive task. A low-resolution EEG gadget transmits EEG signals. There are four EEG channels connected with the left frontal lobe. To generate preprocessed EEG signals, a Hilbert-Huang Transform (HHT) filter is used to reduce noise associated with one or more non-cerebral artifacts. The preprocessed EEG signals are used to extract features such as alpha and theta band power using the Fast Fourier Transform (FFT). The feature vector is created from the features. To ascertain the subject's cognitive load, a Support Vector Machine (SVM) classifier is used to classify the feature vector.

2. **METHOD AND SYSTEM FOR MEASURING EEG SIGNALS (WO2020255142A3)**

   Inventor: DEUTSCH ISRAEL [IL]

   A system for monitoring EEG signals includes a wearable body designed to fit over a head, a number of electrodes mounted on the wearable body, and, optionally, a number of controlled actuators for applying force to the electrodes. A controller can optionally direct each actuator or set of actuators to exert force on at least one electrode. A signal processor receives and processes signals from the electrodes, then optionally delivers control signals to the controller.

3. **EEG ANALYSIS SYSTEM (EP2029009A1)**

   Inventor: LILEY DAVID TIBOR JULIAN [AU]

An electroencephalogram signal is used to analyze brain activity. The process involves the following steps: i) creating coefficient data for a signal representation of a portion of the signal; ii) creating first gain data, which represents the average amplitude of an output signal generated based on the signal representation and the coefficient data; iii) creating second gain data, which represents the average amplitude of said portion; and iv) creating brain state data, which represents subcortical activity of said brain, based on said first gain data and said second gain data.

2.3 Inference drawn

The combination of numerous studies in EEG technology and cognitive assessment demonstrates substantial progress in understanding cognitive processes and neurological illnesses. Researchers have made significant advances in predicting attention levels, diagnosing cognitive decline, and evaluating cognitive performance across varied populations by utilising EEG data. These findings highlight the potential of EEG technology to revolutionise tailored learning experiences, early identification of neurodegenerative illnesses, and focused therapies for cognitive deficiencies.

Moving forward, improving BCI systems for assessing cognitive capacities necessitates a multifaceted approach. Firstly, integrating modern machine learning algorithms with EEG data can increase the accuracy and reliability of cognitive tests. By training models on vast, diversified datasets that include a variety of cognitive tasks and demographics, BCI systems can better capture the subtle patterns of brain activity associated with distinct cognitive functions. This method not only allows for tailored cognitive training but also increases engagement and motivation, maximising the effectiveness of therapies.

Furthermore, by combining EEG with other brain imaging techniques, researchers can acquire a better understanding of how different brain regions interact during cognitive activities. Working across fields and embracing these breakthroughs will allow BCI systems to grow even better at assessing and developing cognitive capacities, potentially benefiting persons with cognitive problems and improving overall human performance in many aspects of life.

2.4 Comparison with the existing system

Table: 2.3.1 Comparison of Existing Systems

Aspect	Existing System	Proposed Solution
Sensitivity to Deficits	May lack sensitivity to subtle cognitive deficits	Aims for improved sensitivity to deficits

Real-time Feedback	Typically lacks real-time feedback	Aims to provide real-time feedback
Personalised Recommendations	Typically lacks personalised recommendations	Aims to provide personalised recommendations
Methodological Focus	Traditional cognitive testing	EEG signal processing and machine learning

Chapter 3: Requirement Gathering for the Proposed System

3.1 Introduction to Requirement Gathering

Requirement Gathering is the process of discovering requirements, generating a list of requirements, or collecting as many requirements as possible by end users. It is also called as requirements elicitation or requirement capture.

USE CASE	DESCRIPTION
PDF Upload	Enables users to upload EEG reports in PDF format for analysis and processing of the PSD values.
PDF Preview	Allows users to preview uploaded EEG reports to verify data accuracy and completeness before analysis.
Result Generation	Processes EEG data to generate insightful visualisation of the report, displayed in a dedicated result tab.
Decision Support	Provides neurologists with decision-making assistance based on analysed EEG data for clinical assessments and treatment planning.

Table No: 3.1 Requirements of the system

3.2 Functional Requirements

1. Data Acquisition:

a. The system shall be able to collect EEG data from a non-invasive EEG cap.

b. It should support the placement and configuration of electrodes on the cap.

c. The system must provide real-time data visualisation for signal quality checks during data collection.

d. It should allow users to start and stop data acquisition sessions.

2. Preprocessing:

a. The system should perform noise and artefact removal on collected EEG data.

b. It must segment the data into manageable time intervals.

c. Provide the option to visualise preprocessed data for quality control.

3. Feature Extraction:

a. The system shall extract relevant features from EEG data, including spectral power, coherence, and ERPs.

b. It must offer dimensionality reduction techniques to improve computational efficiency.

4. Machine Learning Model Training:

a. The system should allow users to label EEG data segments with corresponding commands or states.

b. It must offer a variety of machine learning algorithms for model training.

c. Provide options for model validation and hyperparameter tuning.

5. BCI Model Development:

a. The system must integrate the trained machine learning model for real-time processing.

b. It should allow the mapping of EEG feature classifications to control signals.

c. Support model calibration for individual users.

6. Evaluation:

a. The system should calculate and display performance metrics, including classification accuracy, false positives, and false negatives.

b. It must support user feedback collection to assess usability and effectiveness.

7. User Interface Design:

a. The user interface shall provide intuitive controls for users to interact with the BCI system.

b. It must be accessible to users with different abilities, including those with motor or communication impairments.

c. Support customization and personalization of the interface to meet individual user needs.

8. Report Generation:

a. The system must generate a technical report summarising the development and evaluation of the BCI system.

b. Provide options for report customization, such as the inclusion of specific sections and recommendations.

3.3 Non-Functional Requirements

1. **Data Acquisition:-**
   a. Reliability of Data Collection: The EEG cap demonstrates high reliability to minimise data loss during collection.
   b. Data Resolution: The system facilitates high-resolution EEG data acquisition for enhanced signal processing accuracy.
2. **Preprocessing:**
   a. Processing Speed: Efficient noise and artefact removal ensures minimal processing time.
   b. Segmentation Accuracy: Data segmentation maintains precision, minimising overlap or gaps between segments.
3. **Feature Extraction:**
   a. Timely extraction of relevant features supports real-time processing.
   b. Consistency of Features: Extracted features remain consistent and stable across different data segments.
4. **Machine Learning Model Training:**
   a. Scalability: The system efficiently handles large datasets for model training.
   b. Training Time: Model training and validation are time-effective, enabling swift iterations.
5. **BCI Model Development:**
   a. Real-Time Processing Performance: The BCI system should provide low-latency real-time processing to enable rapid user interactions.
   b. Feedback Responsiveness: The feedback mechanism should be highly responsive to translate EEG feature classifications into control signals.
6. **Evaluation:**

a. Metric Reporting: The system should provide clear and comprehensive reporting of accuracy and reliability metrics.

b. Data Integrity: Ensure the integrity of evaluation data, and implement safeguards against data corruption.

7. **User Interface Design:**

a. Responsiveness: The user interface should be responsive, ensuring smooth interaction with the BCI system.

b. Cross-Platform Compatibility: The interface should work seamlessly on various devices and platforms.

8. **Report Generation:**

a. Efficiency in Report Generation: Technical report generation is efficient without significantly impacting system performance.

b. Data Privacy in Reporting: User data privacy and confidentiality are maintained during the report generation process.

3.4 Hardware, Software, Technology and Tools Utilised

Hardware Requirements:

1. **Processor:** Intel i3 or AMD equivalent
2. **Disk Space:** < 500 MB
3. **RAM:** 4 GB
4. **OS:** Windows 10 32-bit or higher
5. **GPU:** Nvidia GPU or Intel integrated graphics

Software Requirements:

Python Libraries:

1. **scikit-learn**: A Python library for machine learning, including feature extraction and model building.
2. **Matplotlib:** A popular Python library for creating static, animated, and interactive visualisations.

3. **Seaborn:** Built on top of Matplotlib, Seaborn provides a higher-level interface for creating statistical visualisations.

Tools and Technologies Used:

1. **ReactJS:** Employed for constructing the website's front end and facilitating user input.
2. **VS Code:** Serving as the primary integrated development environment (IDE) for code editing.
3. **Google Colab:** Utilised for the execution of the machine learning model and its testing.

Chapter 4: Proposed Design

4.1 Block diagram of the system

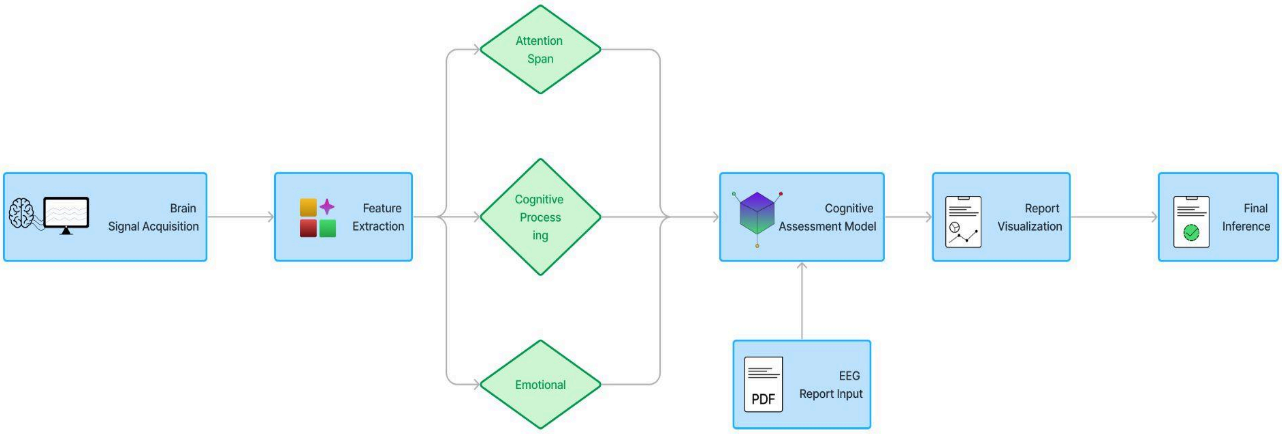


Figure 4.1.1 Block diagram of the System

4.2 Modular design of the system

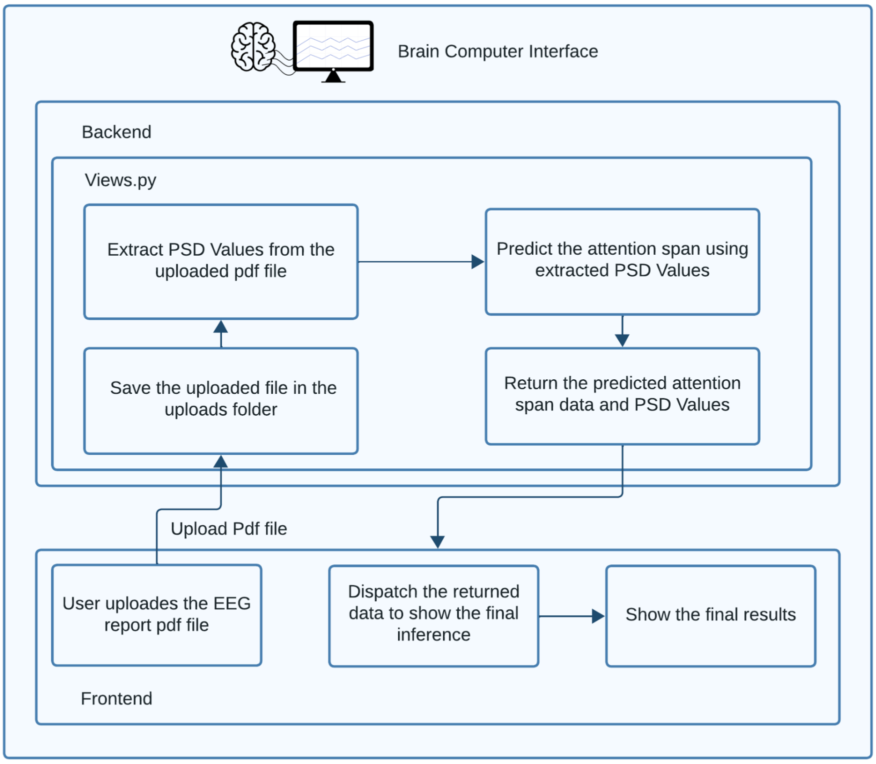


Figure 4.2.1 Modular Diagram of the System

4.3 Detailed Design

Figure 4.3.1 outlines the core processes of the EEG-based project, including PDF File Management, EEG report analysis, EEG report inference and visualisation of the result generated.

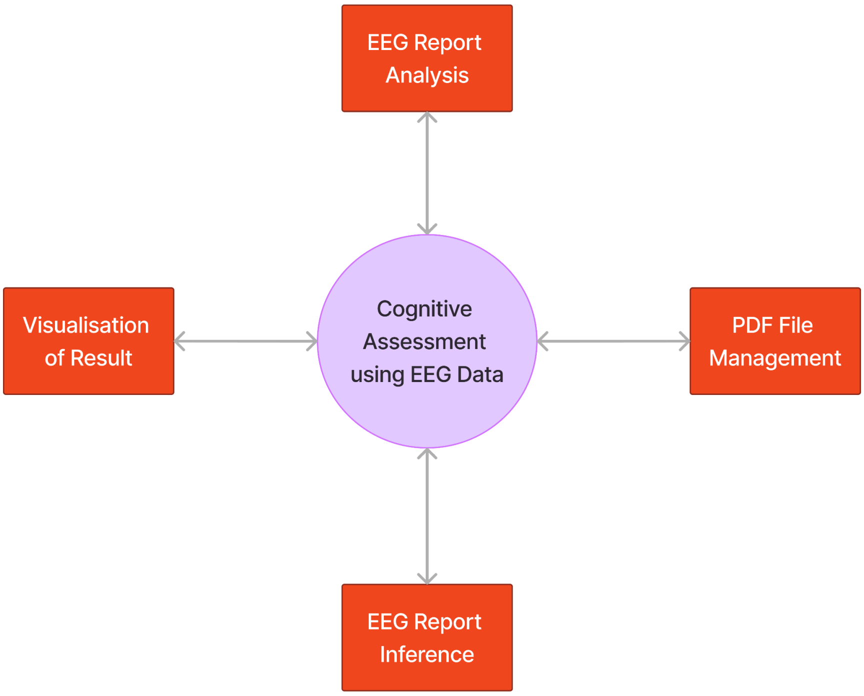


Figure 4.3.1: Level-0 DFD

Flowchart for the proposed system :

Our project's workflow is outlined in **Figure 4.3.2**, which includes training our cognitive assessment model and using it to make predictions for new user data to draw valuable conclusions.

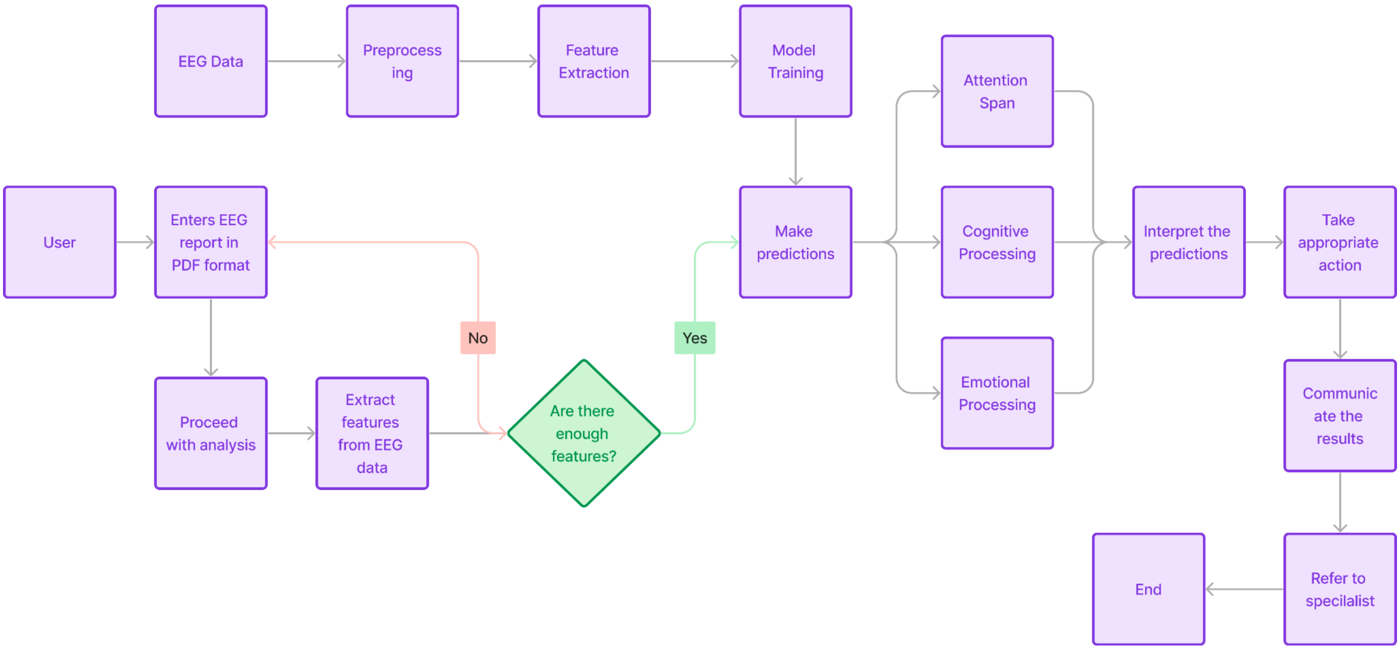


Fig 4.3.2 Flowchart of Model

4.4 Project Scheduling & Tracking using Timeline / Gantt Chart

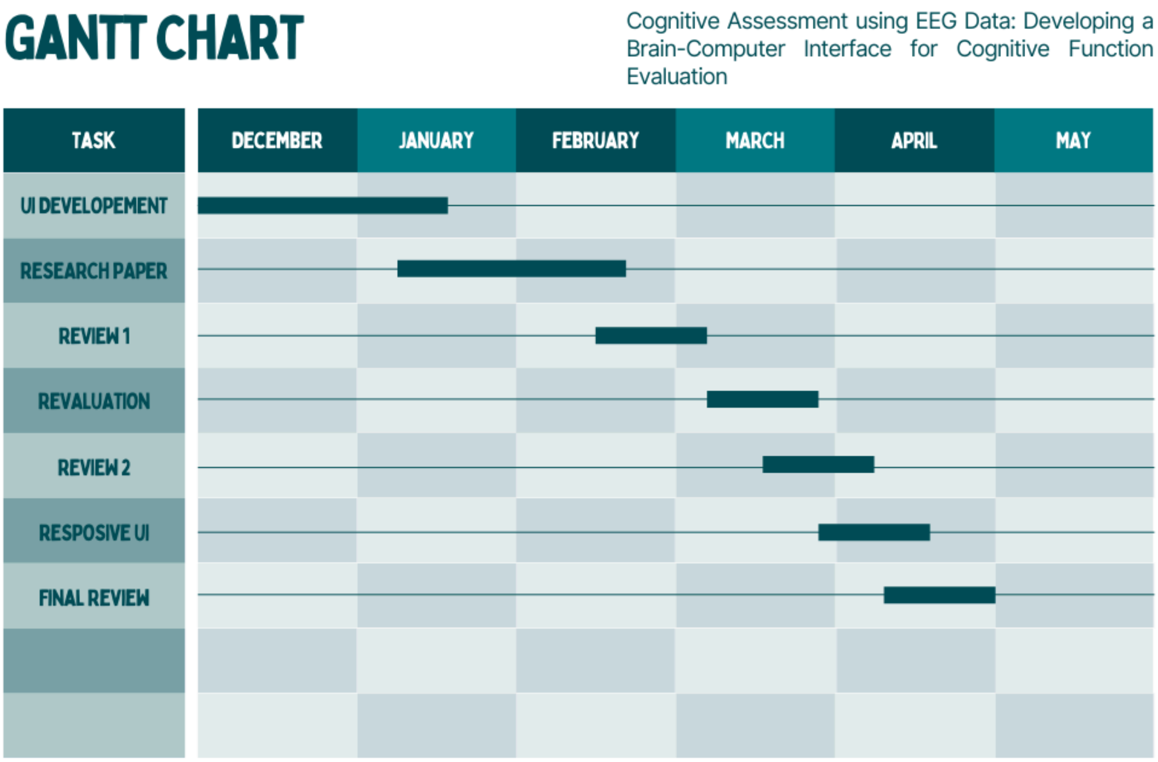


Figure 4.4.1: Timeline of the project

Chapter 5: Implementation of the Proposed System

5.1. Methodology employed for development

Developing a Brain-Computer Interface (BCI) for cognitive function evaluation using EEG data involves a systematic approach. Firstly, the dataset is preprocessed by splitting it into training and testing sets. Relevant features, such as frequency bands and theta/beta ratios for key sensors like F3 and F4, are extracted. Optimization techniques are then applied to select the most informative features for the BCI model. Next, a suitable machine learning algorithm, such as random forests or deep learning models, is chosen for model development and trained using the preprocessed EEG data. Evaluation metrics, including accuracy, precision, recall, and F1-score, tailored to cognitive function evaluation, are defined to assess the model's performance. A user-friendly interface is designed to facilitate easy interaction with the BCI system. Ethical considerations regarding data privacy, informed consent, and proper use of EEG data are addressed throughout the development process. Once validated and meeting desired performance levels, the BCI system is deployed for cognitive function evaluation, with regular updates and maintenance ensuring ongoing accuracy and reliability.

5.2 Algorithms and flowcharts for the respective modules developed

We have used the following algorithms for our project:

a) **Random Forest Classifier Algorithm:**

The Random Forest classifier is a powerful machine learning algorithm known for its robustness and versatility in handling various types of data. It operates by creating a multitude of decision trees during training, where each tree independently predicts the outcome. Through a process of averaging or voting across these trees, the Random Forest algorithm provides highly accurate predictions while mitigating overfitting issues common in individual decision trees. Its ability to handle large datasets, feature importance analysis, and resistance to noise and outliers make it a popular choice for classification tasks across domains such as finance, healthcare, and natural language processing.

$$Gini\ Index = 1 - \sum_{i=1}^{n} (P_i)^2$$

Here, P_i represents the relative frequency of the class in the dataset

n represents the number of classes.

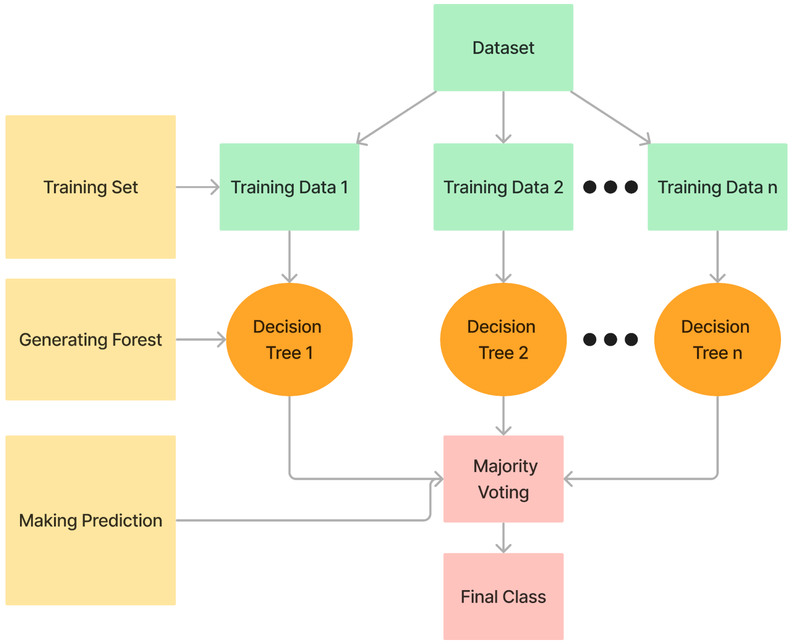


Figure 5.2.1 Flowchart of Random Forest Classifier

1. **Voting for Classification:**

For classification tasks, each decision tree in the forest predicts a class label. The final prediction is often determined by majority voting among the individual tree predictions.

Mathematically:

$$\hat{y}_{\mathrm{RF}} = \mathrm{mode}(\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n)$$

Where $\hat{y}_{\mathrm{RF}}$ is the Random Forest prediction, and $\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n$ are the predictions from individual trees.

2. **Averaging for Regression:**

In regression tasks, each tree predicts a numerical value. The Random Forest prediction is often calculated as the average of these predicted values.

Mathematically:

$$\hat{y}_{\mathrm{RF}} = \frac{1}{n}\sum_{i=1}^{n}\hat{y}_i$$

Where $\hat{y}_{\mathrm{RF}}$ is the Random Forest prediction, n is the number of trees, and $\hat{y}_i$ the prediction from the i-th tree.

These formulas illustrate how the Random Forest combines the predictions from individual trees to make a final prediction for classification and regression tasks.

5.3 Datasets source and utilisation

The dataset "EEG data / Distance learning" from Kaggle utilised the Emotiv Epoc X 14-channel headset to capture EEG signals. An experimental study during the COVID-19 shutdown involved students from various educational levels to examine cognitive reactions to online lectures. Baseline knowledge was assessed before lectures, videos were selected based on understanding levels, and EEG signals were analysed using a binary variable (1 = comprehended, 0 = did not grasp). The dataset includes features like "Video Utilised," "Viewer Identification," "Raw EEG Data," "Brain Wave Metrics," and "Comprehension Status," offering insights into cognitive engagement during remote learning amidst pandemic disruptions.

Column content in data:

1. The first column contains a variable that indicates the video used during the experiment. The videos can be found in Video_details.csv.
2. The second column contains a variable that indicates who watched the video. More details about the student can be found in Subject_details.csv.
3. Columns 3-16 contain raw EEG data from the 14 sensors.
4. Columns 17-86 contain 5 Brain waves for each sensor.
5. Column 87 contains the binary variable that indicates whether the subject understood the lecture or not.

Chapter 6: Testing of the Proposed System

6.1 Introduction to Testing

Software testing is the sequence of activities that happen during software testing. By employing a sane software testing life cycle, an organisation ends up with a quality strategy more likely to produce better results. Why is this so important, though? It all boils down to customer satisfaction. Presenting a perfect product to the customer is the end goal of every organisation.

Nothing puts off customers more than a bug-filled user experience. So when enterprises realised this, they began to include testing as a mandatory part of the SDLC. Since then, testing has become an integral part of every organisation.

Project Testing Phase means a group of activities designated for investigating and examining the progress of a given project to provide stakeholders with information about actual levels of performance and quality of the project. It is an attempt to get an independent view of the project to allow stakeholders to evaluate and understand the potential risks of project failure or mismatch. The purpose of the testing phase is to evaluate and test declared requirements, features, and expectations regarding the project prior to its delivery in order to ensure the project matches initial requirements stated in specification documents.

6.2 Types of tests Considered:

A. Unit testing

Unit testing is crucial for evaluating individual components and functions in isolation. In the frontend, test each component, such as the PDF preview component and form component was tested independently to ensure they perform their tasks as expected and handle different inputs and states correctly. In the backend, unit tests were focused on functions, classes, or methods such as PDF parsing functions and database interaction methods. By thoroughly testing these components, it was possible to identify and fix bugs early in the development process, improving the overall reliability and quality of the application.

B. Functional testing

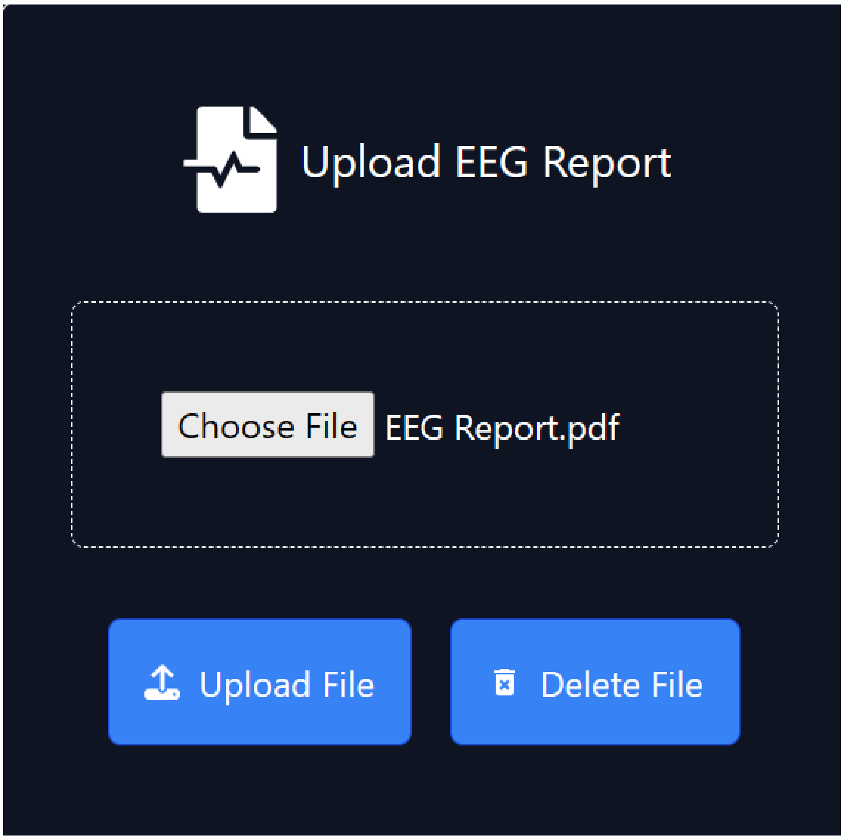
Functional testing involved verifying that each feature of our application performs as intended. For instance, we tested the PDF file upload and preview functionality, ensuring that the PDF is successfully uploaded and displayed correctly in the frontend. Additionally, the data extraction process from the PDF files was also tested to verify that the data matches the expected format and is consistent with the application's requirements. Moreover, functional testing also includes checking the accuracy of visualizations based on the extracted data. These tests help confirm that the application behaves as intended and that all features work properly.

C. Integration testing

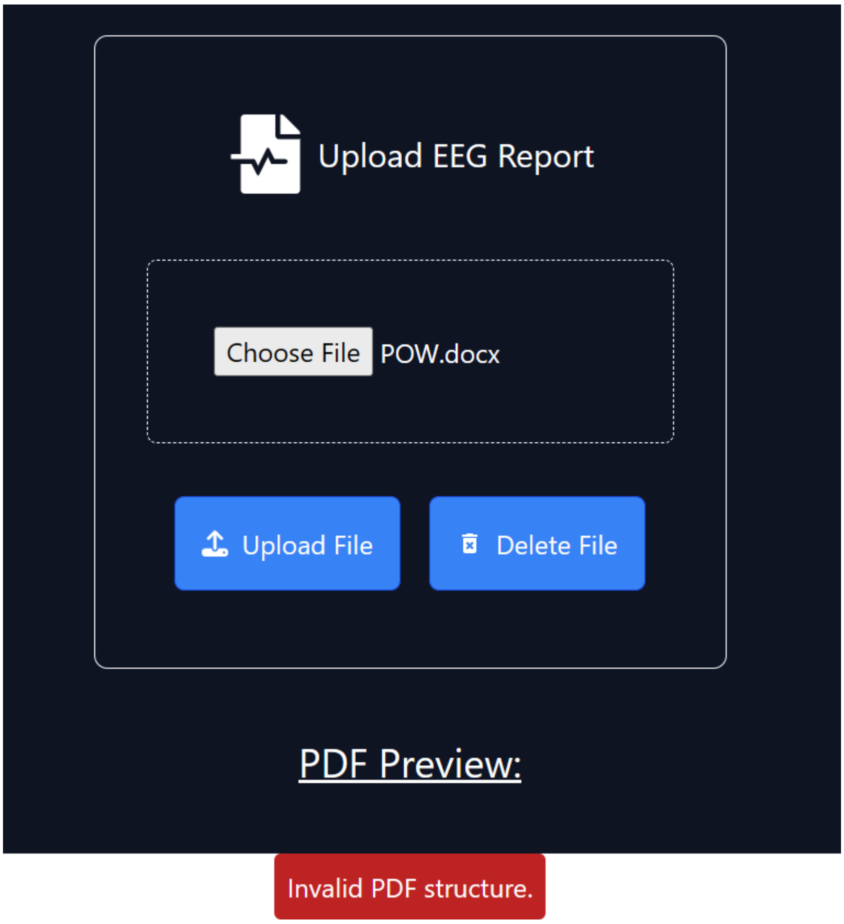
Integration testing focuses on the interaction between different parts of the application, such as the frontend and backend. This type of testing verified our end-to-end flow, including file uploads, PDF parsing, data extraction, and subsequent processes. Integration tests ensure that data is accurately and efficiently passed between the frontend and backend, confirming that the responses are consistent and as expected. By testing these interactions, we identified and resolved any issues related to Cross-Origin requests that arose from the combination of different components, ensuring a cohesive and reliable user experience throughout the application.

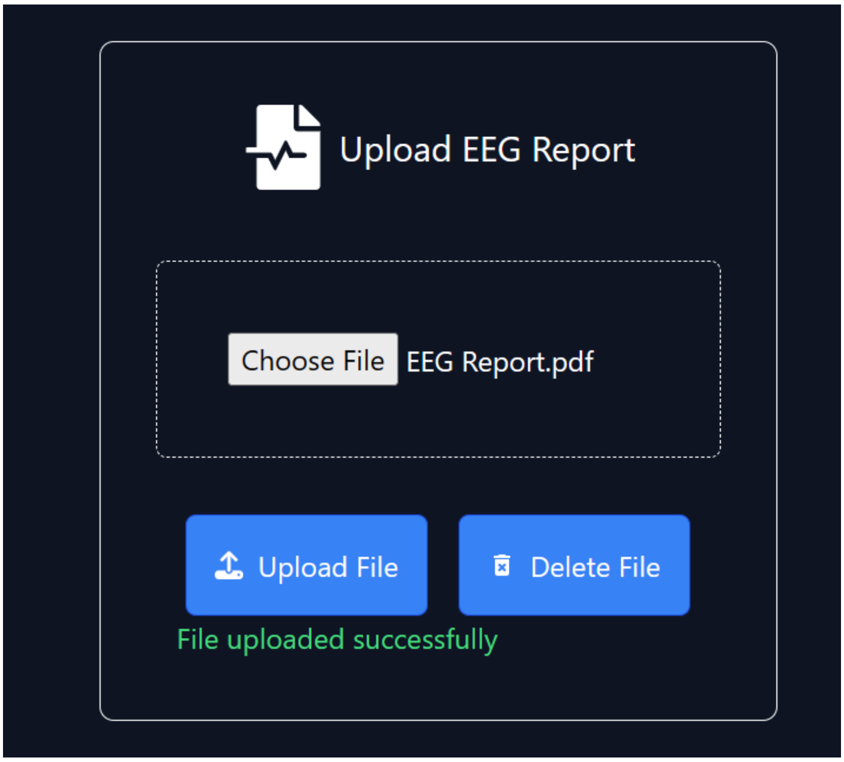
6.3 Various test case scenarios considered:

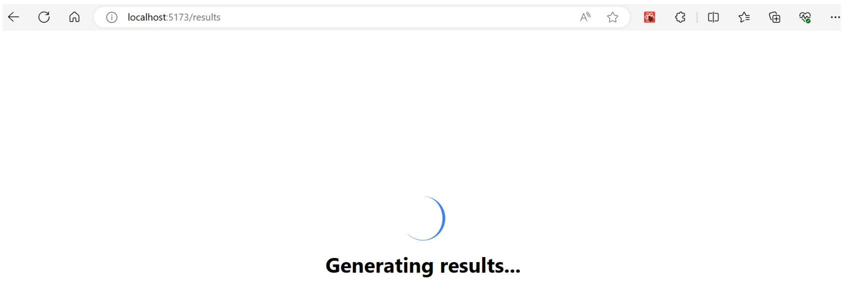
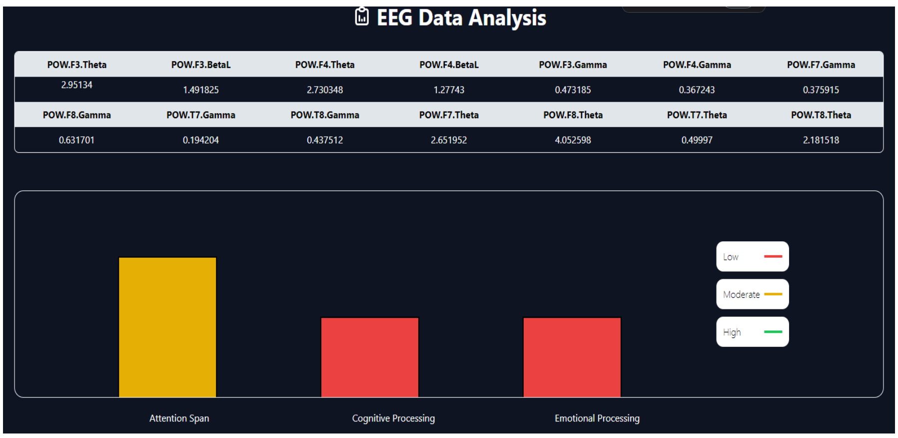
TABLE 6.3.1 Test Case Scenarios

Case no.	Test Cases
Case 1: The Selected File’s name should be displayed correctly	

<table>
<tr>
<td>Case 2:

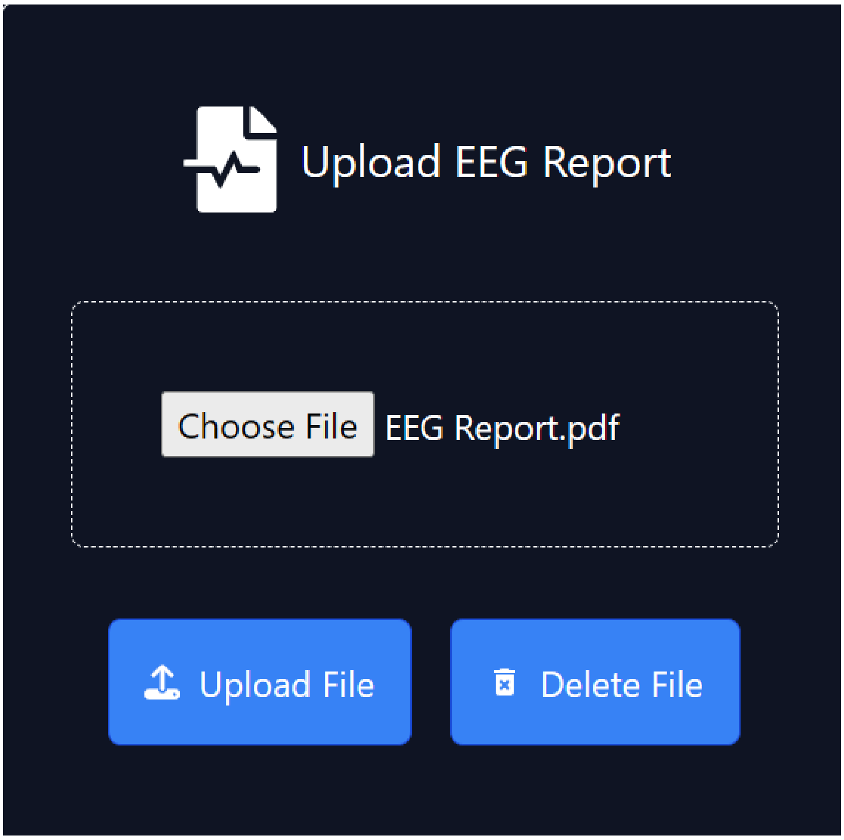
The input field for file should only accept valid file type(.pdf)</td>
<td>
</td>
</tr>
<tr>
<td>Case 3:

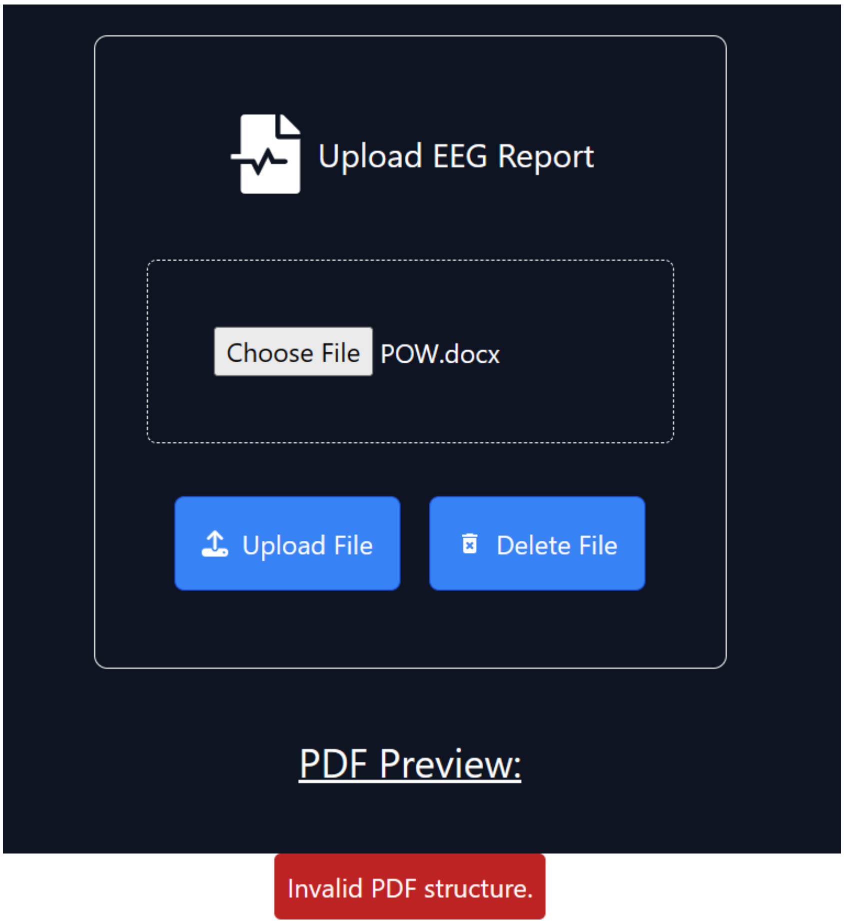
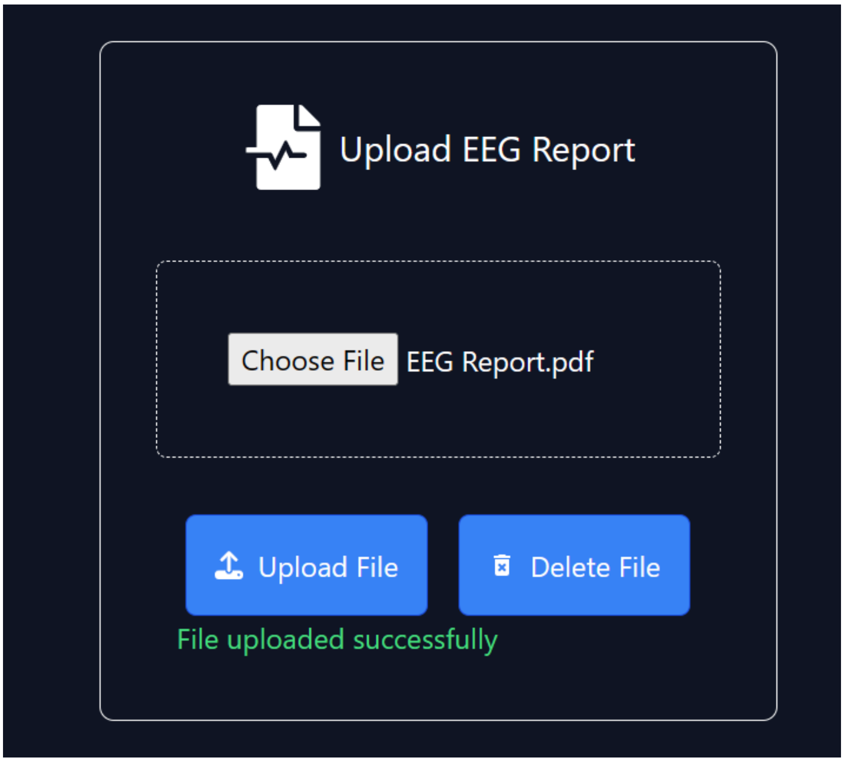
When the user clicks on the Upload button then a popup showing file upload status should be displayed</td>
<td>
</td>
</tr>
</table>

Case 4: On selecting the file,a preview of that file should be displayed.	
Case 5: If the file upload is successful,then the page should automatically redirect to a results page	

6.4 Inference drawn from the test cases:

TABLE 6.4.1 Inference drawn from Test Cases

Case no.	Test Cases
Case 1: The Selected File's name should be displayed correctly. This file contains the power of the different waves which have to be extracted in the back-end.	

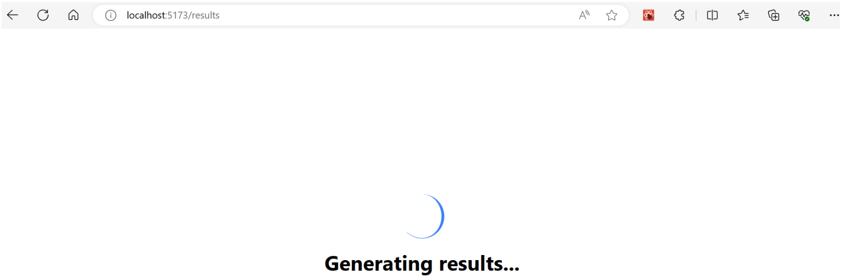
Case 2: The input field for the file should only accept valid file type (.pdf). Python's library pdfplumber can only be used on files with a .pdf extension	
Case 3: When the user clicks on the Upload button then a popup showing file upload status should be displayed.The file contains the values which will then be used by the ML model for prediction	

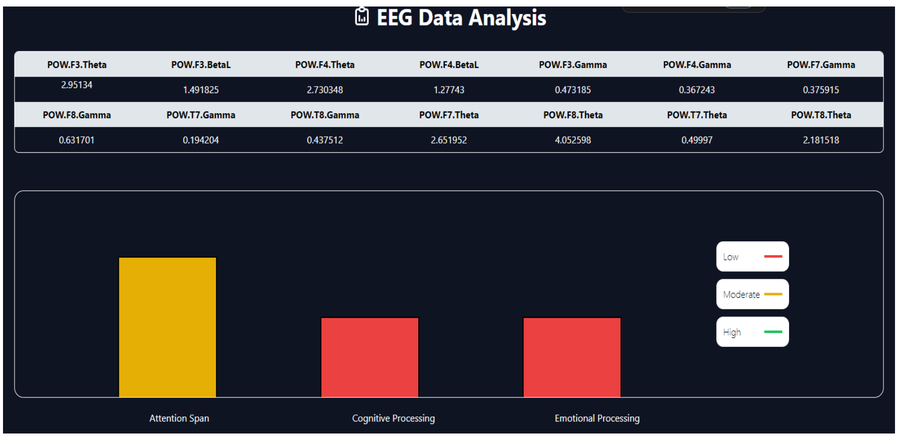
Case 4:

On selecting the file,a preview of that file should be displayed in order so that the EEG Report values can be seen which can later be used for verification after they have been extracted

Case 5:

If the file upload is successful,then the page should automatically redirect to a results page.This type of testing verified our end-to-end flow, including file uploads, PDF parsing, data extraction, and subsequent processes.





Chapter 7: Results and Discussion

7.1. Screenshots of the User Interface (UI) for the respective module

Figure 7.1.1 depicts the user-friendly landing page of our project, built with React JS and Tailwind CSS. It prioritises user experience with two tabs: "Home," the current view, likely showcasing the project's core functionalities. The "About" tab delves deeper, providing details about the project itself. This section also introduces the project team members who have contributed to this project.

For personalization, users can switch between light and dark themes using a toggle button, with dark being the default. The central focus of this landing page is EEG report management. Here, users can conveniently browse and upload their EEG reports using the "Upload File" button. They also have the option to delete uploaded reports with the "Delete File" button.

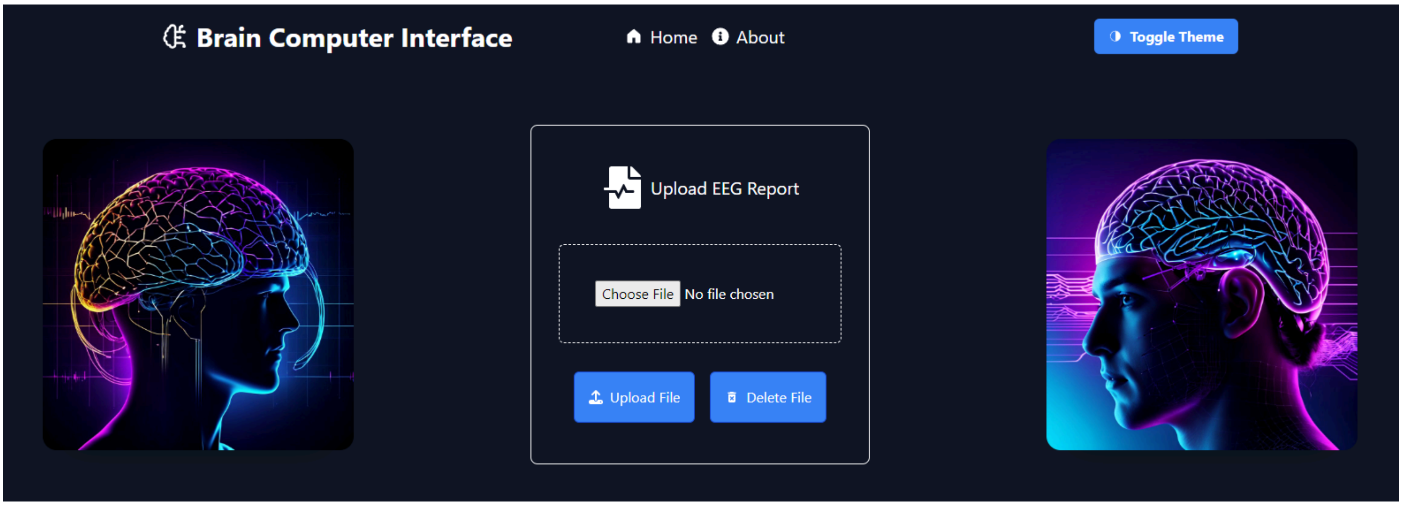


Figure 7.1.1 Screenshot of user interface

The user interface (UI) for the results section shown in **Figure 7.1.2** presents a clear and informative overview of the processed EEG data.

1. **PSD (Power Spectral Density) Analysis:** The upper section of the main page focuses on Power Spectral Density (PSD) analysis. It displays labels for different PSD attributes for different electrodes along with their corresponding numerical values extracted from the uploaded EEG report.

2. **Cognitive Function Visualization:** The lower section of the main page presents the results in a visual format. Here, three cognitive functions - attention span, cognitive processing, and emotional processing - are each represented by a visualisation, likely a bar graph. The colour of the bars indicates the level of the result, with red signifying low, orange signifying moderate, and green

signifying high. This colour-coding scheme provides a quick and easy way to grasp the results at a glance.

3. **Informative Descriptions:** Below the visualisations, there are short descriptions which explain each cognitive function in simpler terms. This additional context helps users understand the implications of the analysed data.

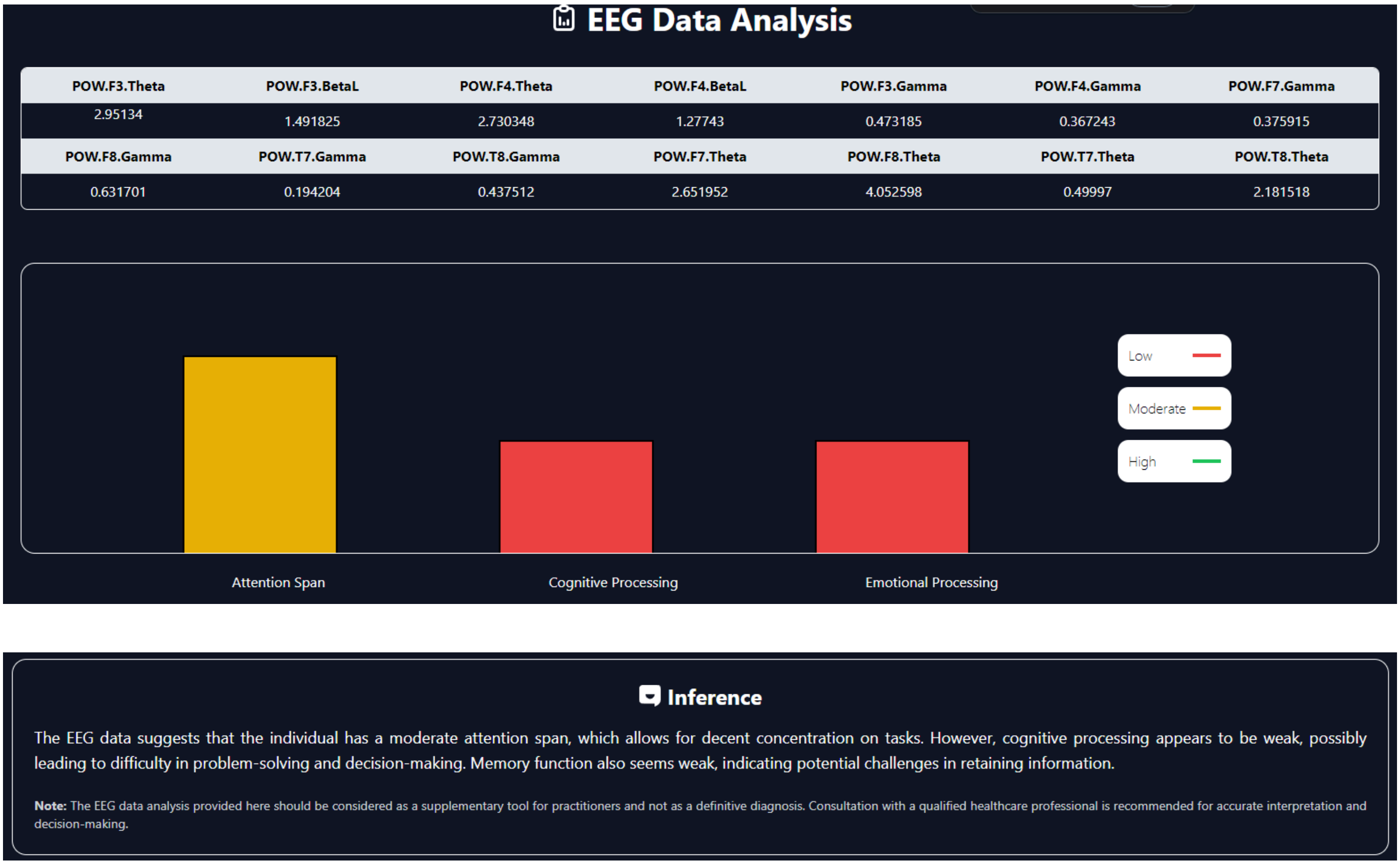


Figure 7.1.2 Screenshot of results page

7.2. Performance Evaluation measures

Table 7.2.1 presents the accuracy of different algorithms used in our project for cognitive function evaluation using EEG data. The table shows the accuracy scores achieved by each algorithm, including Random Forest, Gradient Boosting, KNN (K-Nearest Neighbors), and Decision Tree. These accuracy scores reflect the performance of each algorithm in predicting attention spans based on EEG features, with Random Forest achieving the highest accuracy of 97.16%, followed closely by Gradient Boosting at 95.69%. KNN and Decision Tree algorithms also demonstrate strong performance with accuracy scores of 95.85% and 93.83%, respectively.

TABLE 7.2.1 Accuracy Of The Algorithms

ALGORITHMS	ACCURACY
RANDOM FOREST	0.97159
GRADIENT BOOSTING	0.95685
KNN	0.95845
DECISION TREE	0.93825

Table 7.2.2 conveys the evaluation metrics (Precision, Recall, and F1-Score) of a Random Forest Classifier across different classes (High Attention, Low Attention, and Moderate Attention). It shows how well the classifier performs in terms of precision, recall, and overall F1-Score for each attention level class.

TABLE 7.2.2. Evaluation Metrics of Random Forest Classifier

CLASS	PRECISION	RECALL	F1-SCORE
High Attention	0.98	0.95	0.96
Low Attention	0.95	0.99	0.96
Moderate Attention	0.99	0.99	0.99

Table 7.2.3 presents the evaluation metrics (Precision, Recall, and F1-Score) of a Gradient Boosting model across different classes (High Attention, Low Attention, and Moderate Attention). It shows the model's performance in terms of precision, recall, and overall F1-Score for each attention level class.

TABLE 7.2.3. Evaluation Metrics of Gradient Boosting

CLASS	PRECISION	RECALL	F1-SCORE
High Attention	0.98	0.89	0.93
Low Attention	0.98	0.98	0.98
Moderate Attention	0.91	0.95	0.93

Table 7.2.4 displays the evaluation metrics (Precision, Recall, and F1-Score) of a K-Nearest Neighbors (KNN) model across different classes (High Attention, Low Attention, and Moderate Attention). It illustrates the model's performance regarding precision, recall, and overall F1-Score for each attention level class.

TABLE 7.2.4. Evaluation Metrics of KNN

CLASS	PRECISION	RECALL	F1-SCORE
High Attention	0.96	0.95	0.96
Low Attention	0.98	0.97	0.97
Moderate Attention	0.92	0.94	0.93

Table 7.2.5 presents the evaluation metrics (Precision, Recall, and F1-Score) of a Decision Tree model across different classes (High Attention, Low Attention, and Moderate Attention). It showcases the model's performance in terms of precision, recall, and overall F1-Score for each attention level class.

TABLE 7.2.5. Evaluation Metrics of Decision Tree

CLASS	PRECISION	RECALL	F1-SCORE
High Attention	0.93	0.92	0.93
Low Attention	0.97	0.96	0.97
Moderate Attention	0.89	0.90	0.90

7.3. Input Parameters / Features Considered

Table 7.3.1 provides a comprehensive overview of the significance of electrodes used in the EEG analysis. Each electrode's significance is detailed along with the corresponding brainwave power measurement and its interpretation in terms of cognitive processes and attentional mechanisms. For instance, the power of theta brainwaves at electrodes F3, F4, F7, and F8 reflects cognitive processing, attentional allocation, and executive functions. Low-beta brainwaves at F3 and F4 are linked to focused attention, cognitive engagement, and sustained attention, while gamma brainwaves at various electrodes contribute to higher cognitive functions, information processing, memory, language processing, perception, decision-making, and neural synchronisation. This table serves as a valuable reference for understanding the specific cognitive functions and attention-related processes associated with each electrode's brainwave activity in EEG analysis.

TABLE 7.3.1 Significance of Electrodes used

Electrodes Used	**Significance**
POW.F3.Theta:	Power of theta brainwaves at electrode F3, indicative of cognitive processing and attention.
POW.F3.BetaL:	Power of low-beta brainwaves at electrode F3, associated with focused attention and cognitive engagement.
POW.F4.Theta:	Power of theta brainwaves at electrode F4, reflecting cognitive function and attentional processes.
POW.F4.BetaL:	Power of low-beta brainwaves at electrode F4, linked to sustained attention and cognitive control.
POW.F3.Gamma:	Power of gamma brainwaves at electrode F3, associated with higher cognitive functions and information processing.
POW.F4.Gamma:	Power of gamma brainwaves at electrode F4, involved in cognitive processing and neural synchronisation.
POW.F7.Gamma:	The power of gamma brainwaves at electrode F7 contributes to cognitive functions such as memory and attention.
POW.F8.Gamma:	The power of gamma brainwaves at electrode F8 is involved in cognitive processing and executive functions.
POW.T7.Gamma:	The power of gamma brainwaves at electrode T7 influences cognitive processes such as language and memory.
POW.T8.Gamma:	The power of gamma brainwaves at electrode T8 contributes to cognitive functions such as perception and decision-making.
POW.F7.Theta:	Power of theta brainwaves at electrode F7, indicating cognitive processing and attentional allocation.
POW.F8.Theta:	Power of theta brainwaves at electrode F8, reflecting cognitive processes related to attention and executive function.
POW.T7.Theta:	The power of theta brainwaves at electrode T7 is involved in cognitive functions such as language processing and memory retrieval.
POW.T8.Theta:	The power of theta brainwaves at electrode T8 is associated with cognitive processes such as attention and executive control.

7.4. Graphical and statistical output

Figure 7.4.1 and Figure 7.4.2 provide detailed visual representations of attention indexes for EEG channels 'F3' and 'F4,' respectively, contributing to a deeper understanding of cognitive processes and attentional mechanisms captured through EEG signals. These figures offer a nuanced analysis through three distinct subplots arranged vertically.

The first subplot, depicting Theta/Beta Ratio, elucidates the dynamic equilibrium between theta and beta wave activities, shedding light on the individual's cognitive state, whether it's a state of relaxation or heightened alertness. This ratio is pivotal in discerning shifts in cognitive focus and mental states.

Moving to the second subplot, focusing on Alpha/Beta Ratio, unveils critical insights into the delicate balance between alpha and beta waves. This equilibrium is fundamental in gauging levels of attention and cognitive engagement. Variations in this ratio can signify shifts in cognitive workload, concentration levels, and the individual's ability to sustain attention over time.

The third subplot, delving into Alpha/Theta Ratio, unveils the intricate relationship between alpha and theta waves. This ratio offers valuable information regarding cognitive workload, mental effort, and relaxation levels. Understanding this interplay aids in comprehending cognitive processes related to workload management, mental clarity, and overall cognitive performance.

Each subplot's legend plays a pivotal role in deciphering the data, providing key indicators and trends that aid in the interpretation of attention dynamics and cognitive states recorded by EEG signals from the 'F3' and 'F4' electrodes. These visualisations serve as powerful tools for researchers and practitioners in the field of cognitive neuroscience, enabling them to gain nuanced insights into cognitive functioning and attentional processes.

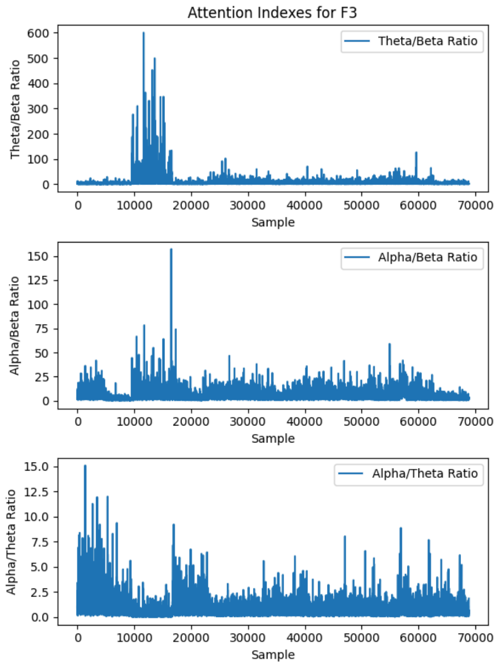


Figure 7.4.1 Attention indexes for F3

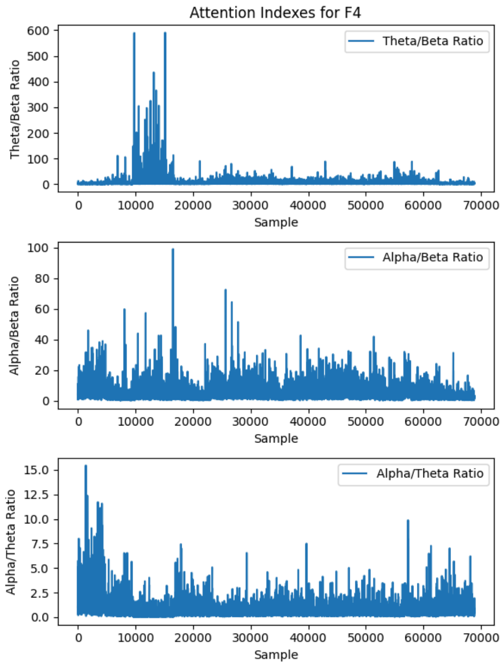


Figure 7.4.2 Attention Indexes for F4

7.5 Comparison of results with existing systems

Table: 7.5.1 Comparison of Existing Systems

Aspect	Existing System	Proposed Solution
Sensitivity to Deficits	May lack sensitivity to subtle cognitive deficits	Aims for improved sensitivity to deficits
Real-time Feedback	Typically lacks real-time feedback	Aims to provide real-time feedback
Personalised Recommendations	Typically lacks personalised recommendations	Aims to provide personalised recommendations
Methodological Focus	Traditional cognitive testing	EEG signal processing and machine learning

7.6. Inference drawn

The current system relies on traditional testing methods and may miss subtle issues. It also doesn't provide feedback or personalised recommendations during the assessment. The proposed solution aims to improve upon this by using EEG and machine learning to increase sensitivity to cognitive problems. Additionally, it would offer real-time feedback and personalised recommendations, potentially making cognitive assessment more accurate and helpful.

Chapter 8: Conclusion

8.1 Limitations

- **Time-Consuming:** Traditional cognitive tests can be time-consuming to administer and score. This can hinder their practicality, particularly in settings where efficient and quick assessments are required.
- **Lack of Proper Inference:** The current traditional systems do not provide proper statistics and visualisation of Electroencephalogram(EEG) data resulting into lack of proper inference and delay in diagnosis.

8.2 Conclusion

The conclusion of the project underscores a multi-faceted impact on advancing cognitive neuroscience and personalised medicine. By leveraging advanced EEG data analysis techniques, the project aims to revolutionise cognitive evaluations for diverse populations and cultural backgrounds. Through a comprehensive understanding of neural signals and cognitive processes, the project seeks to create a paradigm shift in how cognitive functioning is assessed and personalised interventions are developed.

Furthermore, the project's emphasis on continuing research and technological innovations signifies a commitment to ongoing improvement and refinement in the field of EEG-based cognitive assessment. This dedication not only enhances the accuracy and specificity of cognitive evaluations but also opens doors to new avenues of research and application in areas such as education, clinical diagnosis, and cognitive enhancement.

In summary, the project's conclusive vision extends beyond the immediate outcomes to a broader mission of empowering individuals and healthcare professionals with sophisticated tools and insights to optimise cognitive health and well-being across diverse populations and cultural landscapes.

As we navigate the dynamic landscape of cognitive neuroscience, the insights gained from this project serve as catalysts for ongoing advancements, beckoning us to continue unravelling the mysteries of the human mind and paving the path towards a more cognitively aware and empowered society.

8.3 Future Scope

- **Privacy-Focused System:-** Our EEG BCI system prioritises privacy, safeguarding user data through encryption, anonymization, and strict access controls, ensuring confidentiality while enabling accurate cognitive function evaluation.

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Appendix

Paper I Details

a. Paper I

Cognitive assessment using EEG data: developing a brain-computer interface for cognitive function evaluation

*Siddhant Kodolkar[1], Sahil Madhyan[2],Harsh Karira[3], Indu Dokare[4]

[1,2,3,4] Vivekanand Education Society's Institute of Technology, Mumbai, India
[1]2020.siddhant.kodolkar@ves.ac.in
[2]2020.sahil.madhyan@ves.ac.in
[3]2020.harsh.karira@ves.ac.in
[4] indu.dokare@ves.ac.in

* Corresponding Author

Abstract. Electroencephalography (EEG) is a non-invasive technique for monitoring brain activity in real time, offering insights into cognitive processes such as attention, memory, and problem-solving. A methodology is presented for developing a brain-computer interface for cognitive function evaluation using EEG data. The methodology involves data preprocessing, feature extraction, optimization, machine learning model development, testing, and validation. Novel attention indexes based on the power spectral density ratios of theta, alpha, and beta frequency bands are proposed, and the efficiency of four machine learning algorithms in predicting attention spans from EEG features is evaluated. A 10-fold cross-validation shows a mean accuracy of 93.96%, indicating promising EEG features for predicting attention span.

Keywords: EEG, brain-computer interface, random forest, gradient boosting, KNN, decision tree, attention indexes

1 Introduction

The human brain is a complex and intricate organ that continues to captivate researchers in its many facets. Among the various techniques for studying brain function, electroencephalography has gained significant attention as a non-invasive method for monitoring brain activity in real-time. Our study embarks on a comprehensive exploration of the methodologies and procedures used to analyse EEG data and their associations with cognitive function.

Cognitive function encompasses a wide array of mental processes such as perception, attention, memory, and problem-solving, which is the core of human cognition and plays a pivotal role in our daily lives. Investigating the intricacies of cognitive function and its manifestations in EEG data offers the potential to uncover valuable insights into brain activity. Techniques for electrode placement, such as high-density placement and electrode grids, have been explored to overcome limitations of the 10-20 system, a standardised method for accurately positioning electrodes on the scalp. The 10-20 system was based on the relative distances between specific landmarks on the skull, including the nasion (bridge of the nose), inion (bump on the back of the head), and preauricular points (points in front of the ears), as well as the distances between the ears. Attempts to locate cortical generators of electrical potentials have led to methods involving additional electrode positions and cross-sectional atlases of the head. Our study aims to evaluate the efficacy of software tools in processing and interpreting EEG signals. By doing so, it aspires to enable the extraction of meaningful information related to cognitive processes. Our study delves into a multitude of research studies that have examined EEG-based approaches to cognitive function, from the pioneering work of Klimesch on EEG alpha and theta oscillations [1] to more recent investigations like Ward's exploration of EEG correlates in the spectrum of cognitive decline [2]. Furthermore, the scope of this investigation extends beyond academic curiosity to consider the practical ramifications of integrating EEG-based cognitive assessment into educational and cognitive rehabilitation settings. The potential applications of EEG data in clinical and practical contexts have been widely explored, such as research into EEG-neurofeedback as a therapeutic approach for cognitive deficits in various clinical conditions.[3]. By drawing on an extensive body of literature and the expertise of renowned researchers in the field, our study sheds light on the evolving landscape of EEG analysis and its implications for our understanding of cognitive function. As the studies referenced here demonstrate, EEG-based methodologies have the potential to inform not only our fundamental knowledge of the human brain but also to shape the future of clinical interventions, cognitive rehabilitation, and even advanced driver-assistance systems [4]. In this journey of scientific exploration, we aim to provide a comprehensive overview of the state-of-the-art EEG analysis tools, their applications in cognitive research, and the potential to translate these findings into practical solutions for a wide range of cognitive-related challenges. In the footsteps of pioneers and contemporary researchers, our study aspires to contribute to the ever-evolving landscape of cognitive neuroscience and EEG-based investigations. The electrical voltages in the brain that oscillate during brain waves are only a few millionths of a volt. The primary frequencies of human EEG waves are presented in Table 1 along with their properties. Five brain waves are commonly recognised [28].

Table 1 Features of the Five Primitive Brain Waves

Frequency band	**Frequency**	**Brain states**
Gamma (γ)	> 35 Hz	Concentration
Beta (β)	12–35 Hz	Anxiety-dominant, active, external attention, relaxed
Alpha (α)	8–12 Hz	Very relaxed, passive attention
Theta (θ)	4–8 Hz	Deeply relaxed, inward-focused
Delta (δ)	0.5–4 Hz	Sleep

2 Related work

The literature survey encompasses studies focusing on attention measurement utilizing EEG signals. The first study proposes a brain-computer interface (BCI) system for online learning, aiming to objectively assess student attention levels during classes. Employing power spectral density (PSD) features extracted from EEG signals, the study applies classification algorithms like k-nearest neighbours (KNN), support vector machine (SVM), and random forest (RF), achieving a notable 96% accuracy with the RF model. The findings highlight the potential for real-time monitoring and adjustment of teaching strategies based on attention assessment. In the second study, attention classification is explored in a 13-year-old with Autism Spectrum Disorder (ASD). EEG signals are utilized to detect various attention-related features, and machine learning models, particularly the multi-layer perceptron neural network (MLP-NN), exhibit promising performance metrics. Our study underscores the significance of EEG-based attention assessment in enhancing learning experiences for individuals with ASD, offering insights for tailored educational interventions and diagnostic accuracy. Future directions include real-time implementation, deep learning exploration, and mobile-based platforms to broaden the scope of attention processes and improve standard estimation. A neurodevelopmental disorder known as autism spectrum disorder (ASD) is responsible for repetitive behaviour, poor communication skills, and difficulties interacting with others. This study describes a method for measuring attention in a 13-year-old child with ASD using electroencephalographic (EEG) data. The best-performing neural network model is the multi-layer perceptron neural network model (MLP-NN), which gives educators and therapists measurable progress data. Neuroimaging methods such as fMRI, fNIRS, and EEG are used in neuroergonomics to investigate how people perform in a range of cognitive activities. In 143 studies, mental tiredness, mental burden, mental effort, visual fatigue, emotion, and stress were examined in a systematic review. Research gaps, trends, and prospective avenues for further investigation were noted in the evaluation. Emotional, cognitive, and physiological factors are linked by new technologies that measure biological markers and neuro-communications. [6], [7], [14], [18].

3 Proposed Work

In our research, we explore the methodologies and procedures employed to analyse EEG data and their associations with cognitive function. Our primary objective is to evaluate the efficacy of software tools in processing and interpreting EEG signals, thereby enabling the extraction of meaningful information related to cognitive processes. Moreover, our investigation extends to considering the potential ramifications, both in clinical and practical terms, of integrating EEG-based cognitive assessment into educational and cognitive rehabilitation settings. This study is highly relevant due to its potential to advance cognitive assessment methods significantly. Exploring the use of EEG data for cognitive evaluation addresses the need for more accurate and objective assessments of cognitive abilities. This relevance extends to the early detection of cognitive deficits, critical for timely intervention and support. Additionally, the project has implications for education, offering insights into tailored teaching methods, and for cognitive rehabilitation, potentially providing more precise tracking of progress. It also holds promise in clinical settings for better diagnosis and treatment planning. Finally, the project contributes to scientific advancement by deepening our understanding of EEG data's relationship with cognitive function, fostering future research and innovation.

3.1 Dataset Used

We have used the dataset from Kaggle titled “EEG data / Distance learning”[27]. The device that was used in the dataset to capture the EEG signals for the experiment is the Emotiv Epoc X 14-channel headset. Some studies have correlated EEG findings with metabolic activation measured by positron emission tomography (PET) [5]. During the Covid-19 shutdown, an experimental study was carried out with students from various educational backgrounds, including high school, middle school, and undergraduate levels. The goal was to study cognitive reactions to online lectures by recording EEG data and brain waves. Before the lectures, the students' baseline knowledge was examined using targeted inquiries. Following that, a collection of videos was picked based on their understanding levels, spanning from simple to complex information. During the lectures, EEG signals were analysed and a binary variable was used to indicate understanding success (1 = comprehended the lecture, 0 = did not grasp the lecture). The acquired data, such as EEG recordings, subject characteristics, and video details, were combined into a single file. This complete method provides insights into cognitive engagement during remote learning, which has important implications for educational initiatives in the face of pandemic-related interruptions. [6,27] The dataset contains a variety of features. First, there is "Video Utilised," which identifies the precise movie used throughout the experiment, providing insight into the content analysed. Second, "Viewer Identification" allows you to trace who viewed the video and provide context about the participants. Third, "Raw EEG Data" includes information from 14 sensors that record the brain's electrical activity during the session. Fourth, "Brain Wave Metrics" provides a full collection of measures for each sensor, revealing extensive information about cognitive reactions and processes. Finally, "Comprehension Status" serves as a binary indicator, indicating whether or not the subject understood the lecture material, influencing the interpretation of the collected data.[6]Power Spectral Density (PSD) analysis is a crucial technique in the field of electroencephalography (EEG), offering a detailed insight into the frequency distribution of neural signals. We have examined the practical implications of PSD analysis in diverse research domains, emphasising its role in investigating attention, memory, and cognitive states. PSD is a mathematical tool used to describe the distribution of power in a signal across different frequencies. Derived from Fourier analysis, PSD represents the magnitude squared of the Fourier transform of a signal. In the context of EEG, PSD is calculated to reveal the intensity of neural oscillations within distinct frequency bands such as Delta, Theta, Alpha, Beta, and Gamma.[6]

3.2 Planned Research

Attention, a multifaceted cognitive process, plays a pivotal role in human behaviour, affecting perception, memory, and decision-making. Understanding and quantifying attention levels are crucial for various domains, including education, clinical psychology, and human-computer interaction. A novel method for attention index estimation using EEG-derived ratios of power spectral density in the theta, alpha, and beta frequency bands [6]. Selecting, focusing on, and continuously understanding information are made possible by the cognitive function of attention. The focus of attention may be on an external stimulus that is being actively processed by the senses, or it is associated with data produced by continuous cognitive processes. This enables us to focus on stimuli that are relevant to us and required to start the process [7].

Many approaches for evaluating attention have been documented in the literature, including eye-tracking/gaze [9,10], fMRI [11,12], program [13], biofeedback [14], and EEG signals [15], [16], [17] among others. The last one has significant advantages over other neuroimaging techniques due to its high temporal resolution [18], neurodevelopmental diagnosis accuracy [19], cognitive-related bioelectrical data [20], low cost [21], and non-invasive application methods [22].

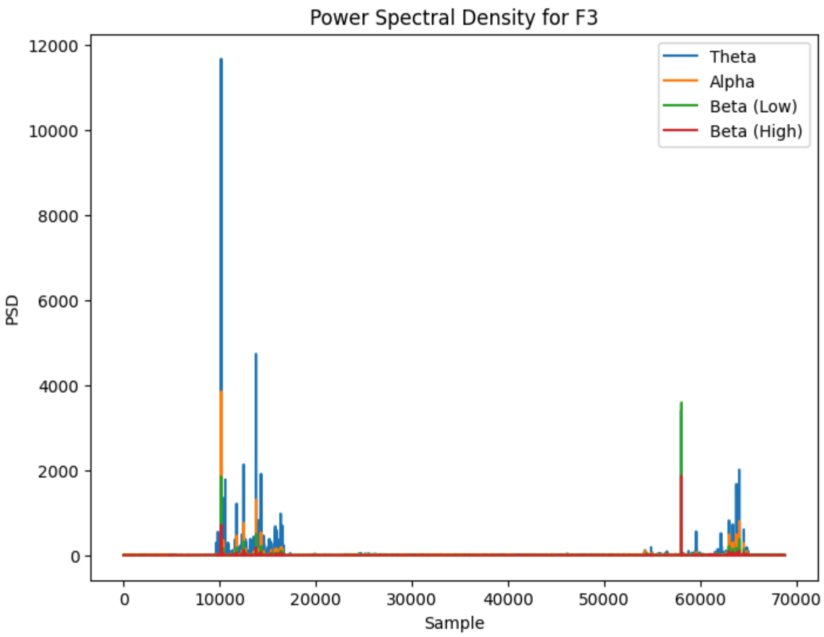

Fig 1. Power Spectral Density for F3

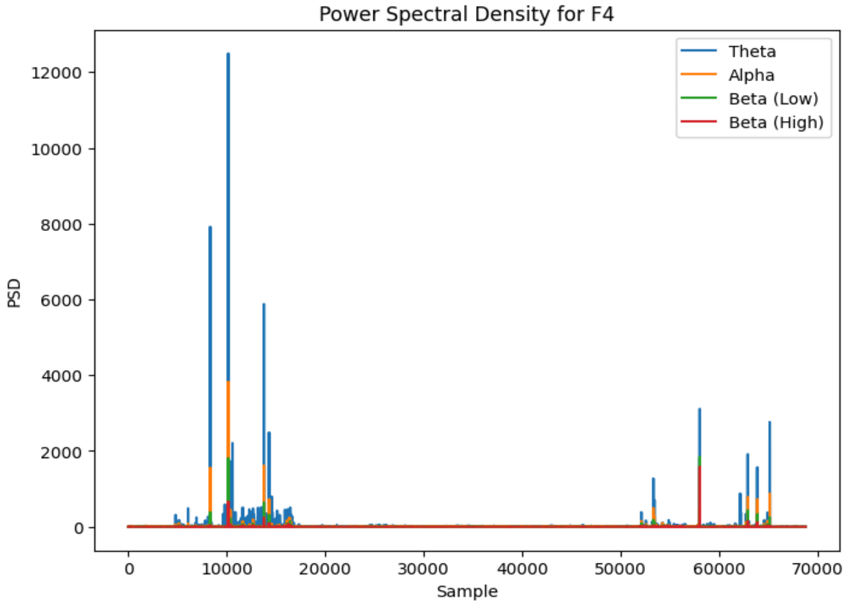

Fig. 2. Power Spectral Density for F4

The power of each wave at the F3 and F4 electrodes refers to the magnitude or intensity of electrical activity within each frequency band at that specific electrode site. Higher power indicates stronger electrical activity within a particular frequency band.

3.3 Calculating Attention Indexes

By leveraging the distinctive characteristics of theta, alpha, and beta frequency bands, we aim to establish robust attention indexes that reflect variations in cognitive states. The methodology for computing these ratios, their theoretical underpinnings, and the potential implications for applications in attention assessment and cognitive neuroscience. The choice of theta, alpha, and beta frequency bands is grounded in existing literature highlighting their association with cognitive processes. Theta oscillations have been linked to memory and attention, alpha rhythms are associated with sensory inhibition and attention regulation, while beta oscillations are indicative of cognitive control and motor planning. The proposed ratios aim to capture the nuanced interplay between these frequency bands during attention-demanding tasks.[6]

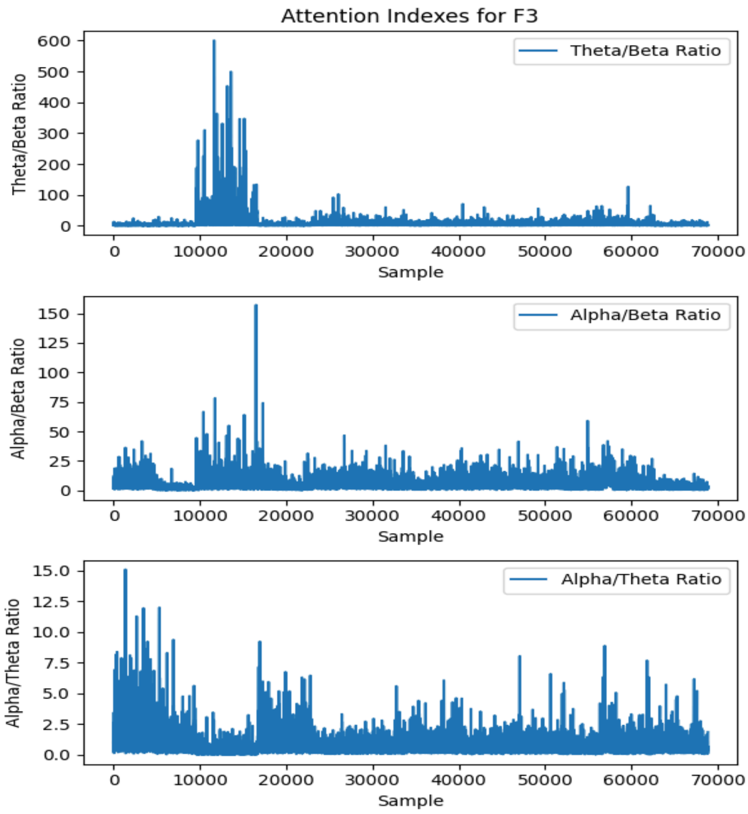

Fig 3. Attention indexes for F3

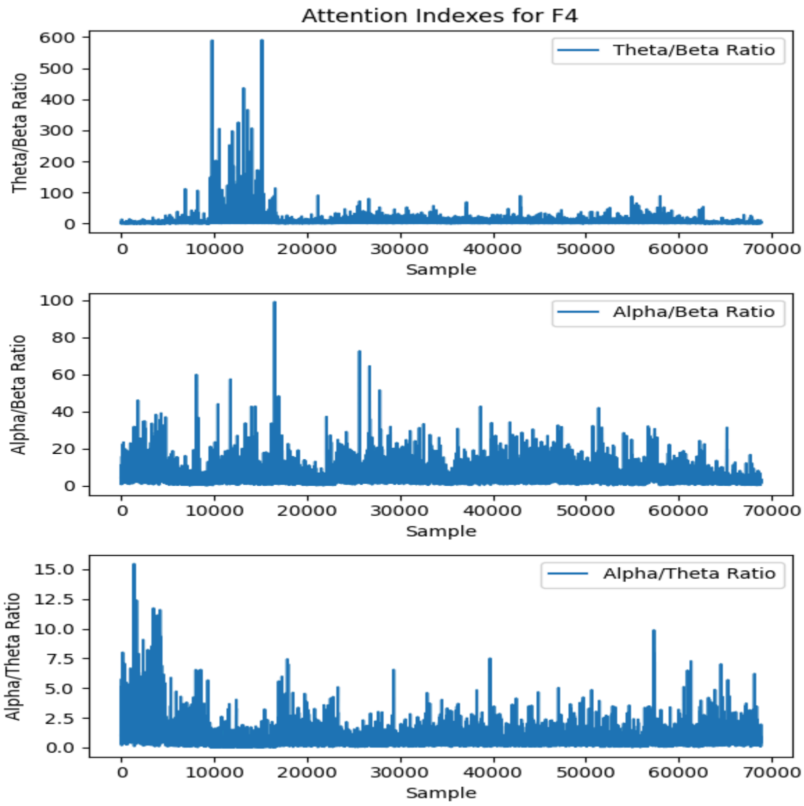

Fig. 4. Attention indexes for F4

As shown in Figure 3 and Figure 4, the attention indexes derived from the F3 and F4 electrodes hold potential applications in diverse domains, including education, clinical psychology, and neurofeedback interventions. These measures may serve as objective indicators of attentional states, facilitating tailored interventions and personalised cognitive training programs. The theta/beta ratio, alpha/beta ratio, and alpha/theta ratio are key metrics in EEG analysis, offering insights into different aspects of brain activity. The theta/beta ratio assesses attention and cognitive processing, with higher ratios indicating potential difficulties in focus and impulse control. Meanwhile, the alpha/beta ratio reflects the balance between relaxation and alertness, with higher ratios suggesting a more relaxed mental state. Lastly, the alpha/theta ratio signifies the balance between wakefulness and drowsiness, where an increased ratio indicates heightened alertness, while a decreased ratio may suggest a more relaxed or drowsy state. These ratios serve as valuable tools in understanding cognitive states, monitoring mental performance, and investigating neurological conditions. The findings pave the way for future investigations, including the validation of thresholds, machine learning applications, and the translation of research outcomes into practical tools for attention assessment and intervention.[6]

These measures may serve as objective indicators of attentional states, facilitating personalised cognitive interventions and contributing to the development of cognitive training programs.

3.4 System Design

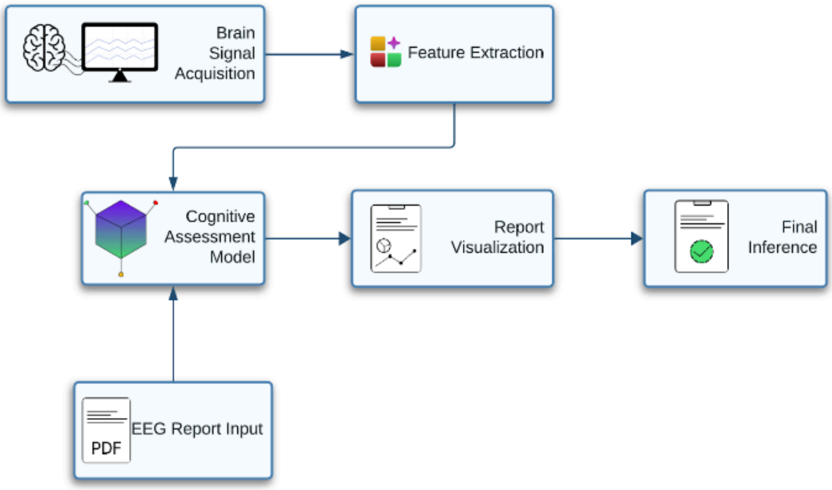

Fig. 5. Block Diagram of the System

In developing a Brain-Computer Interface (BCI) system according to Figure 5 for cognitive function evaluation, several crucial steps are undertaken. Firstly, the dataset is split into training and testing sets to assess model performance accurately. Next, relevant features are extracted from preprocessed EEG data, such as calculating the theta/beta ratio for F3 and F4 sensors, known to influence attention span. Subsequently, optimization techniques are applied to select the most informative features for input into the BCI model. For the BCI model development, a suitable machine learning algorithm, like random forests or deep learning models, is chosen, and the model is trained using the preprocessed EEG data and extracted features. To evaluate the BCI model's performance, appropriate metrics such as accuracy, precision, recall, and F1-score are defined, focusing on cognitive function assessment. A user-friendly interface is then designed to enable easy interaction with the BCI system. Ethical considerations regarding data privacy, informed consent, and responsible EEG data usage are addressed throughout the development process. Finally, once validated and meeting desired performance levels, the BCI system is deployed for actual cognitive function evaluation, with regular updates and maintenance to ensure continued accuracy and reliability over time. This comprehensive approach ensures the effective development, evaluation, and deployment of the BCI system while upholding ethical standards and user-centric design principles.

4 Result Analysis

4.1 Selecting the index ratio

Theta and beta oscillations are recognized as key components in the neural correlates of attention. Theta activity, associated with memory and cognitive control, often increases during periods of heightened attention. In contrast, beta activity, linked to motor planning and execution, tends to decrease during attentive states. The theta/beta ratio is hypothesised to capture the balance between these oscillatory patterns, reflecting the dynamic interplay of neural processes underlying attention. Theta waves, known for their association with cognitive processes such as memory and attention, exhibit regional variability that can provide valuable insights into neural dynamics. The study employs a dataset to investigate the distribution and intensity of theta wave activity across the F3 and F4 electrodes. Our findings reveal elevated power spectral density in theta waves specifically in the F3 and F4 regions, suggesting localised neural processes. The heightened activity in these frontal areas suggests localised neural processing associated with cognitive functions linked to theta oscillations. This finding aligns with existing literature on the frontal theta rhythm's involvement in memory retrieval, attention regulation, and executive functions.[6]

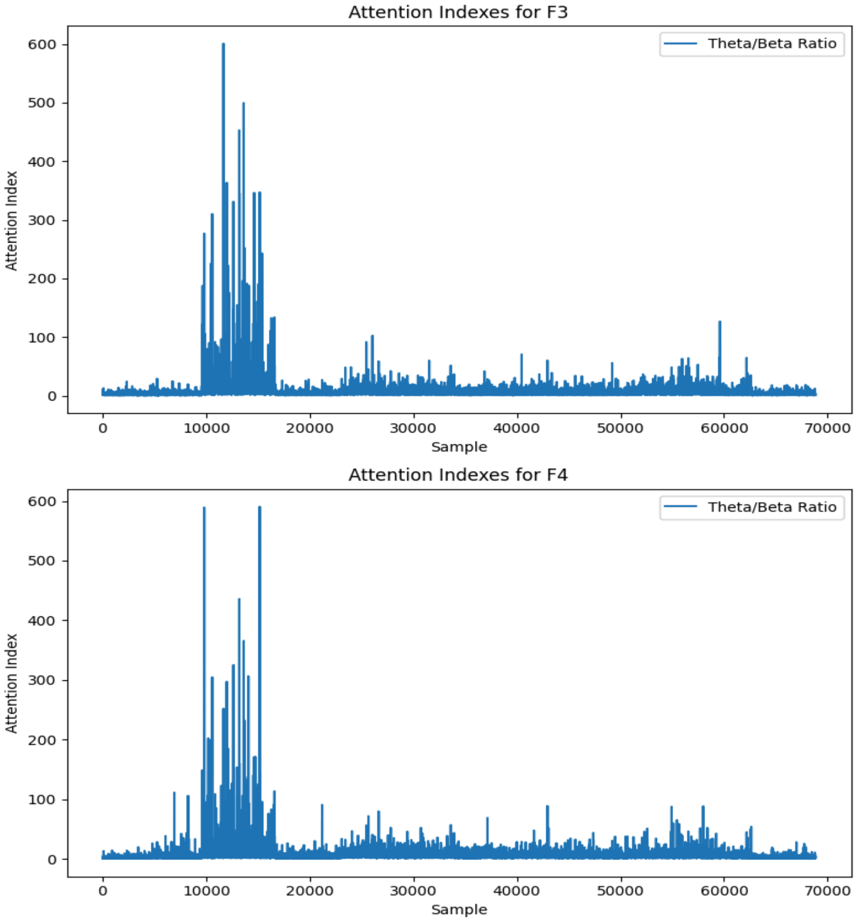

Fig. 6. Attention indexes for F3 and F4

Theta and beta oscillations at F3 and F4 electrodes as shown in Figure 6, are associated with cognitive functions, including attention and working memory. Integrating information from both electrodes provides a more holistic representation of the underlying neural dynamics, considering potential asymmetries or variations in attention-related processes between the left and right frontal regions [6].
An innovative approach to attention estimation in EEG by integrating F3 and F4 theta/beta ratios. The findings suggest that this integrated methodology enhances the accuracy and granularity of attention span categorization. By combining information from both frontal electrodes, the study contributes to a deeper understanding of attention-related neural dynamics and holds promise for applications in cognitive neuroscience, human-computer interaction, and clinical diagnostics [6].

4.2 Classifiers

The methodology employed in this study involves the extraction and analysis of EEG features for the prediction of attention indexes using 4 different classification algorithms. EEG data is obtained from electrodes F3 and F4, focusing on the power spectral density (PSD) ratios of Theta and Beta frequencies. The selected features include 'POW.F3.Theta', 'POW.F3.BetaL', 'POW.F4.Theta', and 'POW.F4.BetaL'. To ensure robust model training and evaluation, the dataset is split into training (80%) and testing (20%) sets, with a fixed random seed (42) to ensure reproducibility.
1. Random Forest Classifier is chosen for its ensemble learning capabilities, which make it well-suited for capturing complex relationships within the data.[23]
2. Gradient boosting is a powerful machine learning technique that builds a robust predictive model by sequentially adding weak learners, such as decision trees, and optimising them to minimise the loss function. It combines the predictions of several weak learners into one strong learner.[24]
3. K-nearest neighbours (KNN) is a simple yet effective supervised learning algorithm used for classification and regression tasks. It works by finding the K closest training examples in the feature space to a given query point and making predictions based on the labels or values of those neighbours.[25]
4. A Decision tree is a supervised learning algorithm used for classification and regression tasks in machine learning. It partitions the data into subsets based on feature values, aiming to create a tree-like structure where each internal node represents a "decision" based on a feature, leading to subsequent nodes or leaves representing the outcome.[26]
The model is trained on the training set, learning the associations between the selected features and attention spans. Subsequently, the trained model predicts attention spans for the test set, and its performance is assessed using accuracy metrics and a detailed classification report, including precision, recall, and F1-score. This comprehensive methodology aims to investigate the efficacy of ML algorithms in predicting attention indexes from EEG features, providing valuable insights into the potential applications of machine learning in the realm of cognitive

neuroscience and attention assessment.

4.3 Achieving Classification

To achieve the classification process based on EEG-derived attention indexes, it is essential to map these indexes to discrete categories such as "High attention," "Moderate attention," and "Low attention" using predefined thresholds or criteria. This mapping process involves calculating attention index ratios, which are indicative of different brain activity patterns related to attention levels, such as the Theta/Beta ratio or Alpha/Theta ratio. These ratios provide insights into the relative dominance of specific frequency bands in EEG signals, reflecting variations in attention states. By defining thresholds or criteria for each ratio, we can effectively categorize attention levels. For instance, a Theta/Beta ratio less than 2 may signify "High attention," while a ratio greater than 4 may indicate "Low attention." Implementing a mapping function based on these thresholds allows us to assign attention-level labels to each EEG sample in the dataset. Subsequently, with labelled data, we can train supervised machine learning models, using EEG features as inputs and assigned attention level labels as targets. Through iterative refinement and model evaluation, we can develop robust classification models capable of automatically categorizing attention levels based on EEG signals, facilitating insights into cognitive states and attention dynamics.[6][7]

4.4 Evaluation Metrics

Our study investigates the predictive capabilities of four distinct machine learning algorithms—Random Forest, Gradient Boosting, K-Nearest Neighbors (KNN), and Decision Tree—in estimating attention spans based on electroencephalography (EEG) data. The study employs Random Forest, Gradient Boosting, KNN, and Decision Tree classifiers. Remarkably, all four algorithms exhibit accuracy rates exceeding 95%, highlighting their efficacy in capturing attentional states.

Table 2. Accuracy Of The Algorithms

Algorithms	**Accuracy**
Random Forest	0.97159
Gradient Boosting	0.95685
KNN	0.95845
Decision Tree	0.93825

The consistent accuracy rates exceeding 95% across all algorithms underscore their effectiveness in predicting attention spans from EEG data. The findings advocate for the diverse applicability of these models in understanding cognitive processes, paving the way for practical implementations in fields requiring accurate attention span estimation. Future research may explore model interpretability, generalisation across diverse populations, and real-time applications for enhanced cognitive assessments.

Table 3. Evaluation Metrics of the Algorithms

Algorithm	**Class**	**Precision**	**Recall**	**F1-Score**
Random Forest Classifier	**High Attention**	0.98	0.95	0.96
	Low Attention	0.95	0.99	0.96
	Moderate Attention	0.99	0.99	0.99
Gradient Boosting	**High Attention**	0.98	0.89	0.93
	Low Attention	0.98	0.98	0.98
	Moderate	0.91	0.95	0.93

	Attention			
KNN	**High Attention**	0.96	0.95	0.96
	Low Attention	0.98	0.97	0.97
	Moderate Attention	0.92	0.94	0.93
Decision Tree	**High Attention**	0.93	0.92	0.93
	Low Attention	0.97	0.96	0.97
	Moderate Attention	0.89	0.90	0.90

Precision: It is determined by dividing the total number of accurate positive predictions made by the model by the ratio of true positive forecasts.

Recall: It quantifies the percentage of real positives that the model successfully classified, or the model's capacity to locate all pertinent cases. The ratio of genuine positive forecasts to the total number of real positive occurrences is used to compute it.

F1 Score: Precision and recall's harmonic mean is the F1 score. It offers a single statistic that strikes a balance between recall and precision. When the number of good and negative incidents is unbalanced, the F1 score becomes especially valuable.

4.5 Selection of Algorithm

Random Forest is a highly advantageous algorithm for predictive modelling tasks, particularly in classification scenarios. Its foremost strength lies in its ability to deliver consistently high accuracy across various datasets. By aggregating multiple decision trees trained on random subsets of both data and features, Random Forest effectively mitigates overfitting and generalizes well to unseen data. The algorithm's capability to provide feature importance scores aids in identifying significant predictors, facilitating a better understanding of the data's underlying relationships. Random Forest exhibits robustness to noise and outliers, thanks to its ensemble nature, ensuring reliable performance even in challenging datasets. Furthermore, its parallelization capability enables efficient training on large datasets, leveraging multiple CPU cores for accelerated processing. Compared to other algorithms, Random Forest demonstrates less sensitivity to hyperparameters, making it easier to tune and less prone to overfitting due to hyperparameter choices. Overall, Random Forest stands out as a powerful, robust, and versatile algorithm, making it a preferred choice for achieving high accuracy and reliability in classification tasks.

$$\hat{Y} = \text{argmax}_j + \sum_{i=1}^{k} I(Y_i = j) \tag{1}$$

where Ŷ is the predicted class,
Y_i is the predicted class from the ith decision tree,
k is the total number of decision trees in the forest,
I is the indicator function which returns 1 if the condition inside is true and 0 otherwise,
j iterates over all possible classes.

4.6 Partition of data

The predictive model demonstrates consistent and reliable performance across diverse subsets of the dataset. The cross-validation scores obtained from each of the 10 folds consistently indicate strong predictive ability, with accuracy scores ranging from approximately 87.72% to 97.43%. This consistent performance across multiple folds suggests that the model's effectiveness is not heavily reliant on the specific partitioning of the data. Moreover, the mean cross-validation accuracy, computed as approximately 93.97%, provides a robust estimate of the model's overall performance. These findings instil confidence in the reliability of the model's predictive capabilities and its ability to generalize well to unseen data. The consistent performance across folds underscores the suitability of the model for the research study's objectives and emphasizes its potential for reliable predictions in practical applications.

4.7 Discussions

Efficiency:

Optimizing the efficiency of Random Forest (RF) models, acknowledging the computational demands associated with hyperparameter tuning and model training. To address this, our methodology incorporates downsampling techniques, which involve reducing the size of the dataset while preserving its representativeness. By downsampling the data, the computational overhead is mitigated, enabling faster experimentation without compromising the integrity of the model. This approach not only accelerates the optimization process but also ensures that computational resources are utilized more efficiently, contributing to overall model efficiency.

Performance:

Improving the performance of Random Forest (RF) models is a central objective of our study. Leveraging Bayesian optimization, our methodology navigates the hyperparameter space with precision, guiding the search for optimal configurations that yield superior predictive performance. By iteratively refining model configurations based on past evaluations, Bayesian optimization streamlines the optimization process and facilitates the identification of hyperparameters that enhance model performance. Through extensive experimentation, our approach demonstrates significant improvements in model performance, as evidenced by better predictive accuracy across diverse datasets.

Accuracy:

Enhancing the accuracy of Random Forest (RF) models is a critical aspect of our study endeavour. Bayesian optimization, integrated into our methodology, plays a pivotal role in achieving this objective. By leveraging probabilistic models and past evaluations, Bayesian optimization efficiently explores the hyperparameter space, identifying configurations that maximize predictive accuracy. This iterative approach not only streamlines the hyperparameter tuning process but also ensures that RF models are fine-tuned to deliver optimal accuracy on unseen data. Through rigorous experimentation, our approach showcases remarkable improvements in model accuracy, underscoring its efficacy in real-world applications.

5 Conclusion

In conclusion, the utilization of EEG data for the quantification of cognitive function and the development of a Brain-Computer Interface system for cognitive evaluation. The findings suggest that EEG signals can be employed to monitor attention, memory, and other cognitive processes. This information has potential applications across various fields, including education, clinical psychology, and human-computer interaction. The outcomes of this study are encouraging and indicate that EEG-based BCI systems could serve as a valuable tool for assessing and enhancing cognitive function. Future research on EEG-based BCI systems includes the development of BCI systems capable of measuring a broader spectrum of cognitive functions., more user-friendly and accessible, for rehabilitation purposes. Exploration of the use of BCI systems in other fields, such as healthcare, military, and sports. The potential applications of EEG-based BCI systems are vast, and the field is still in its early stages of development. With continued research, these systems could have a significant impact on our understanding of the brain and our ability to enhance human cognition.

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b. Certificate of publication

INTERNATIONAL CONFERENCE ON
INNOVATIONS AND ADVANCES IN COGNITIVE SYSTEMS
ICIACS 2024
27-28, May 2024 | Kangayam, India
https://iciacs.com/
iciacshelpdesk@gmail.com

Letter of Acceptance

Details of accepted manuscript:

Paper ID	*Paper Title*	*Author(s)*
ICIACS-046	**Cognitive assessment using EEG data: developing a brain-computer interface for cognitive function evaluation**	**Siddhant Kodolkar, Sahil Madhyan,Harsh Karira, Indu Dokare**

Dear Authors,
Hearty Congratulations!

We are pleased to inform you that your peer-reviewed and refereed full paper entitled "Cognitive assessment using EEG data: developing a brain-computer interface for cognitive function evaluation" has been accepted for presentation at the International Conference on Innovations and Advances in Cognitive Systems [ICIACS 2024]. The conference will be held at Builders Engineering College Kangeyam, Tamil Nadu, India, from 27-28, May 2024.

c. Plagiarism report

Cognitive assessment using EEG data: developing a brain-computer interface for cognitive function evaluation

ORIGINALITY REPORT

21%	20%	22%	15%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

d. Project review sheet

i. Review 1 (10th February, 2024)

Inhouse (R) (25)

Group No: 25

Project Evaluation Sheet 2023 - 24

Title of Project: Cognitive Assessment Using EEG Data: Developing a brain-computer interface for cognitive function evaluation

Group Members: Sachin Choudhary (15), Harsh Karira (24), Siddhant Kodolkar (28), Sahil Madhyan (33)

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environment Friendly (2)	Ethics (2)	Team work (2)	Presentation Skills (2)	Applied Engg&Mgmt principles (3)	Life-long learning (3)	Professional Skills (3)	Innovative Approach (3)	Research Paper (5)	Total Marks (50)
4	4	4	2	4	2	2	2	2	2	2	2	2	3	2	39

Comments: Work on next cognitive ability analysis.

Name & Signature Reviewer1

Inhouse/ Industry _Innovation/Research:

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environment Friendly (2)	Ethics (2)	Team work (2)	Presentation Skills (2)	Applied Engg&Mgmt principles (3)	Life-long learning (3)	Professional Skills (3)	Innovative Approach (3)	Research Paper (5)	Total Marks (50)
4	4	4	2	4	2	2	2	2	2	2	2	2	3	4	41

Comments:

Date: 10th february, 2024

Name & Signature Reviewer 2

ii. Review 2 (9th March, 2024)

Inhouse/ Industry _Innovation/Research: Inhouse

Class: D17 A/B/C

Sustainable Goal: Good Health & Well-Being

Project Evaluation Sheet 2023 - 24

Group No.: 25

Title of Project: Cognitive Assessment using EEG Data: Developing a Brain-Computer interface for cognitive Function Evaluation

Group Members: Sachin Choudhary (15), Harsh Karira (24), Siddhant Kodolkar (28), Sahil Madhyan (33)

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environment Friendly (2)	Ethics (2)	Team work (2)	Presentation Skills (2)	Applied Engg&Mgmt principles (3)	Life-long learning (3)	Professional Skills (3)	Innovative Approach (3)	Research Paper (5)	Total Marks (50)
4	4	4	3	4	2	2	2	2	2	3	3	3	3	3	44

Comments:

Name & Signature Reviewer1

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environment Friendly (2)	Ethics (2)	Team work (2)	Presentation Skills (2)	Applied Engg&Mgmt principles (3)	Life-long learning (3)	Professional Skills (3)	Innovative Approach (3)	Research Paper (5)	Total Marks (50)
4	4	4	3	4	2	2	2	2	2	3	3	3	3	3	43

Comments:

Date: 9th March, 2024

Name & Signature Reviewer 2