A
Major Project Report

On

"Neurofeedback Meditation Web Application"

Submitted in partial fulfillment of the

Requirements for the award of the degree of

Bachelor of Technology

In

Computer Science & Engineering –

Artificial Intelligence & Machine Learning

By

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2024

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CERTIFICATE

This is to certify that the project entitled **"Neurofeedback Meditation App"** has been submitted by **Mettu Nagasridivya (20R21A6636), Nagella Samhitha (20R21A6642), Lohitha Rasakonda (20R21A6646), T Lalith Reddy (20R21A6649)** in partial fulfilment of the requirements for the award of degree of Bachelor of Technology in Computer Science & Engineering – Artificial Intelligence & Machine Learning from Jawaharlal Nehru Technological University, Hyderabad. The results embodied in this project have not been submitted to any other University or Institution for the award of any degree or diploma.

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DECLARATION

We hereby declare that the project entitled **"Neurofeedback Meditation Web Application"** is the work done during the period from **January 2024 to May 2024** and is submitted in partial fulfilment of the requirements for the award of degree of Bachelor of Technology in Computer Science & Engineering – Artificial Intelligence & Machine Learning from Jawaharlal Nehru Technology University, Hyderabad. The results embodied in this project have not been submitted to any other university or Institution for the award of any degree or diploma.

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ACKNOWLEDGEMENT

The satisfaction and euphoria that accompany the successful completion of any task would be incomplete without the mention of people who made it possible, whose constant guidance and encouragement crowned our efforts with success. It is a pleasant aspect that we now have the opportunity to express our guidance for all of them.

First of all, we would like to express our deep gratitude towards our internal guide **Mr. Gouse Pasha** Associate Professor, Dept. of CSE-AIML for his support in the completion of our dissertation. We wish to express our sincere thanks to **Dr. K. SAI PRASAD,** HOD, Dept. of CSE-AIML and principal **Dr. K. SRINIVAS RAO** for providing the facilities to complete the dissertation.

We would like to thank all our faculty and friends for their help and constructive criticism during the project period. Finally, we are very much indebted to our parents for their moral support and encouragement to achieve goals.

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ABSTRACT

In the technology-driven world of today combining the latest data science with mental health care has emerged as a strategic intersectional area in facing the great diversities which affect our mental well-being. This paper introduces about a breakthrough application called NeuroFeedback Meditation Web App, which makes use of the features of Machine Learning and Neurofeedback techniques to ensure a state-of-the-art mental health management. The former web application applies the data of Electroencephalography (EEG) and MLP (Multi-Layer Perceptron) model that has been pre trained to identify specific mental health disorders. Via an indicative interface, users can place input EEG data and have personalized recommendations for meditation, yoga sessions, and audio yoga selective to their individual need. This notably, holistic nature of the mental health management indeed bears marks of a significant advancement in the proactive approach of mental health, and confers users with the tools that are not only accessible, but that aid in fostering well-being in their daily lives as well. In addition to its cutting-edge features, the NeuroFeedback Meditation Web App empowers users with actionable insights, fostering holistic well-being through accessible tools and personalized interventions tailored to individual needs.

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LIST OF ABBREVIATIONS

ABBREVIATIONS

EEG	**Electroencephalogram**
MLP	**Multilayer Perceptron**
SVM	**Support Vector Machine**
ROC	**Receiver Operating Characteristic**

APPENDIX-4

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CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

The NeuroFeedback Meditation Web App represents a groundbreaking fusion of advanced data science methodologies and mental health care strategies. Through the innovative integration of machine learning algorithms and neurofeedback techniques, this application offers a sophisticated approach to managing mental well-being. Users are encouraged to input Electroencephalography (EEG) data, which captures intricate brainwave activity across various frequency bands such as alpha, beta, delta, theta, high beta, and gamma waves. This data undergoes rigorous analysis by a pre-trained Multi-Layer Perceptron (MLP) model, specifically designed to discern patterns indicative of specific mental health disorders. Upon processing the input EEG data, the app provides users with personalized recommendations tailored to their unique requirements. These recommendations encompass various meditation and yoga sessions, meticulously selected based on the individual's mental health profile. Furthermore, the app offers audio guidance during meditation sessions, delivering soothing sounds tailored to address different mental health disorders. Additionally, users benefit from visual feedback on their EEG data, presented through intuitive graphs and visualizations. This feature enables users to track their meditation progress over time, fostering self-awareness and facilitating a deeper understanding of their mental state. In summary, the NeuroFeedback Meditation Web App revolutionizes mental health management by combining state-of-the-art technology with user-centric features. Its holistic approach empowers individuals to proactively engage in self-care and cultivate well-being in their daily lives.

1.2 PURPOSE OF THE PROJECT

The NeuroFeedback Meditation Web App represents a pioneering initiative at the intersection of technology and mental health care, aiming to revolutionize the way individuals manage their well-being. By integrating cutting-edge data science techniques with neurofeedback methodologies, the app provides users with personalized recommendations tailored to their unique mental health needs. Through the analysis of EEG data, the app offers tailored meditation and yoga programs, supplemented by audio guidance designed to promote relaxation and alleviate symptoms of various mental health disorders. With its proactive approach to mental health management, the app empowers individuals to take charge of their well-being, fostering a culture of self-care and mindfulness in today's technology-driven world.

1.3 MOTIVATION

The motivation behind the NeuroFeedback Meditation Web App stems from the pressing need to address mental health challenges in today's fast-paced and stress-filled world. With mental health issues on the rise, there is a growing recognition of the importance of proactive and accessible solutions to support well-being. Traditional methods of mental health care often face barriers such as limited accessibility, stigma, and high costs. This project seeks to bridge these gaps by leveraging advancements in technology, particularly in data science and neurofeedback techniques. By harnessing the power of EEG data analysis and machine learning, the app aims to democratize mental health care, offering personalized support and resources to individuals regardless of their location or socioeconomic status. Ultimately, the motivation is to empower individuals to take control of their mental health, promoting a culture of self-awareness, resilience, and holistic well-being.

CHAPTER 2

LITERATURE SURVEY

An extensive literature survey has been conducted by studying existing systems of Certificate verification and generation. A good number of research papers, journals, and publications have also been referred before formulating this survey.

2.1 EXISTING SYSTEM

The existing system utilizes the computational EEG based technology and integrates brain scan data with machine learning algorithms by which it provides a dependant tool through which the user can use and find out the mental state. They were many kind of approaches which were applied in different ways. Collected various papers related to the neurofeedback meditation application and done the literature survey of them.

The responses to various research articles are documented below by the order of the number that have been used to specify them in the references in the end.

1		
Reference in APA format	H. Alawieh, Z. Dawy, E. Yaacoub, N. Abbas and J. El-Imad, "A Real-Time ECG Feature Extraction Algorithm for Detecting Meditation Levels within a General Measurement Setup," 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Berlin, Germany, 2019, pp. 99-103, doi: 10.1109/EMBC.2019.8857832.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://sci-hub.se/10.1109/EMBC.2019.8857832	H. Alawieh, Z. Dawy, E. Yaacoub, N. Abbas and J. El-Imad.	Electroencephalography (EEG), Electrocardiogram (ECG), Real-time Feature extraction, Meditation levels

The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?
The paper presents an experimental setup for real-time EEG and ECG feature extraction to detect meditation levels, along with an algorithm for real-time meditation detection, without specifying a specific name for the solution.	Aim is to create a setup for real-time detection of meditation levels using EEG and ECG features, potentially for use in virtual reality-based training. The problem need to solved is Develop a method to assess and quantify meditation levels in real-time using physiological signals, contributing to applications in virtual reality-based training and cognitive enhancement.	The components include wearable sensors for EEG and ECG data acquisition, feature extraction algorithms, and a virtual reality system feedback controller for real-time monitoring and optimization of relaxation and meditation experiences.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)
1	The method identifies two clusters: a target cluster representing desired brain signal features and a preliminary cluster representing subjects' brain activities before training.	Real-time monitoring enables immediate feedback.	Lack of specific details on the algorithm used for feature extraction.
2	Feature Extraction and and ECG Feature	Integration with virtual reality enhances the immersive nature of meditation training.	Subjectivity and individual variations in meditation experiences may not be fully accounted for.
3	Setting adaptive thresholds using statistical measures and dynamically estimating relaxation levels improve accuracy.		
4	Feedback Control in VR System		

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The paper doesn't explicitly mention a dependent variable. However, based on the context of the research, the dependent variable could be the "level of relaxation	1. Physiological signals (EEG and ECG) recorded during both meditation and non-meditation states. 2.Feature values extracted from EEG and ECG signals.	Physiological signals during meditation influence relaxation levels, moderated by individuals' predisposition to meditation practices.	Level of relaxation during meditation mediates the impact of physiological signals on the individual's mental state.

Relationship Among the Above 4 Variables in This article
The physiological signals (independent variables), comprising EEG and ECG, influence the algorithmically derived "level of relaxation" during meditation (mediating variable). The estimated "level of relaxation" is the ultimate impact on the individual's mental state (dependent variable). The relationship between physiological signals and the perceived relaxation is potentially influenced by an individual's prior experience or inclination toward meditation practices, serving as a moderating variable. This intricate interplay of variables forms the basis for understanding the dynamics of relaxation during meditation in the proposed research.

Input and Output	Feature of This Solution	Contribution & The Value of This Work

<table>
<tr>
<td>
<table>
<tr><th>Input</th><th>Output</th></tr>
<tr><td>Physiological signals, specifically Electroencephalography (EEG) and Electrocardiogram (ECG) data.</td><td>Real-time estimation of an individual's relaxation state based on the analysis of EEG and ECG signals.</td></tr>
</table>
</td>
<td>The key feature of this solution is the real-time extraction of features from Electroencephalography (EEG) and Electrocardiogram (ECG) signals to indicate the level of focus, relaxation, or meditation of an individual during a given session. These features, such as the ratio of low-frequency band power to middle-frequency band power, serve as quantitative indicators of the individual's mental state. The solution also incorporates wearable sensors for data acquisition and employs virtual reality (VR) and augmented reality (AR) technologies for providing feedback and training in conjunction with neurofeedback signals.</td>
<td>This work offers a real-time EEG and ECG feature extraction setup to assess meditation levels. The proposed algorithm, tested on an ECG dataset, provides accurate results. The research's significance lies in its potential for investigating VR/AR-based EEG training effects on focus, relaxation, and meditation, with applications in enhancing cognitive skills. The non-invasive techniques proposed can be integrated into commercial VR-EEG headsets, widening their usability and impact.</td>
</tr>
</table>

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
This solution revolutionizes cognitive state measurement during meditation by integrating real-time EEG and ECG features with VR/AR and neurofeedback. Its non-invasive, commercial VR-EEG compatibility makes it widely applicable, advancing research in neuroscience, technology, and meditation.	Possible negative impacts include ethical concerns about data privacy, dependency on technology for meditation, and potential psychological stress from constant monitoring. Balancing technological integration with preserving traditional practices is essential to mitigate unintended consequences.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
This work exhibits innovation in integrating EEG, ECG, and VR/AR for meditation assessment, yet it necessitates careful consideration of ethical concerns, potential user dependency, and a more comprehensive exploration of contextual factors.	EEG and ECG measurement devices, virtual reality headsets, neurofeedback systems.	Abstract I. Introduction II. Experimental framework for detecting meditation levels. III. Feature Extraction IV. Results and discussion. V. Conclusion and future work.

Diagram/Flowchart

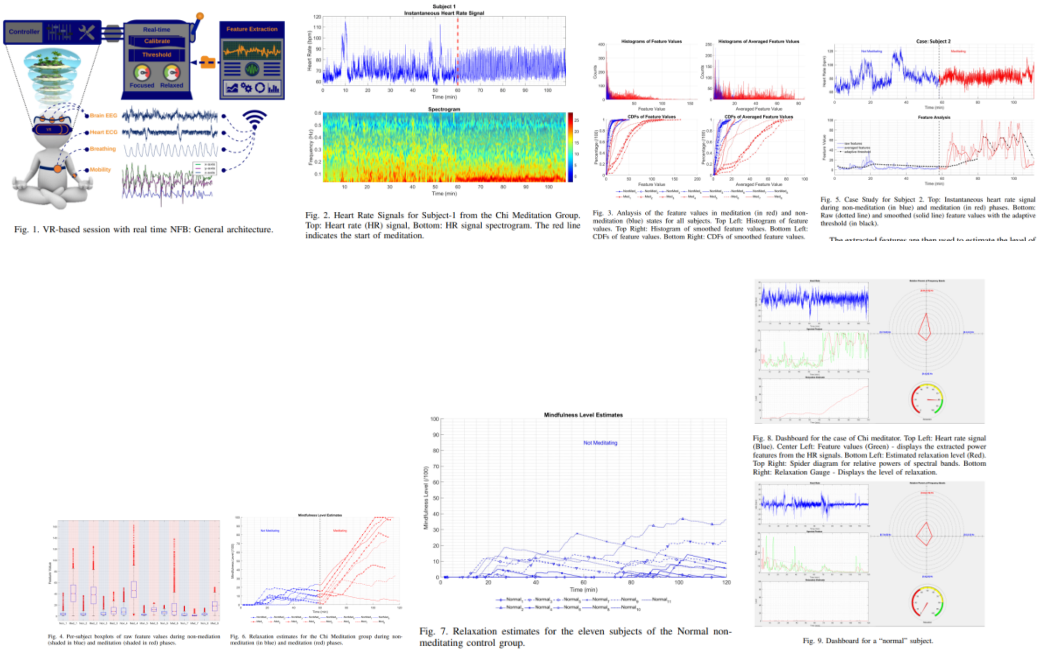


Fig. 1. VR-based session with real time NFB: General architecture.

Fig. 2. Heart Rate Signals for Subject-1 from the Chi Meditation Group. Top: Heart rate (HR) signal, Bottom: HR signal spectrogram. The red line indicates the start of meditation.

Fig. 7. Relaxation estimates for the eleven subjects of the Normal non-meditating control group.

Fig. 9. Dashboard for a "normal" subject.

---End of Paper 1—

2		
Reference in APA format	P. Pandey, J. Rodriguez-Larios, K. P. Miyapuram and D. Lomas, "Detecting moments of distraction during meditation practice based on changes in the EEG signal," 2023 IEEE Applied Sensing Conference (APSCON), Bengaluru, India, 2023, pp. 1-3, doi: 10.1109/APSCON56343.2023.10101045	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://www.researchgate.net/profile/Derek-Lomas-3/publication/365631718_Detecting_moments_of_distraction_during_meditation_practice_based_on_changes_in_the_EEG_signal/links/6384bf0e554def61937e75f5/Detecting-moments-of-distraction-during-meditation-practice-based-on-changes-in-the-EEG-signal.pdf	Pankaj Pandey, Julio Rodriguez Larios, Krishna Prasad Miyapuram, Derek Lomas	EEG, Machine Learning, Neurofeedback, Linear and Non-linear EEG Features, Classification, t-Distributed Stochastic Neighbor Embedding (t-SNE).
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that needs to be solved**	**What are the components of it?**

Machine learning models	The goal is to use machine learning to detect distraction during meditation practice by analyzing EEG signals. The problem is helping novice meditators identify moments of distraction, such as mind wandering or drowsiness, during their practice.	The components of the solution include EEG data collection, feature extraction, machine learning models (supervised and unsupervised), data segregation, and result analysis for detecting moments of distraction during meditation.
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation
1	Data Collection involves gathering EEG data from participants practicing breath-focused meditation. This data is collected using 19 scalp sensors to record neural activity.	The use of EEG data and machine learning allows for real-time detection of moments of distraction during meditation practice. This can provide immediate feedback to meditators, helping them stay focused.	The research focuses o breath focus meditation The effectiveness of th models for other meditatio techniques or practices i not explored, limiting th broader applicability of th findings.
2	Feature Extraction	The process provides an objective assessment of a meditator's mental state, which can be valuable for both beginners and experienced practitioners.	EEG signals can b sensitive to artifacts an signal quality issues.
3	Ten machine learning models classify EEG data into states		
4	t-Distributed Stochastic Neighbor Embedding (t-SNE) is used to visualize the EEG data in lower dimensions.		

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
1.Classifications,2.Performance Metrics, 3.Accuracy of Classifiers	1.Meditation States because it represents different conditions impacting performance, 2.EEG Features as it involves various factors affecting the outcome (exam scores).	There is a strong relationship between different meditation states (Meditation States - Independent Variable) and the accuracy of distraction detection (Classifications - Dependent Variable). Only those participants who have significant meditation experience and a deep understanding of meditation practices may show improved accuracy in distraction detection, which moderates the strength of the association between different meditation states and distraction detection accuracy.	The relationship between different meditation states and distraction detection accuracy may be mediated by the level of mindfulness achieved during meditation. Experiencing different meditation states directly influences distraction detection accuracy, but the intervening variable of mindfulness level explains the mechanism through which meditation states impact accuracy.

Relationship Among The Above 4 Variables in This article
The relationship involves understanding how different meditation states and EEG features impact the outcomes measured by Classifications, Performance Metrics, and Accuracy of Classifiers. The moderation factor considers participants' meditation experience, while mindfulness level serves as an intervening variable in explaining the mechanism of this impact.

Input and Output	Feature of This Solution	Contribution & The Value of This Work
Input: EEG data **Output:** Distractions in EEG data patterns during different meditation states.	Include linear and non-linear features extracted from the EEG data. These features are used to characterize and analyze the EEG signals for the purpose of classifying different meditation states.	Its innovative approach to using EEG data and machine learning to improve meditation practice, particularly by effectively identifying moments of distraction, which is a common challenge for novice meditators.

Input	Output
EEG data	Distractions in EEG data patterns during different meditation states.

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
This solution improves meditation practice by alerting individuals to distractions, potentially enhancing their experience and well-being	Possible drawbacks include technological distractions.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper

The work is a promising exploration of EEG's role in enhancing meditation, but it requires further research, particularly regarding the practical implementation, ethical considerations, and real-world implications.	EEG, Machine Learning Models, t-SNE (t-Distributed Stochastic Neighbor Embedding), Statistical Analysis.

Diagram/Flowchart

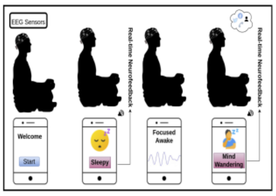
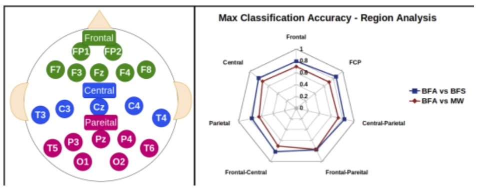


Fig. 1. Exemplary EEG neurofeedback protocol to facilitate meditation practice. A meditation practitioner can be alerted through a sound of moments of distraction during meditation practice based on changes in the EEG signal.



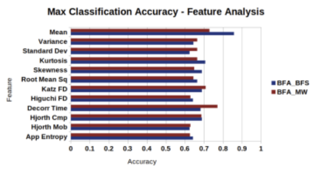


Fig. 3. Max Classification accuracy of each feature is displayed for binary classification.

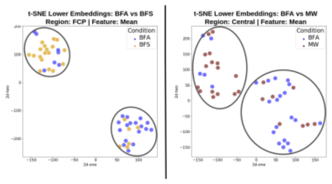


Fig. 4. t-SNE lower dimension visualization of conditions

---End of Paper 2---

3

Reference in APA format	D. Surangsrirat and A. Intarapanich, "Analysis of the meditation brainwave from consumer EEG device," SoutheastCon 2015, Fort Lauderdale, FL, USA, 2015, pp. 1-6, doi: 10.1109/SECON.2015.7133005.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://sci-hub.se/10.1109/SECON.2015.7133005	Decho Surangsrirat, Apichart Intarapanich	Electroencephalography, brainwave, meditation, spectral analysis, consumer EEG device

The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?
Short-time Fourier transform, and spectral analysis.	To explore the feasibility of using a consumer EEG device for recording brainwave activity during meditation and various activities. Problem is the limited accessibility and high cost of traditional EEG devices	Muse (Consumer EEG Device), EEG Data
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	Data collection,	The use of a consumer EEG device makes EEG data collection more affordable and accessible for research.	Consumer EEG devices typically have fewer sensors and may not cover all locations found in traditional EEG systems, potentially leading to less detailed data.
2	Data Analysis	Consumer EEG devices use dry electrodes, making them more user-friendly and less uncomfortable compared to traditional EEG systems.	Consumer EEG devices may have limitations in terms of data quality and accuracy compared to clinical-grade EEG systems.
3	Spectral Analysis	The study demonstrates that consumer-grade EEG devices can be used as research tools.	The study primarily focuses on meditation and may not cover a broad range of potential applications for EEG research.
4	Data collection,	The use of a consumer EEG device makes EEG data collection more affordable and accessible for research.	Consumer EEG devices typically have fewer sensors and may not cover all locations found in traditional EEG systems, potentially leading to less detailed data.

Major Impact Factors in this Work

Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
1.Brainwave Activity, 2.Spectrogram Patterns, 3.Ratio of Brainwaves	Type of activity that impacts and causes variations in brainwave activity	Level of meditation experience. Only those participants who have extensive meditation experience and inclination to engage in focused meditation practices will exhibit distinctive changes in brainwave patterns, moderating the strength of the association between the type of activity and brainwave activity variables.	The relationship between the type of activity (X) and brainwave activity (Y) is mediated by the state of mind during meditation. Engaging in meditation directly influences the state of mind, which, in turn, mediates the observed changes in brainwave patterns.

Relationship Among The Above 4 Variables in This article
The type of activity influences variations in brainwave activity, with this relationship moderated by the level of meditation experience and mediated by the state of mind during meditation.

Input and Output	**Feature of This Solution**	**Contribution & The Value of This Work**

Input	Output
EEG data	Visual representations of brainwave activity

Use of a consumer EEG device (Muse) to provide affordable, non-invasive, and wireless EEG data collection, making it accessible for research and spectral analysis of brainwave activity during various activities.	The work is valuable as it allows for insights into brain activity during different activities, including meditation, which has practical applications in various fields.

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
This solution makes brainwave research more affordable and accessible, benefiting the study of meditation and related activities in the project domain.	The consumer EEG devices may have limitations in data quality and coverage compared to clinical-grade EEG systems, potentially reducing the precision of findings.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
This work presents an exciting opportunity for making EEG research more accessible and cost-effective, especially in the context of meditation studies. However, researchers and readers should critically assess the limitations, potential biases, and the specific focus of the study to draw accurate and meaningful conclusions.	Consumer EEG Device (Muse)	Abstract I. Introduction II. Methods III. Experimental results IV. Conclusion and Discussion

Diagram/Flowchart

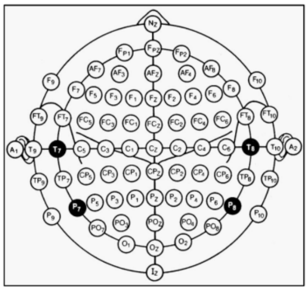


Fig. 1. Location and nomenclature of the 10-10 system as standardized by American Clinical Neurophysiology Society. A = Ear lobe, AF = anterior frontal, C = central, CP = centroparietal, F = frontal, FC = frontocentral, FT = frontotemporal, N = nasion, O = occipital, P = parietal, PO = parieto-occipital, T = temporal [3].

Fig. 2. Muse, a consumer EEG device from InteraXon, Inc. (a) Design of InteraXon Muse. There are total of seven EEG sensors. TP9 (left ear), Fp1 (left forehead), Fp2 (right forehead), and TP10 (right ear) read 4 channels of data. Three sensors on the forehead, Fpz and 2 DRL, are used as the reference. (b) Buddhist monk wore the device during our experiment.

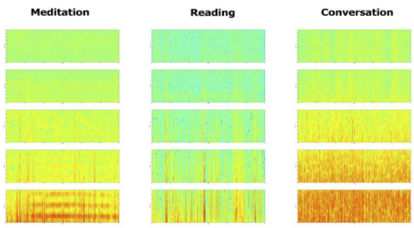


Fig. 3. Segment of spectrogram of the brainwave of experienced meditator I during meditation, reading and conversation. The frequency bands shown here are delta, theta, alpha, beta and gamma, sequentially from bottom to top.

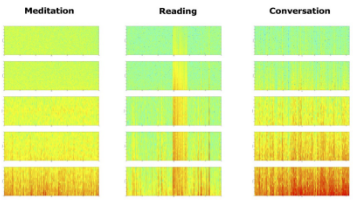


Fig. 4. Segment of spectrogram of the brainwave of experienced meditator II during meditation, reading and conversation. The frequency bands shown here are delta, theta, alpha, beta and gamma, sequentially from bottom to top.

--End of Paper 3—

4		
Reference in APA format	H. Hadavi and N. Sho’ouri, "Soft Boundary-based Neurofeedback Training procedure: A Method to Control EEG Signal Features during Neurofeedback Training Using Fuzzy Similarity Measures," 2019 26th National and 4th International Iranian Conference on Biomedical Engineering (ICBME), Tehran, Iran, 2019, pp. 230-235, doi: 10.1109/ICBME49163.2019.9030420.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://sci-hub.se/10.1109/ICBME49163.2019.9030420	Hedieh Hadavi, Nasrin Sho'ouri	EEG (Electroencephalogram), Neurofeedback, Fuzzy similarity, Scoring index

The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	The Goal (Objective) of this Solution & What is the problem that needs to be solved	What are the components of it?
Soft Boundary-based Neurofeedback Training (SBNFT) method.	Aims to guide subjects in learning how to control specific features of their EEG signals during training while avoiding excessive increases or decreases that may lead to side effects.	Target and preliminary clusters, fuzzy similarity calculation, a threshold, and a variable scoring index.
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	Data collection,	The use of a consumer EEG device makes EEG data collection more affordable and accessible for research.	Consumer EEG devices typically have fewer sensors and may not cover all locations found in traditional EEG systems, potentially leading to less detailed data.
2	Data Analysis	Consumer EEG devices use dry electrodes, making them more user-friendly and less uncomfortable compared to traditional EEG systems.	Consumer EEG devices may have limitations in terms of data quality and accuracy compared to clinical-grade EEG systems.
3	Spectral Analysis	The study demonstrates that consumer-grade EEG devices can be used as research tools.	The study primarily focuses on meditation and may not cover a broad range of potential applications for EEG research.
4	Data collection,	The use of a consumer EEG device makes EEG data collection more affordable and accessible for research.	Consumer EEG devices typically have fewer sensors and may not cover all locations found in traditional EEG systems, potentially leading to less detailed data.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
1. EEG signal features 2. fuzzy similarity measures 3. scores received by the subjects during neurofeedback training	1. Soft Boundary Settings that will impact the range within which subjects' brain signal features should stay. 2. Threshold Values to determine when subjects are rewarded during training. 3. Scoring Index Parameters can impact the number of points awarded to subjects for each success.	Familiarity with neurofeedback moderates the association between the SBNFT method's components and training outcomes.	Subject's Brain Signal Control mediates the relationship between SBNFT method components and training outcomes by reflecting subjects' ability to regulate brain signal features during neurofeedback.

Relationship Among the Above 4 Variables in This article
The SBNFT method is expected to impact training outcomes directly, but the degree of this impact is mediated by how effectively subjects can control their brain signals during neurofeedback training. The relationship among these variables forms the core of the study's exploration into the efficacy and mechanisms of the proposed neurofeedback training method.

Input and Output	Feature of This Solution	Contribution & The Value of This Work

<table>
<tr>
<td colspan="2"><table><tr><th>Input</th><th>Output</th></tr><tr><td>EEG data and Method Parameters</td><td>Training Outcomes.</td></tr></table></td>
<td colspan="2">Offers controlled neurofeedback training, employing fuzzy similarity measures to evaluate subjects' brain activity in relation to a target cluster. It incorporates a dynamic scoring index and aims to prevent excessive changes in brain activity, ultimately enhancing training outcomes and promoting more effective control of brain signals by the subjects.</td>
<td>The SBNFT method brings innovation and potential improvements to the field of neurofeedback training, offering a valuable contribution for researchers and practitioners in the domain of brain signal regulation.</td>
</tr>
<tr>
<th colspan="3">Positive Impact of this Solution in This Project Domain</th>
<th colspan="2">Negative Impact of this Solution in This Project Domain</th>
</tr>
<tr>
<td colspan="3">By enhancing the safety, effectiveness, and user satisfaction in the field of neurofeedback training.</td>
<td colspan="2">The introduction of soft boundaries and adaptive scoring in the SBNFT method may extend training duration, potentially causing subjects to spend more time in training sessions, which could be a negative impact in the project domain.</td>
</tr>
<tr>
<th colspan="2">Analyse This Work By Critical Thinking</th>
<th colspan="2">The Tools That Assessed this Work</th>
<th>What is the Structure of this Paper</th>
</tr>
</table>

The SBNFT method shows promise in addressing challenges in neurofeedback training,ent of adaptability, allowing for personalized training. However, practical implementation may require careful consideration, as it introduces complexity and potentially extends training duration, and user satisfaction needs to be closely monitored to ensure its effectiveness in the real-world project domain.	EEG equipment	Abstract I. Introduction II. Proposed approach III. Results IV. Discussion and Conclusion

Diagram/Flowchart

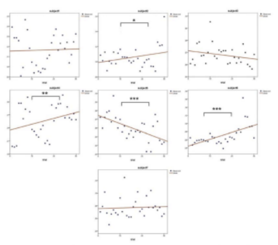


Figure 1. The trends of relative low beta changes for each subject during neurofeedback training (p<0.00: ***, p<0.0: ** ,p<0.05:*).

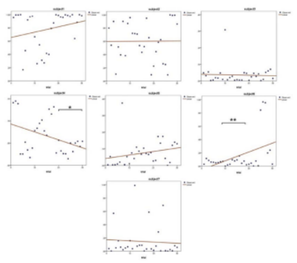


Figure 2. The fuzzy degree of membership of relative low beta power for each subject toward the target cluster center (p<0.00:*** ,p<0.0:** ,p<0.05:*).

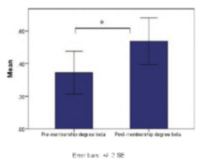


Figure 3. The fuzzy degree of membership values of relative beta power to the target cluster center before and after training (p<0.05:*)

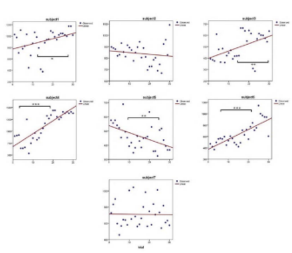


Figure 4. The scores variation trends of each subject for FNFT method (p<0.001:*** ,p<0.01:** ,p<0.05:*).

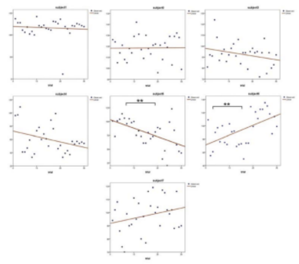


Figure 5. The scores variation trends of each subject for SBNFT method (p<0.001:*** ,p<0.01:** ,p<0.05:*).

---End of Paper 4—

<table>
<tr><td>5</td><td></td><td></td></tr>
<tr><td>Reference in APA format</td><td colspan="2">W. L. Lim, O. Sourina and L. Wang, "MIND - An EEG Neurofeedback Multitasking Game," 2015 International Conference on Cyberworlds (CW), Visby, Sweden, 2015, pp. 169-172, doi: 10.1109/CW.2015.39.</td></tr>
<tr><td>URL of the Reference</td><td>Authors Names and Emails</td><td>Keywords in this Reference</td></tr>
<tr><td>https://personal.ntu.edu.sg/elpwang/PDF_web/07398410.pdf</td><td>Wei Lun Lim, Olga Sourina , Lipo Wang</td><td>EEG, Neurofeedback training, Neurofeedback game, multitasking, game design</td></tr>
<tr><td>The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)</td><td>The Goal (Objective) of this Solution & What is the problem that need to be solved</td><td>What are the components of it?</td></tr>
<tr><td>Multitask In Neurofeedback Driving (MIND).</td><td>To address and enhance the multitasking abilities of individuals, particularly in scenarios relevant to driving or piloting, such as those in the aviation industry.</td><td>A 3D game environment, multiple multitasking tasks, neurofeedback using EEG technology, difficulty levels, a scoring system, various game variants, and a training and testing protocol.</td></tr>
<tr><td colspan="3">The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process</td></tr>
</table>

	Process Steps	Advantage	Disadvantage (Limitation)
1	Create 3D game environment for multitasking simulation, utilizing real-time	EEG data. Provides interactive platform for training multitasking skills.	Requirement of Emotiv EPOC EEG headset may limit accessibility.
2	Adjust game difficulty based on real-time EEG data, implementing scoring system for assessment.	Adaptive training and quantifiable performance assessment.	Learning curve for cognitive tasks may affect training process.
3	Propose multiple game variants for flexibility in testing and training scenarios.	Offers diverse testing and training options for various scenarios.	Development complexity and expertise required for game integration.
4	The game offers various difficulty settings to increase the demands of each task.		
5	Performance in each task is assessed and contributes to an overall multitasking score.		

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Multitasking Performance, Task completion time, Score, Metrics	Difficulty level affects multitasking, neurofeedback presence impacts outcomes, game variant sets engagement	Participants' prior gaming experience moderates the relationship between higher difficulty levels and improved	Neurofeedback-induced cognitive enhancement mediates the relationship between neurofeedback presence and multitasking performance by improving attention,

	conditions, and experimenter controls protocol.	multitasking performance, while neurofeedback responsiveness moderates the association between neurofeedback presence and multitasking performance.	focus, and response time.

Relationship Among The Above 4 Variables in This article
The proposed relationships involve examining how variations in difficulty level and the presence of neurofeedback impact multitasking performance, while considering moderating factors such as prior gaming experience, neurofeedback responsiveness, and age/cognitive ability. Additionally, the mediating variable of neurofeedback-induced cognitive enhancement provides insight into the potential cognitive mechanisms underlying the observed effects on multitasking performance. The overall framework allows for a comprehensive understanding of the proposed training and testing paradigm.

Input and Output	**Feature of This Solution**	**Contribution in This Work**

<table>
<tr>
<td>
<table>
<tr><th>Input</th><th>Output</th></tr>
<tr><td>Participant choices (game variant, difficulty level, presence of neurofeedback) and individual characteristics.</td><td>Performance of the participants in the multitasking game.</td></tr>
</table>
</td>
<td>The solution features a 3D game with neurofeedback to train and test multitasking abilities, addressing a growing interest in improving cognitive skills for tasks like driving and piloting.</td>
<td>The contribution of this work lies in providing a novel 3D game-based approach with neurofeedback to train and test multitasking abilities, potentially offering a valuable tool for enhancing cognitive skills in real-world scenarios like driving and aviation, addressing a significant demand in the industry.</td>
</tr>
</table>

<table>
<tr><th>Positive Impact of this Solution in This Project Domain</th><th>Negative Impact of this Solution in This Project Domain</th></tr>
<tr><td>It offers a potentially effective and engaging method for training and assessing multitasking abilities, particularly in fields like aviation and transportation, where proficient multitasking is crucial for safety and performance.</td><td>An overreliance on the game-based approach, potentially neglecting other important aspects of training and assessment, such as real-world practical experience. Additionally, the effectiveness of neurofeedback may vary among individuals, and not all participants may benefit equally from this approach.</td></tr>
</table>

<table>
<tr><th>Analyse This Work By Critical Thinking</th><th>The Tools That Assessed this Work</th><th>What is the Structure of this Paper</th></tr>
</table>

While the "MIND" project offers a novel approach to multitasking training, critical thinking highlights the need for empirical evidence, ethical considerations, and a thorough evaluation of its potential in real-world contexts. This critical approach ensures a balanced assessment of its value and impact.	EEG equipment	Abstract I. Introduction II. Background III. Materials and Methods IV. Results and Discussion V. Conclusion
Diagram/Flowchart		
 Figure 1. Screenshot from the final game, showing the driving task and the memory recall task with the letter "U" displayed.		

--End of Paper 5--

6

Reference in APA format	I. Wijayanto, R. Hartanto and H. A. Nugroho, "Higuchi and Katz Fractal Dimension for Detecting Interictal and Ictal State in Electroencephalogram Signal," 2019 11th International Conference on Information Technology and Electrical Engineering (ICITEE), Pattaya, Thailand, 2019, pp. 1-6, doi: 10.1109/ICITEED.2019.8929940.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**

https://ieeexplore.ieee.org/document/89	Inung Wijayanto -inung.wijayanto@telkomuniversity.ac.id, rudy-rudy@ugm.ac.id, adinugroho-adinugroho@ugm.ac.id	Epilepsy, EEG, Fractal dimension, HFD, KFD, SVM
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Fractal Dimension-Based EEG Classification for Epilepsy Diagnosis	The goal or objective of the solution described in the provided text is to diagnose and detect epilepsy by analyzing EEG signals	The solution described in the provided text involves several components to achieve its objective of diagnosing and detecting epilepsy using EEG signals Seizure Detection and Diagnosis
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	Segment the EEG data into different states, such as normal, interictal, and ictal states. This segmentation allows for the isolation of specific patterns associated with seizures.	EEG is a noninvasive method, making it safe and well-tolerated by patients. It doesn't involve surgery or invasive procedures, which is important for patient comfort and safety..	The reported high accuracy may not necessarily generalize well to a broader and more diverse patient population. The method's performance may vary when applied to different age groups, ethnicities, or epilepsy
2	Divide the EEG signals into different frequency bands, such as delta, theta, alpha, beta, and gamma. Each frequency band represents different aspects of brain activity and behavior	EEG data can be collected and analyzed in real time, enabling continuous monitoring of patients with epilepsy. This real-time capability can provide valuable insights for clinicians and caregivers.	EEG signals can be sensitive to various types of noise and artifacts, which can impact the accuracy of the seizure detection method. Preprocessing and data cleaning are critical but may not eliminate all sources of noise.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The accuracy in classifying the EEG signals into interictal and ictal states	The method used to analyze the EEG signals (Higuchi fractal dimension, Katz fractal dimension)	The frequency band of the EEG signals (delta, theta, alpha, beta, gamma) that is analyzed	The complexity and fractal characteristics of the different EEG frequency bands that help explain how the independent variable methods are able to detect interictal vs ictal states

Relationship Among the Above 4 Variables in This article
The analysis method directly impacts the measured complexity of the EEG signal. Different methods will extract different complexity features from the signal. The complexity features mediate the relationship between analysis method and accuracy. The complexity provides explanatory information that enables the methods to classify EEG state. The analysis method has a direct effect on classification accuracy but this relationship is influenced by the mediating complexity variable. The frequency band moderates how strongly the analysis method impacts classification accuracy. The strength of the relationship depends on which frequency band is analyzed.

Input and Output	Feature of This Solution	Contribution & The Value of This Work

<table>
<tr>
<td>
<table>
<tr><th>Input</th><th>Output</th></tr>
<tr><td>EEG data from individuals with epilepsy</td><td>Results, findings, and outcomes derived from the analysis of EEG data</td></tr>
</table>
</td>
<td>The solution you described for epilepsy seizure detection in EEG signals using Higuchi and Katz fractal dimensions and a Support Vector Machine (SVM) involves several key features that make it effective for its intended purpose.</td>
<td>The work described, which focuses on epilepsy seizure detection in EEG signals using Higuchi and Katz fractal dimensions and a Support Vector Machine (SVM), offers several valuable contributions to the field of healthcare and medical research</td>
</tr>
</table>

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
The solution described in the project, which focuses on epilepsy seizure detection using EEG signals and machine learning techniques, has the potential to make a positive impact in its domain in several ways.Improved Patient Care,Enhanced Quality of Life	While the solution for epilepsy seizure detection using EEG signals and machine learning has numerous benefits, there are potential negative impacts and challenges in the project domain that should be considered . False Positives and False Negatives, Data Privacy and Security

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**

Analyzing this work through critical thinking, it's evident that the project offers a promising solution for epilepsy seizure detection using EEG data and machine learning. Its potential benefits include improved patient care, early intervention, and reduced healthcare costs.	EEG Equipment	Abstract I. Introduction II. Material and method III. Result and discussion IV. Comparision with other methods V. Conclusion I. Acknowledgement
Diagram/Flowchart		

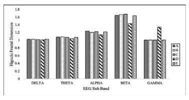


Fig. 2: Average value of HFD in every frequency band

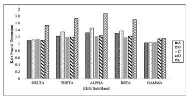


Fig. 3: Average value of KFD in every frequency band

--End of Paper 6--

7

Reference in APA format	C. -Y. Chiang, N. -F. Chang, T. -C. Chen, H. -H. Chen and L. -G. Chen, "Seizure prediction based on classification of EEG synchronization patterns with on-line retraining and post-processing scheme," 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Boston, MA, USA, 2011, pp. 7564-7569, doi: 10.1109/IEMBS.2011.6091865.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/6091865	Cheng-Yi Chiang, Nai-Fu Chang, Tung-Chien Chen, Hong-Hui Chen, and Liang-Gee Chen	EEG, Epilepsy, Seizure Detection, Linear support vector algorithm, post processing.

The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?
It appears to be a research paper that presents a approach to seizure prediction in epilepsy using an online retraining method and post-processing techniques to improve the performance of machine learning-based classification of EEG signals	The goal or objective of the solution described is to improve the reliability of seizure prediction in epilepsy. The problem that needs to be solved is the inherent variability in EEG signals due to factors such as the patient's state (awake or asleep), the severity of epilepsy, and other sources of signal variation. These variations make it challenging to predict seizures accurately using traditional offline training methods that rely on fixed training sets.	The solution described involves several components Online Retraining Method ,Feature Extraction and Classification, Machine Learning Algorithms.
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	Gather EEG data from sources such as ECoG recordings and long-term scalp EEG recordings.	The solution significantly improves sensitivity in seizure prediction. This means that it can more accurately detect and predict seizure events, providing timely warnings to patients or caregivers.	The online retraining method relies on a stream of data for updating the model. continuously
2	Initially, train a machine learning model for seizure prediction using a fixed training set	The online retraining method allows the model to adapt to changes in EEG signals over time	Frequent model updates and adaptations to new data could potentially lead to overfitting, where the model becomes too specialized to the training data and loses its generalization ability.
3	Implement a post-processing scheme to further refine the predictions and reduce false alarms.	The incorporation of a post-processing scheme helps reduce false alarms. False alarms can be distressing for patients and may lead to unnecessary interventions.	The online retraining and post-processing components introduce complexity into the system.
4	Analyze the system's performance on different EEG databases (ECoG and scalp EEG) to assess its reliability.	The solution can be customized to adapt to individual patient characteristics and variations	Real-time monitoring and continuous model updates may introduce some latency in providing seizure predictions.

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Ability to accurately classify EEG signals into preictal (before seizure) or interictal states	EEG synchronization patterns used as features for classification (bivariate features like wavelet coherence between channel pairs)	Type of classifier used (SVM, neural network etc.) impacts the relationship between features and classification performance. The classifier moderates how predictive the patterns are.	The synchronization patterns mediate the relationship between EEG input and seizure classification ability. Certain patterns indicate greater pre-seizure synchronization.

Relationship Among the Above 4 Variables in This article
The EEG input patterns directly affect the degree of synchronization detected in the signals. Certain patterns indicate more pre-seizure synchronization. The synchronization mediates the relationship between EEG patterns and classification accuracy. Increased pre-seizure synchronization enables more accurate identification of preictal states. The EEG patterns have a direct effect on classification accuracy, but this relationship is influenced by the mediating synchronization variable. The choice of classifier moderates how strongly the EEG patterns impact classification accuracy. Different classifiers will enable the patterns to predict seizures with varying effectiveness.

Input and Output	Feature of This Solution	Contribution & The Value of This Work

<table>
<tr>
<td><table><tr><th>Input</th><th>Output</th></tr><tr><td>EEG (Electroencephalography) data</td><td>The primary output is the prediction of potential seizures, which is provided in real-time or near-real-time.</td></tr></table></td>
<td colspan="2">The solution for seizure prediction in epilepsy incorporates several key features that contribute to its effectiveness</td>
<td colspan="2"><table><tr><td>Typically, such work involves co
healthcare professionals, and pot</td></tr></table></td>
</tr>
<tr>
<th colspan="2">Positive Impact of this Solution in This Project Domain</th>
<th colspan="3">Negative Impact of this Solution in This Project Domain</th>
</tr>
<tr>
<td colspan="2">Few of the positive impacts of the project are Improved Quality of Life ,Safety, Reduced Anxiety</td>
<td colspan="3">The following are the negative impacts af the project False Alarms,Patient Anxiety,Dependence on Technology.</td>
</tr>
<tr>
<th>Analyse This Work By Critical Thinking</th>
<th colspan="2">The Tools That Assessed this Work</th>
<th colspan="2">What is the Structure of this Paper</th>
</tr>
</table>

The work described focuses on developing a solution for the prediction of seizures in individuals with epilepsy. The analysis of this work can provide insights into its potential impact, strengths, and areas for improvement	EEG device	Abstract I. INTRODUCTION II. REVIEW OF MACHINE LEARNING BASED CLASSIFICATION OF PATTERNS METHODS III. THE PROPOSED METHODS IV. RESULTS & DISCUSSION I. REFERENCES

Diagram/Flowchart

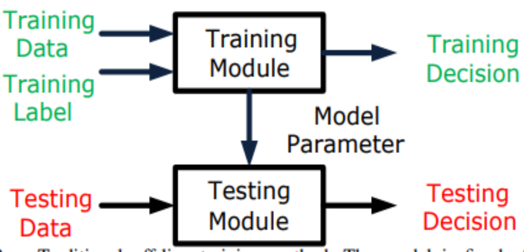
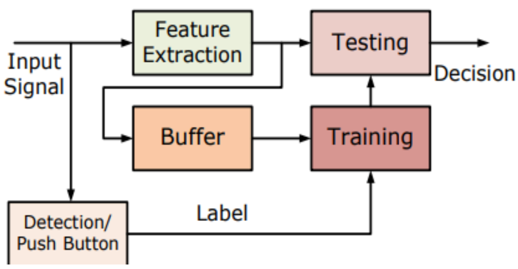


Fig. 2. Traditional off-line training method. The model is fixed after training, and the testing data is obsoleted after testing.



--End of Paper 7–

8

Reference in APA format	S. Gupta, S. Bagga, V. Maheshkar and M. P. S. Bhatia, "Detection of Epileptic Seizures using EEG Signals," 2020 International Conference on Artificial Intelligence and Signal Processing (AISP), Amaravati, India, 2020, pp. 1-5, doi: 10.1109/AISP48273.2020.9073157.		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**	
https://ieeexplore.ieee.org/abstract/document/9073157	Sarthak Gupta - sarthakgupta259@gmail.com, Siddhant Bagga- siddhantbagga1@gmail.com, Vikas Maheshka-vikas.maheshkar@gmail.com, M.P.S. Bhatia - bhatia.mps@gmail.com	EEG, Epilepsy, Seizure Detection, Discrete Wavelet Transform, CNN, Neural Network	
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**	
In this paper, an approach has been proposed that uses Discrete Wavelet Transform to convert the EEG signal into the time-frequency domain.	Initially the epileptic seizures is a time consuming process so by using classfiers the model gives the quick and 99.6 accurate output.	EEG signals, automatic seizure detection	
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process			

	Process Steps	Advantage	Disadvantage (Limitation)
1	Apply Discrete Wavelet Transform (DWT) to EEG signals for automated seizure detection.	Automates seizure detection, reducing reliance on subjective interpretation and accelerating diagnostics.	Techniques like DWT and CNNs introduce computational complexity, limiting real-time application suitability.
2	Convert EEG signals into time-frequency domain using DWT, enhancing efficiency in analysis.	Streamlines analysis, yielding high-quality results compared to manual methods.	Variability in EEG data may limit universal applicability and performance consistency of the approach.
3	Utilize classification techniques like CNNs and random forests for feature analysis.	Achieves 99.29% accuracy, crucial for reliable medical diagnostics.	Approach effectiveness depends heavily on input EEG data quality, potentially impacting seizure detection accuracy.
4	Fusing the extracted details into single image using fusion rule.	Fusion can combine the strengths of different modalities and algorithms to reduce the amount of data required for diagnosis.	The choice of fusion rule can affect the accuracy of diagnosis as it introduces artifacts and distortions into the image.
5	Post processing of the fused image to enhance its quality and remove artifacts.	Post processing can improve quality of the final image as it removes the artifacts which can reduce the risk of misdiagnosis.	Post preprocessing can be time consuming and require specialized knowledge as it can remove important details from the final image.

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Performance of seizure detection (accuracy)	Signal processing method (Discrete Wavelet Transform)	Choice of classifier model (SVM, CNN, etc) that is used for seizure detection	The features extracted from the EEG signal coefficients after applying DWT, like mean, standard deviation, entropy etc.

Relationship Among the Above 4 Variables in This article
The DWT signal processing directly affects the features that can be extracted from the EEG signal coefficients. Different features are obtained after applying DWT. The extracted features mediate the relationship between DWT and detection accuracy. The features provide explanatory power to classify the EEG signals into seizure/non-seizure. DWT has a direct effect on detection accuracy, but this relationship is influenced by the mediating feature extraction process. The classifier model impacts how strongly the DWT processing affects detection accuracy. Different classifiers enable the features to predict seizures with varying effectiveness.

Input and Output	Feature of This Solution	Contribution & The Value of This Work

<table>
<tr><td><table><tr><th>Input</th><th>Output</th></tr><tr><td>EEG dataset</td><td>EEG signals</td></tr></table></td><td>The key feature of the proposed solution is the utilization of Discrete Wavelet Transform (DWT) for the analysis of EEG signals.</td><td>The work achieves a remarkable accuracy rate of 99.29% in epileptic seizure detection. This high level of accuracy signifies a substantial improvement over conventional methods, demonstrating the effectiveness of the proposed approach.</td></tr>
</table>

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
The proposed solution for epileptic seizure detection using EEG signals has the potential to generate several positive impacts -Improved Patient Outcomes,Enhanced Diagnostic Efficiency,Better Resource Utilization,Potential for Early Intervention.	While the proposed solution for epileptic seizure detection using EEG signals offers substantial benefits, it's crucial to consider potential negative impacts and challenges -False Positives and Negatives,Overreliance on Automated Systems,Limited Generalizability.

<table>
<tr><th>Analyse This Work By Critical Thinking</th><th>The Tools That Assessed this Work</th><th>What is the Structure of this Paper</th></tr>
<tr><td>The utilization of Discrete Wavelet Transform (DWT) and advanced classifiers suggests a thoughtful and sophisticated approach to signal processing and classification, which is suitable for analyzing complex EEG signals</td><td>Jupyter Notebooks,Version Control ,Matplotlib and Seabor,TensorFlow and PyTorch,MATLAB</td><td>Abstract
V. INTRODUCTION
VI. RELATED WORK
VII. PROPOSED WORK
VIII. DATASET
IX. RESULTS
I. CONCLUSION AND FUTURE WORK</td></tr>
<tr><th colspan="3">Diagram/Flowchart</th></tr>
</table>

III. Proposed Work

The complete process of the method has been described in Figure 2.

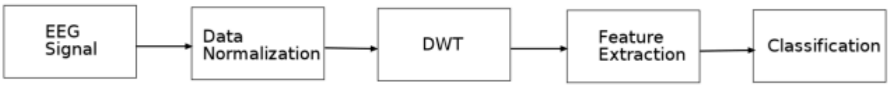


Fig. 2: Schematic representation of proposed method

---End of Paper 8---

9

Reference in APA format	B. Van Hal, S. Rhodes, B. Dunne and R. Bossemeyer, "Low-cost EEG-based sleep detection," 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Chicago, IL, USA, 2014, pp. 4571-4574, doi: 10.1109/EMBC.2014.6944641.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/6944641	Bryan Van Hal Samhita Rhodes Bruce Dunne Robert Bossemeyer.	EEG (Electroencephalography) Sleep Detection NeuroSky Mindset Frequency Bands Real-time Detection
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**

Gives the warning of sleep using neurosky mindset.	The paper outlines the methodology for analysing EEG signals recorded by the low-cost EEG headset, focusing on frequency bands associated with different sleep stages. The authors propose an algorithm that combines a counting approach and an algorithmic approach to enhance the accuracy of sleep detection. Overall it contributes the development of low-cost and accessible EEG-based systems for drowsiness detection, with potential applications in transportation safety.	NeuroSky Mindset Single dry-sensor electrode Frequency bands Piezoelectric buzzer LEDs Arduino Uno board
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	Set up NeuroSky Mindset with Arduino, utilizing cost-effective EEG headset.	Utilizes inexpensive EEG headset for cost-effective solution.	False positive rate of about 20% may lead to unnecessary alerts, reducing user trust.
2	Instruct subjects to stay awake, filter EEG signals, and compute thresholds for sleep onset.	Issues auditory warning upon detecting sleep onset, enhancing alertness.	Algorithm tends to indicate sleep earlier than clinically determined, increasing false alarms.
3	Implement sleep detection using C programming on Arduino, ensuring system accessibility.	Implements system on widely available hardware, promoting accessibility.	Relying on specific hardware components may limit scalability and integration.
4	Monitor EEG frequency changes. Update sleep counter per second. Declare stage 1 sleep if counter exceeds threshold.	Presents a straightforward algorithm combining a counting approach and an algorithmic approach for effective sleep detection.	Monitor EEG frequency changes. Update sleep counter per second. Declare stage 1 sleep if counter exceeds threshold.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Monitor EEG frequency changes. Update sleep counter per second. Declare stage 1 sleep if counter exceeds threshold.	EEG signal processing method (frequency band separation, thresholding)	Choice of thresholds and constants used in the sleep detection algorithm	Power in EEG frequency bands like alpha, beta, theta, which change as sleep onset nears

Relationship Among the Above 4 Variables in This article
● The processing method directly impacts the power measured in different EEG frequency bands ● Changes in band power enable detection of transition to sleep. ● Processing method affects sleep detection accuracy, mediated by band power changes. ● Threshold and constant choices impact how well the processing method can leverage EEG changes to detect sleep onset.

Input and Output	Feature of This Solution	Contribution & The Value of This Work

<table>
<tr>
<td>
<table>
<tr><th>Input</th><th>Output</th></tr>
<tr><td>Signal recorded using the NeuroSky Mindset</td><td>Detection of the onset of stage 1 sleep or drowsiness.</td></tr>
</table>
</td>
<td>The feature of the presented sleep detection system is its ability to provide real-time detection of the onset of stage 1 sleep or drowsiness using a low-cost single dry-sensor EEG headset, specifically the NeuroSky Mindset. This system analyzes the EEG signal, filters it into different frequency bands, and employs a customized algorithm to monitor changes in the signal indicative of the transition from wakefulness to sleep.</td>
<td>The contribution and value of this work lie in the development of a real-time, low-cost sleep detection system using a single dry-sensor EEG headset, providing early warnings for drowsiness and contributing to the reduction of sleep-related accidents.

The practical implementation and focus on addressing safety concerns in transportation enhance the value of the work.</td>
</tr>
</table>

<table>
<tr><th>Positive Impact of this Solution in This Project Domain</th><th>Negative Impact of this Solution in This Project Domain</th></tr>
<tr><td>The positive impact of this solution in the project domain is the potential reduction of sleep-related accidents in transportation through real-time, low-cost, and accessible detection of drowsiness, enhancing overall safety.</td><td>The potential false positive rate in sleep detection may lead to unwarranted alarms, impacting user trust and acceptance in real-world applications.</td></tr>
</table>

<table>
<tr><th>Analyse This Work By Critical Thinking</th><th>The Tools That Assessed this Work</th><th>What is the Structure of this Paper</th></tr>
</table>

While the low-cost EEG-based sleep detection system presents a practical solution for drowsiness monitoring, its reliance on a single dry-sensor headset introduces limitations in accuracy. The significant false positive rate and variability in baseline data call for refinement, and broader testing is necessary to assess its robustness across diverse user profiles and conditions.	NeuroSky Mindset (EEG headset) Arduino Uno (main processor) BlueSMiRF module The software implementation is in the C programming language on the Arduino platform.	Abstract Introduction Sleep Detection Method Testing Implementation Results Conclusion

Diagram/Flowchart

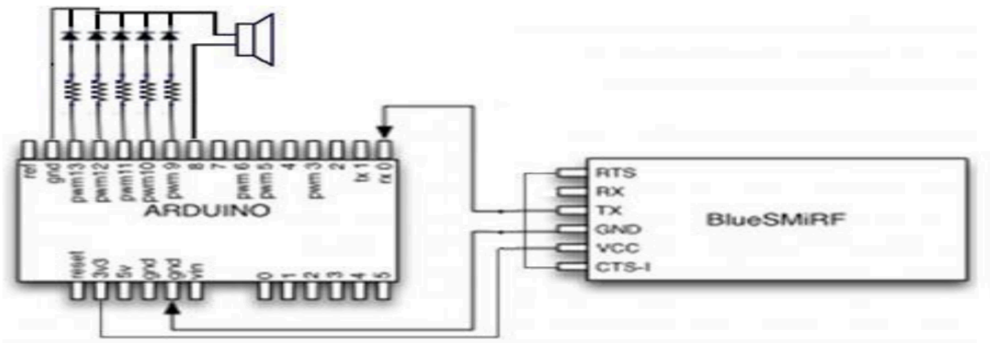


Figure 3. Hardware Configuration of Sleep Detection System

---End of Paper 9--

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Reference in APA format	R. S. Wadekar, P. V. Kasambe and S. S. Rathod, "Development of LabVIEW platform for EEG signal analysis," 2017 International Conference on Intelligent Computing and Control (I2C2), Coimbatore, India, 2017, pp. 1-5, doi: 10.1109/I2C2.2017.8321942	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**

https://ieeexplore.ieee.org/document/8321942	Richa S. Wadekar Prashant V. Kasambe Surendra S. Rathod.	EEG sensor, Neurosky, Signal processing, LabVIEW
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Development of LabVIEW Platform for EEG Signal Analysis	The goal of the solution is to develop a LabVIEW platform for EEG signal analysis, aiming to provide a cost-effective method for acquiring and analyzing brain signals, particularly for detecting abnormalities, using a Neurosky headset. The problem being addressed is the expense and complexity associated with traditional EEG signal acquisition methods, which often require expensive equipment and intricate preparation, hindering widespread use in medical and research applications.	Neurosky headset LabVIEW (Virtual Instrumentation Engineering Workbench) Digital filters (specifically, Butterworth filter of order 6)
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	LabVIEW-based platform for EEG signal analysis using a Neurosky headset.	Low-cost alternative for EEG signal acquisition, enhancing accessibility.	Single-channel EEG device may limit spatial information.
2	Single-channel EEG device with forehead and earlobe sensors for signal processing.	LabVIEW streamlines data acquisition, analysis, and visualization.	Butterworth filter may not fully address EEG signal complexity.
3	LabVIEW software facilitates data processing with Butterworth filter.	Enables study of neurological disorders by analyzing EEG signals.	Lack of details on subjects involved in real-time signal testing.
4	Fused image quality and information assessed using performance metrics.	Ensures assessment of fused image quality and information content. .	Sole reliance on performance metrics may overlook essential aspects

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Fused image quality: It reflects the overall quality of the fused image obtained through the EMD and DWT-based fusion method.	Empirical Mode Decomposition (EMD) of images and discrete wavelet transform (DWT) method: It represents the methods used for multimodal image fusion.	Hybrid Fusion Response: It represents the overall outcome of the proposed approach as it moderates the contribution of both EMD and DWT in the image fusion process.	Spatial Characteristics of the Original Image: The method claims to retain the spatial characteristics of the original image in the fused result, indicating a mediating role in preserving the structural information during the fusion process.

Relationship Among the Above 4 Variables in This article

- The processing method directly impacts the features that can be extracted from the EEG signals
- The extracted statistical features enable abnormal EEG detection.
- Processing method affects abnormality detection accuracy, mediated by feature extraction.
- The digital filter impacts how well the processing method can extract predictive features from the EEG.

Input and Output	Feature of This Solution	Contribution in This Work

<table>
<tr><td colspan="2">Ability to detect abnormalities in EEG signals</td><td colspan="2">EEG signal processing method (frequency band separation, filtering, feature extraction)</td><td>Choice of digital filter used for smoothing EEG signals</td></tr>
<tr><td colspan="3">Positive Impact of this Solution in This Project Domain</td><td colspan="2">Negative Impact of this Solution in This Project Domain</td></tr>
<tr><td colspan="3">democratization of EEG signal analysis, making it more affordable and accessible. By using low-cost hardware and LabVIEW, the platform facilitates real-time monitoring and analysis of brain signals, potentially enhancing early detection of abnormalities and improving the efficiency of biomedical research in the domain of neurological conditions.</td><td colspan="2">Project domain could be the limited scalability and versatility of a single-channel EEG device (Neurosky headset). This limitation might constrain the system's ability to capture detailed spatial information from the brain, potentially affecting the depth and accuracy of EEG signal analysis for certain applications.</td></tr>
<tr><td colspan="2">Analyse This Work by Critical Thinking</td><td colspan="2">The Tools That Assessed this Work</td><td>What is the Structure of this Paper</td></tr>
</table>

This work presents a commendable effort in developing an affordable EEG signal analysis platform using LabVIEW and a Neurosky headset. While the cost-effectiveness is a notable advantage, the reliance on a single-channel EEG device and simplified signal processing may limit its applicability for more complex research or medical scenarios, highlighting the need for further validation and consideration of system scalability.	LabVIEW Neurosky headset Butterworth filter of order 6	I. Abstract II. Introduction III. Literature Survey IV. Methodology V. Result VI. Conclusion VII. References I.

Diagram/Flowchart

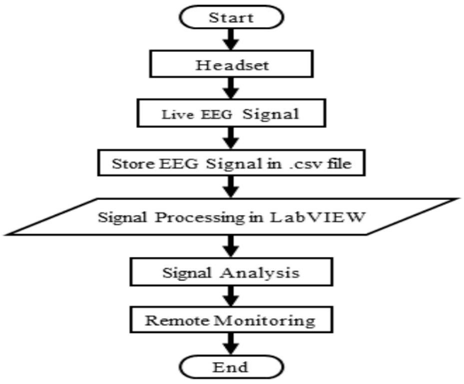


Fig. 1. Flowchart for Acquiring live EEG signal.

---End of Paper 10—

11

<table>
<tr><td>Reference in APA format</td><td colspan="2">A. Tiwari and R. Tiwari, "Monitoring and detection of EEG signals before and after yoga during depression in human brain using MATLAB," 2017 International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2017, pp. 329-334, doi: 10.1109/ICCMC.2017.8282702..</td></tr>
<tr><td>URL of the Reference</td><td>Authors Names and Emails</td><td>Keywords in this Reference</td></tr>
<tr><td>https://ieeexplore.ieee.org/document/8282702</td><td>1. Ankita Tiwari
(ankitaiit15@gmail.com)
2. Rajinder Tiwari
(trajan@gmail.com)</td><td>Questionnaires, Mindfullness , Electroencephalography,
EEG headset, MATLAB,
Bluetooth Wireless, yoga exercises</td></tr>
<tr><td>The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)</td><td>The Goal (Objective) of this Solution & What is the problem that need to be solved</td><td>What are the components of it?</td></tr>
<tr><td>MATLAB</td><td>Aim of the author is to concentrated on understanding how mood swings affect EEG waves and how yoga practice might help avoid these swappings</td><td>EEG stands for electrical impulses from the nerves related to actions done. Every source of ideas, actions, and emotions is signaled electrically by the brain's nerves.</td></tr>
<tr><td colspan="3">The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process</td></tr>
</table>

	Process Steps	Advantage	Disadvantage (Limitation)
1	Data Analysis and Visualization.	It is appropriate for EEG data analysis since it offers a variety of signal processing toolboxes and features.	For those with little programming knowledge, it might not be the best choice to devote time to studying MATLAB's functions and programming language because it can be somewhat complex for novices.
2	Customization	For the purpose of researching the particular effects of yoga on EEG signals, flexibility is crucial.	For certain researchers and institutions, the cost of MATLAB licenses may be prohibitive, given that the software is proprietary.
3	Signal processing	A wide range of preprocessing methods for EEG data, including feature extraction, noise reduction, and filtering, are available in MATLAB.	While MATLAB can process EEG data offline effectively, real-time processing for immediate feedback during yoga sessions may be more challenging

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The electrical activity in the brain measured through EEG signals is a key dependent variable. Changes in EEG patterns may indicate alterations in brain activity related to depression.	The application of yoga serves as a primary independent variable. The study likely involves participants engaging in yoga sessions, and the effects of yoga on EEG signals are examined.	The initial mental health condition of participants could act as a moderating variable. It might influence how the yoga intervention affects EEG signals differently for individuals with varying baseline mental health states.	The neurophysiological changes induced by yoga could serve as a mediating variable. Yoga may influence various physiological processes, such as stress hormone levels or neurotransmitter activity, which, in turn, mediate the impact on EEG signals.

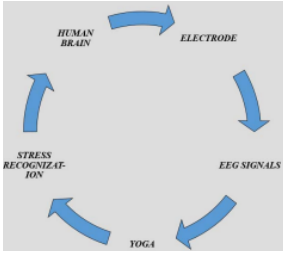
Relationship Among The Above 4 Variables in This article
The neurophysiological changes induced by yoga could serve as a mediating variable. Yoga may influence various physiological processes, such as stress hormone levels or neurotransmitter activity, which, in turn, mediate the impact on EEG signals.

Input and Output	Feature of This Solution	Contribution & The Value of This Work

<table>
<tr>
<td colspan="2"><table><tr><th>Input</th><th>Output</th></tr><tr><td>EEG signals of brain activity</td><td>This indicates that yoga directly affects mental health by inducing breathing vibrations that alter the frequency of EEG signals in a positive way.</td></tr></table></td>
<td colspan="2">Observing and analyzing EEG signals before and after yoga during depression in the human brain using MATLAB involves various features and components that makes it a comprehensive solution .</td>
<td colspan="2">I am glad to read this paper as we got now a lot of knowledge about the brain wave activity before and after yoga.</td>
</tr>
<tr>
<th colspan="3">Positive Impact of this Solution in This Project Domain</th>
<th colspan="3">Negative Impact of this Solution in This Project Domain</th>
</tr>
<tr>
<td colspan="3">A MATLAB-based method for tracking and identifying EEG signals before and after yoga in depression has the potential to advance scientific understanding, enhance mental health therapies, and enhance the wellbeing of depressed people.</td>
<td colspan="3">While there are several benefits to using a MATLAB based method for tracking and identifying EEG signals in the context of yoga and depression research, there are drawbacks as well, including issues with complexity, expense, data quality, interpretation, and ethical issues.</td>
</tr>
<tr>
<th colspan="2">Analyse This Work By Critical Thinking</th>
<th colspan="2">The Tools That Assessed this Work</th>
<th colspan="2">What is the Structure of this Paper</th>
</tr>
</table>

The critical examination of this experiment demonstrates a well-reasoned and scientifically rigorous methodology for investigating how yoga affects EEG signals in depressed persons..	.EEG Analyzer	I. Introduction II. Brain activity during stress III. Yoga IV. Yoga and Stress V. Methods VI. System Design VII. Experimental setup VIII. Result and Discussion IX. Future Scope X. Conclusion

Diagram/Flowchart



---End of Paper 11---

12

Reference in APA format	B. P. Harne, Y. Bobade, R. S. Dhekekar and A. Hiwale, "SVM classification of EEG signal to analyze the effect of OM Mantra meditation on the brain," 2019 IEEE 16th India Council International Conference (INDICON), Rajkot, India, 2019, pp. 1-4, doi: 10.1109/INDICON47234.2019.9030339	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**

https://ieeexplore.ieee.org/document/9030339	Bhavna P.Harne (bdhekekar@yahoo.com) YoginiBobade (ritubobde@gmail.com) Dr.R.S.Dhekekar (rsdhekekar@yahoo.co.in) Dr.AnilHiwale (ashiwale@gmail.com)	EEG, OM Mantra, Multi-class features, SVM, Radial Basis Kernel
The Name of the Current Solution (Technique/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Support Vector Machine(SVM)	This method aims to classify EEG signals using Support Vector Machine (SVM) classification in order to assess the impact of OM Mantra meditation on the brain. Finding out how OM Mantra meditation impacts brain activity and whether certain EEG patterns are connected to this type of meditation are the main objectives.	EEG Data Acquisition, Data Preprocessing , Feature Extraction, Data Labeling, data splitting, SVM Model Selection.
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

In order to investigate the impact of OM mediation, the primary goal of this work is to construct the classifier to classify the two distinct classes, i.e., before and after EEG band.

	Process Steps	**Advantage**	**Disadvantage (Limitation)**
1	In order to investigate the impact of OM mediation, the primary goal of this work is to construct the classifier to classify the two distinct classes, i.e., before and after EEG band.	Brain activity can be directly and objectively measured with an EEG.	Since it's a broad measure, it might not fully reflect the nuances of how the brain changes during meditation.
2	Standard deviation of delta band of EEG before and after OM meditation Changes in EEG power inside the delta band can affect the standard deviation. A higher standard deviation could be an indication of more dynamic brain activity.	A higher standard deviation could be an indication of more dynamic brain activity.	The standard deviation alone does not provide specific information about the underlying neural processes that may be altered during meditation
3	Variance of EEG signal for before and after OM meditation	Changes in EEG power inside the delta band can affect the standard deviation.	A quantitative way to assess changes in this particular frequency range is by calculating the mean of the delta band.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The output or response variable representing the EEG signal characteristics, which are being classified. It encompasses the brainwave patterns recorded during the OM Mantra meditation.	The input variable representing various features or attributes extracted from the EEG signals. These features are used to train the SVM model and classify the brainwave patterns based on their response to OM Mantra meditation.	Considering meditation experience as a moderating variable allows for a nuanced understanding of how the effectiveness of OM Mantra meditation on the brain might vary among individuals with different levels of experience.	mediating variable helps unravel the intricate processes within the brain that mediate the relationship between the practice of OM Mantra meditation and the observed EEG signal patterns.

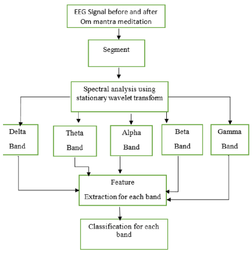
Relationship Among the Above 4 Variables in This article
The relationship among these four variables involves exploring how meditation expertise moderates the relationship between EEG features and brainwave patterns during meditation, while neurophysiological changes act as a mediating mechanism in this process.

Input and Output	Feature of This Solution	Contribution & The Value of this Work

<table>
<tr>
<td>
<table>
<tr><th>Input</th><th>Output</th></tr>
<tr><td>EEG signals</td><td>This work mainly focused on the method having high computational accuracy with less complexity and less computational time with the SVM classifier</td></tr>
</table>
</td>
<td>SVM excels in handling high-dimensional data, making it suitable for processing the complex information extracted from EEG signals during OM Mantra meditation.

The solution provides a robust and accurate classification, offering insights into how brain activity changes during meditation.</td>
<td>SVM excels in handling high-dimensional data, making it suitable for processing the complex information extracted from EEG signals during OM Mantra meditation.

The solution provides a robust and accurate classification, offering insights into how brain activity changes during meditation.</td>
</tr>
<tr>
<th colspan="2">Positive Impact of this Solution in This Project Domain</th>
<th>Negative Impact of this Solution in This Project Domain</th>
</tr>
<tr>
<td colspan="2">The SVM classification of EEG signals to analyze the effect of OM Mantra meditation on the brain provides valuable insights into how meditation practices, specifically OM Mantra, influence brain activity. Understanding these effects contributes to the broader field of neurology and mental health.</td>
<td>Findings may be specific to OM Mantra meditation and may not be easily generalized to other meditation techniques. This limits the broader applicability of the study's results to the entire field of meditation research.</td>
</tr>
<tr>
<th>Analyse This Work by Critical Thinking</th>
<th>The Tools That Assessed this Work</th>
<th>What is the Structure of this Paper</th>
</tr>
</table>

This involves considering if SVM is the best tool for handling complex EEG data and questioning why OM Mantra meditation was specifically chosen. We should also ponder the limitations, like assuming linearity in SVM models and potential biases in the dataset.	Data Analytics	1.Introduction 2.Materials and Methods 3.Results 4. Discussion 5.Conclusion 6.Reference
Diagram/Flowchart		
		

---End of Paper 12---

13		
Reference in APA format	N. Gupta, N. Sood and I. Saini, "Statistical Feature Based Comparison of EEG in Meditation for Various Wavelet," 2018 First International Conference on Secure Cyber Computing and Communication (ICSCCC), Jalandhar, India, 2018, pp. 73-77, doi: 10.1109/ICSCCC.2018.8703266.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/8703266	Neha Gupta (guptaneha030@gmail.com) Neetu Sood (soodn@nitj.ac.in) Indu Saini (sainii@nitj.ac.in)	brain, meditation, electroenchelograph, wavelet transform, fast fourier transform

The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	The Goal (Objective) of this Solution & What is the problem that needs to be solved	What are the components of it?
Statistical Feature Based Comparison of EEG in Meditation for Various Wavelet	Different wavelet functions give different observations in all bands of EEG. The ratio of powers is calculated.	EEG Data
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	1 Data collection, EEG data is collected from individuals engaged in meditation. . . .	Understanding the impact of various wavelet process steps enables researchers to customize the analysis for specific research questions	By comparing EEG data under different wavelet process steps, researchers may gaiIndividual differences in meditation practices and brain responses may introduce variability that is challenging to account for.n insights into specific states of consciousness during meditation.
2	Preprocessing, Raw EEG data may undergo preprocessing steps to remove noise or artifacts.	By comparing EEG data under different wavelet process steps, researchers may gain insights into specific states of consciousness during meditation.	EEG data collection, especially during meditation, involves ethical considerations related to privacy and informed consent.
3	Wavelet Processing, EEG signals are processed using various wavelet techniques.	Statistical methods offer an objective way to analyze EEG data, reducing subjectivity in interpretation	Collaboration between experts in statistics, neuroscience, and signal processing is necessary, posing challenges in interdisciplinary research.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Power (P): This is the dependent variable in the equation. Power is the outcome or result that is being measured or predicted based on changes in other variables.	Power Spectral Density (PSD): In the equation, PSD is one of the independent variables. Bandwidth (BW): Bandwidth is another independent variable in the equation.	This variable represents the participants' level of experience or expertise in meditation. The idea is that the impact of changes in Power Spectral Density and Bandwidth on Power during meditation might be different for individuals with varying levels of meditation experience.	The mediating variable helps to explain the underlying physiological mechanisms by which changes in EEG features may lead to alterations in meditation states.

Relationship Among The Above 4 Variables in This article
The relationship is complex, with brainwaves acting as influencers, moderated by meditation experience, and the physiological process of neurotransmitter release serving as an intermediary mechanism.

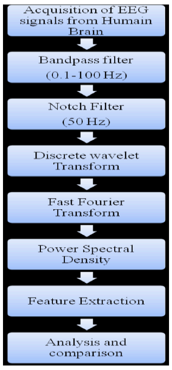
Input and Output	Feature of This Solution	Contribution & The Value of this Work

<table>
<tr>
<td colspan="2">
<table>
<tr><th>Input</th><th>Output</th></tr>
<tr><td>Acquisition of EEG signals from Human Brain.</td><td>It implies that Haar wavelet gives better performance than other wavelet functions</td></tr>
</table>
</td>
<td colspan="2">The solution involves statistical analysis of EEG data, indicating a quantitative and rigorous approach to studying brainwave patterns during meditation.

The use of wavelet transform suggests a sophisticated signal processing technique. Wavelet analysis allows for a more detailed examination of different frequency components in EEG signals, providing a more nuanced understanding of brain activity during meditation.</td>
<td>I am glad to read this paper as we got now a lot of knowledge about the Statistical Feature Based Comparison of EEG in Meditation for Various Wavelet.</td>
</tr>
<tr>
<td colspan="3">Positive Impact of this Solution in This Project Domain</td>
<td colspan="2">Negative Impact of this Solution in This Project Domain</td>
</tr>
<tr>
<td colspan="3">the solution's positive impacts lie in advancing scientific knowledge, contributing to meditation research, and potentially influencing clinical applications and personalized approaches to meditation practices.</td>
<td colspan="2">The use of statistical features and wavelet analysis may introduce complexity in data interpretation. Researchers and practitioners might face challenges in translating the findings into practical insights, especially for those without a strong background in signal processing.</td>
</tr>
<tr>
<td colspan="2">Analyse This Work By Critical Thinking</td>
<td colspan="2">The Tools That Assessed this Work</td>
<td>What is the Structure of this Paper</td>
</tr>
</table>

The study on "Statistical Feature Based Comparison of EEG in Meditation for Various Wavelet" aims to explore and understand the patterns of brainwaves during meditation. The researchers employed a statistical approach and wavelet analysis to delve into electroencephalogram (EEG) data.	Data Signal Analyzer	Abstract I. Introduction II. Materials and Methods III. Methodology IV. Conclusion V. References

Diagram/Flowchart



---End of Paper 13---

14

Reference in APA format	B. Ülker, M. B. Tabakcıoğlu, H. Çizmeci and D. Ayberkin, "Relations of attention and meditation level with learning in engineering education," 2017 9th International Conference on Electronics, Computers and Artificial Intelligence (ECAI), Targoviste, Romania, 2017, pp. 1-4, doi: 10.1109/ECAI.2017.8166407.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**

https://ieeexplore.ieee.org/document/8166407	Büşra Ülker, Mehmet Barış, Tabakcıoğlu, Hüseyin Çizmeci1,Doruk Ayberkin2	Brain Computer Interface (BCI), EEG, Brainwaves, Neurosky, EEG,, Biosensor.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
The Neurosky EEG biosensor is used to evaluate students' degrees of attention and meditation.	A program is developed in C# medium. The developed program records raw brainwave data, attention and meditation average while the students are studying	Attention Measurements, Meditation level Assesment, psychological factor.
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

The proposed framework consists of several steps, each with its advantages and disadvantages:

	Process Steps	Advantage	Disadvantage (Limitation)
1	Connect the biosensor: Select the biosensor settings, check that the dry sensors are positioned properly, then pair it with your smartphone via Bluetooth.	Determining individual differences in meditation and attention spans can help with the creation of tailored learning strategies.	Using brain-monitoring tools raises privacy and consent issues that need careful consideration.
2	Get Brainwave Information: To collect brainwave data on meditation and focus, use the biosensor.	The varied learning preferences and styles of engineering students may be accommodated with the aid of this modification.	Focusing too much on brain factors may oversimplify the many influences on learning.
3	This level of concentration and meditation might be raised by altering the color scheme of the space. various room colors have various effects on meditation and attention levels.	. The use of devices like the Neurosky Mindwave Biosensor can pave the way for the development of novel educational technologies that leverage real-time feedback on attention and meditation.	Implementing interventions based on research may require significant time and financial investments.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
. As the students are studying, the developed program records the meditation and attention average	the brain composes brainwaves, detected by EEG, such as alpha, beta, gamma, delta and theta.	It's possible that the relationship between detected brainwaves and meditation/attention levels is moderated by the students' level of experience with meditation. Students with more meditation experience might exhibit different patterns in the relationship compared to those with less experience.	If, for instance, beta waves are associated with increased attention (independent variable), the mediator variable might explain that these beta waves trigger the release of neurotransmitters that, in turn, influence meditation and attention levels (dependent variable).

Relationship Among the Above 4 Variables in This article
The brainwaves detected (IV) influence how students meditate and concentrate (DV). This relationship might change based on the students' meditation experience (moderation), and the process of how beta waves specifically impact meditation and attention is explained by neurotransmitter levels (mediation). These relationships collectively form a more nuanced understanding of how brainwaves and meditation/attention are connected, considering the influence of experience and underlying mechanisms.

Input and Output	Feature of This Solution	Contribution & The Value of This Work

<table>
<tr>
<td>
<table>
<tr><th>Input</th><th>Output</th></tr>
<tr><td>Neurosky EEG biosensor brainwave activity.</td><td>Since the students' levels of focus and concentration are sufficiently high, it is acknowledged that they are learning the course material. Students have worse exam marks because they meditate and pay less attention on average.</td></tr>
</table>
</td>
<td>Uses a special brain sensor called Neurosky Mindwave to measure how focused and relaxed students are.

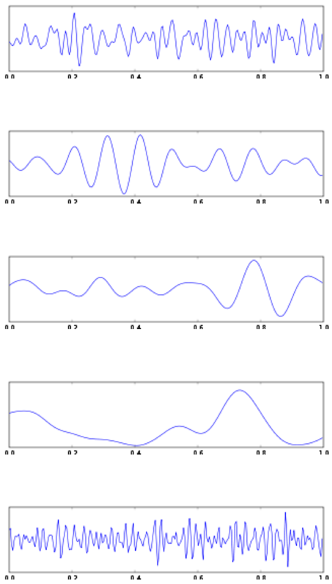
Not just for education—can be used in other areas like making driving safer or developing technology for people with disabilities.</td>
<td>Helps us understand how paying attention and staying calm influence learning in engineering.

Gives insights into how our brains work, which could help in understanding and improving mental well-being.</td>
</tr>
<tr>
<th>Positive Impact of this Solution in This Project Domain</th>
<th colspan="2">Negative Impact of this Solution in This Project Domain</th>
</tr>
</table>

Teachers can make smarter choices about how to teach and help students based on real data. Can be used not just in school but also in real life, making things like driving safer, making video games more fun, and helping people with disabilities.	Could worry some people because it checks our brain, raising questions about privacy. Might need a lot of money and time to use this kind of technology, which could make it hard for some places to use it.

Analyse This Work by Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
Although the research on the relationships between attention and meditation and learning in engineering education is promising, its overall impact and credibility will be strengthened by careful consideration of methodology transparency, ethical issues, long-term effects, and balanced presentations.	This biosensor is a key technology employed to assess and collect data related to brainwave activity, attention, and meditation levels. The Neurosky Mindwave Biosensor utilizes dry active sensor technology, eliminating the need for gel during electrode placement. It operates within a specific frequency range (0.05-0.5 Hz) and communicates the perceived brainwave data with Bluetooth technology.	Abstract I. Introduction II. Methodology III. Measurements IV. Conclusion I.

Diagram/Flowchart



Gamma Waves

---End of Paper 14---

15

Reference in APA format	L. Shaw and A. Routray, "EEG Traced Microstates Detection during Meditation- A State of Consciousness," 2020 IEEE 15th International Conference on Industrial and Information Systems (ICIIS), RUPNAGAR, India, 2020, pp. 253-257, doi: 10.1109/ICIIS51140.2020.9342712.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/9342712	Laxmi Shaw (laxmishaw1983@gmail.com) Aurobinda Routray (aurobinda.routray@gmail.com)	Global Field Potential (GFP), kriya yoga (KY), topography, Consciousness, discrete wavelet transform(DWT).

The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	The Goal (Objective) of this Solution & What is the problem that needs to be solved	What are the components of it?
The highest level of consciousness which might be seen in proficient Kriya practitioners.	This study, whose subjects are long-term KY meditation practitioners, offers a topographical method for identifying microstates throughout the whole brain.	Band pass filtering, Notch filtering, Baseline removal, Wavelet thresholding .

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The proposed MS-DAYOLO framework improves the robustness and accuracy of object detection in cross-domain scenarios, making it a promising solution for real-world applications.

	Process Steps	Advantage	Disadvantage (Limitation)
1	Experimentation and data collection.	Helps us understand how the brain works during meditation.	Outside factors like noise can affect measurements, making control challenging.
2	Region of Interest(ROI) selection	Provides a clear, measurable view of brain activity, which is crucial for studying meditation.	People show different brain patterns, making it hard to find universal markers for meditation.
3	EEG Microstate detection using global field power (GFP) and topographical representation	Integrating EEG with other measures gives a full picture of mind-body connections during meditation.	Interpreting EEG data is complex and requires specialized knowledge.

Major Impact Factors in this Work

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Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
. P (Pressure) J(V)	Ki,vi(t),Vmean(t),Kc,xi,vj(where i and j are indices in the summation)	The equation relating the dependent variable P (Pressure) and the independent variables is that the specific nature of this influence can be understood by examining how changes in the independent variables affect the pressure as per the formula.	It provides insight into the underlying mechanism or pathway by which the independent variable affects the dependent variable. The mediating variable comes into play between the cause-and-effect relationship of the independent and dependent variables.

Relationship Among The Above 4 Variables in This article
The mediating variable gives insight into the process behind the link between the independent and dependent variables in the supplied equations, while the moderating variable affects the relationship's direction or intensity.

Input and Output	Feature of This Solution	Contribution & The Value of This Work

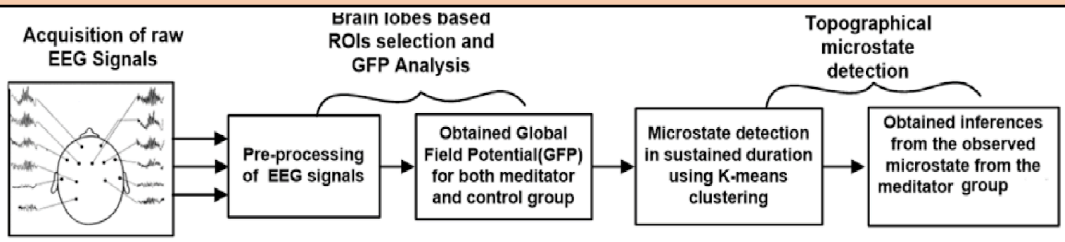
<table>
<tr>
<td colspan="2">
<table>
<tr><th>Input</th><th>Output</th></tr>
<tr><td>.EEG Data</td><td>the initial microstate activation of frontal-right temporal lobe brain states remained stable for a few milliseconds before rapidly evolving into another quasi-stable microstate</td></tr>
</table>
</td>
<td colspan="2">Microstates refer to short-lived, quasi-stable, topographical brain patterns.

EEG (Electroencephalogram) is used to trace these microstates, capturing the electrical activity of the brain.</td>
<td colspan="2">The research on EEG Traced Microstates Detection during Meditation advances our knowledge of the complex connection between brain activity and the altered states of consciousness brought on by meditation, which is of great benefit.

The possible uses might influence therapeutic strategies and meditation techniques in addition to scientific research.</td>
</tr>
<tr>
<th colspan="3">Positive Impact of this Solution in This Project Domain</th>
<th colspan="3">Negative Impact of this Solution in This Project Domain</th>
</tr>
<tr>
<td colspan="3">The EEG Traced Microstates Detection during Meditation project has a multitude of beneficial effects, from scientific breakthroughs to real-world implementations in mental health and education. It represents a significant advancement in the field of consciousness studies and meditation science</td>
<td colspan="3">. Although the EEG Traced Microstates Detection during Meditation project has a lot of potential, it is important to carefully consider any potential drawbacks. To lessen any project downsides, ethical issues must be addressed, reductionism must be avoided, and findings must be responsibly communicated.</td>
</tr>
<tr>
<th colspan="2">Analyse This Work By Critical Thinking</th>
<th colspan="2">The Tools That Assessed this Work</th>
<th colspan="2">What is the Structure of this Paper</th>
</tr>
</table>

By critically analyzing these aspects, one can form a nuanced understanding of the strengths and weaknesses of the work, contributing to a more informed assessment of its validity and significance in the broader academic and scientific context.	Combining such tools offers a thorough method for evaluating the many aspects of a research project. It guarantees a comprehensive assessment of the field's total contribution, quality, repeatability, ethics, and methodology.	Abstract I.Introduction II.Methods III.Result IV. Discussion V.Conclusion VI.Acknowledgement VII.Referencences

Diagram/Flowchart



---End of Paper 15---

16

Reference in APA format	N. Murali Krishna et al., "An Efficient Mixture Model Approach in Brain-Machine Interface Systems for Extracting the Psychological Status of Mentally Impaired Persons Using EEG Signals," in IEEE Access, vol. 7, pp. 77905-77914, 2019, doi: 10.1109/ACCESS.2019.2922047.

URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8734062	N. MURALI KRISHNA , KAUSHIK SEKARAN , ANNEPU VENKATA NAGA VAMSI , G. S. PRADEEP	Brain–computer interaction (BCI), emotion recognition, affective computing, electroencephalography

	GHANTASALA , P. CHANDANA , SEIFEDINE KADRY, TOMAS BLAŽAUSKAS , AND ROBERTAS DAMAŠEVIČIUS	(EEG), Gaussian mixture, cepstral analysis
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
An Efficient Mixture Model Approach in Brain-Machine Interface Systems for Extracting the Psychological Status of Mentally Impaired Persons Using EEG Signals	Classify different emotions by analysing physiological changes in the brain from the Central Nervous system.	Generalised mixture distribution Model, Emotion Recognition system vectors based on Mel-frequency cepstrum coefficients, MFCC-LPC and MFCC-LPC-SDC.
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	The brain signals are extracted using an EEG device and processed to minimise Noise.	It captures the brain activity which contains the data related to emotions which is used for emotion classification.	It mainly depends on the device and the limitations of the device which can also include the noise or the limited electrode coverage.

2	The Amplitude signals are then extracted and normalised into different ranges based on the rhythm.	By reducing the noise in the signals the accuracy of emotion recognition is Improved.	It may not completely eliminate all the noise from the signals and there may be chances of eliminating the actual data.
3	Feature vectors are created using Mel-Frequency Cepstrum Coefficients MFCC and MFCC-LPC.	Normalising the signals into different ranges helps in standardising the data.	The effectiveness of normalising the amplitude into different ranges may vary on the specific characteristics of the signals.
4	These features are used for dimensionality reduction, Data Feature extraction and emotion classification.	Feature vectors capture important characteristics of the signals enabling effective Dimensionality reduction for Emotion Recognition.	The MFCC and MFCC-LPC vector feature extraction mat not capture all the relevant information leading to Reduced accuracy in emotion classification.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Emotional State or the size of Emotional dimensions. The subject experiences in response to the stimulus.	The physiological parameters used to evaluate the emotional state such as GSR, ECG, EMG.	The relation between the event of the stimulus and the subjects responses. Here the MFCC variables may also lead to the dimensionality	The Intervening variable is the emotional state of the subject. These emotions induce physiological changes in the brain which are

		reduction and the Accuracy score.	captured and analysed to understand the subject's emotional state.

Relationship Among the Above 4 Variables in This article
The relation among the Emotional signals of the brain is the dependent variable which depends on the parameters to evaluate the emotions which are Galvanic Skin Response, ElectroCardiogram , Electromyography. They are the independent variables which do not depend on the emotional states irrespective of the dependent factors. Where the MFCC strengthens the relation among the emotion classification.

Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	**Output**	General Mixture Distribution Model, which allows accurate feature extraction from EEG signals. Truncation and Skew GMM, this allows the handling of Asymmetric data distributions.	It focuses on the Brain Machine Interface and Emotion Recognition using EEG, which contributes to HCI and the application of Artificial Intelligence using Emotion Recognition. It gives a viable opportunity to people suffering from various physical health conditions.
EEG signals obtained from differently disabled people like Parkinson's using GMDM.	Identification of emotion and classifying the emotions.		

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain

Increase accuracy in Emotion Recognition, Effective Signal Extraction and Suitable for higher Variability.	It may affect the generalizability of the results and applicability of the approach to a larger population. The effectiveness may vary upon specific stimuli.

Analyse This Work by Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
It involves extracting brain signals using EEG devices, minimising and extracting amplitude signals normalized into ranges. Where we classify them based on Rhythm and the dimensionality reduction is done by MFCC and other techniques.	The tools involved are Sensory systems, data discovery methods, knowledge imaging methods and principles of Artificial Intelligence. Further machine training and pattern recognition techniques are commonly used to transform physiological parameter to emotion states.	Abstract I. Introduction II. Outline of Methodology III. Generalized Mixture Model Distribution IV. Experimental Results V. Conclusion VI. References

Diagram/Flowchart

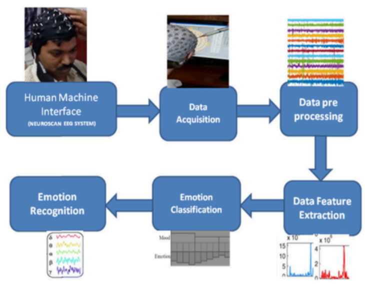


FIGURE 2. Block diagram for emotion recognition using EEG signals.

---End of Paper 16---

17

Reference in APA format	R. Majid Mehmood, R. Du and H. J. Lee, "Optimal Feature Selection and Deep Learning Ensembles Method for Emotion Recognition From Human Brain EEG Sensors," in IEEE Access,

	vol. 5, pp. 14797-14806, 2017, doi: 10.1109/ACCESS.2017.2724555.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=7997991	RAJA MAJID MEHMOOD , RUOYU DU , AND HYO JONG LEE	EEG pattern recognition, Hjorth parameter, EEG feature extraction, EEG emotion recognition
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Optimal Feature Selection and Deep Learning Ensembles Method for Emotion Recognition From Human Brain EEG Sensors	Efficiently recognise emotion states by analysing the features of EEG. To enable emotional communication via BCI	Ear EEG sensors, Hjorth parameters, Balanced One – way ANOVA.
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	Compute p-values	Selecting feature vectors for the required conditions.	The feature vectors accurately represent emotions being classified.
2	Classification of Emotions	Computation on GPU allows to obtain accurate classification	It requires specialised hardware and may not feasible in all settings

3	They are evaluated and set using a specific Equation.	Helps in identification of most relevant feature for emotion recognition	It is time taking especially with larger data sets and complex emotions.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Emotion recognition rate.	Feature selection and classifier methods used for emotion recognition	Size bands of the Emotion States	Signal Band of each State.

Relationship Among the Above 4 Variables in This article
As the variables are interlinked to each other where the independent variable performs operations on dependent variables to determine the Moderating variables such as the State of Emotions, the Mediating variable helps in classifying the provided data.

Input and Output	Feature of This Solution	Contribution & The Value of This Work
<table><tr><th>Input</th><th>Output</th></tr><tr><td>Scalp EEG data recorded through 14 channel EEG machine</td><td>Classification results for Emotional states.</td></tr></table>	EEG Emotion classification using One – way ANOVA to select optimal feature set for Emotion Recognition. It helps in identifying the feature vectors that satisfy a specific condition.	It improvises the Emotion recognition rate when compared to the commonly used spectral power band method.

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
It improves the existing method and improves the exact analysis of emotion state.	The collection and analysis of sensitive brain activity data could potentially be misused or compromised.

Analyse This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
It is technologically advanced version where the algorithms used are improved and functionally result in giving improved results	Emotiv – EPOV system, Auto – weka libraries (pre training classifiers data), IRB (Study protocol).	Abstract I. Abstract II. Introduction III. Methods and Materials IV. Results and Discussions V. Conclusion VI. References

Diagram/Flowchart
 FIGURE 7. Emotion classification process diagram.

---End of Paper 17---

18

Reference in APA format	A. Zachariah, J. Jai and G. Titus, "Automatic EEG artefact removal by independent component analysis using critical EEG rhythms," 2013 International Conference on Control Communication and Computing (ICCC), Thiruvananthapuram, India, 2013, pp. 364-367, doi: 10.1109/ICCC.2013.6731680.

URL of the Reference	Authors Names and Emails	Keywords in this Reference
https://ieeexplore.ieee.org/document/6731680	Anusha Zachariah , Jinu Jai, Geevarghese Titus	EEG rhythm; Independent Component Analysis; artefact; wavelet component; Kurtosis
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Automatic EEG Artifact Removal by Independent Component Analysis Using Critical EEG Rhythms	Aims to automate artefact removal from multi channel EEG signals using ICA	Wavelet filter, Kurtosis parameters, ICA.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)
1	Artefact removal from multichannel EEG	It helps in extracting different frequency components for better analysis and removal of artefacts	It increases redundancy of signals, and may sometimes result in rejection of useful data.
2	Wavelets correspond to each rhythm for separately stored channels. Kurtosis value is used to perform ICA.	Identifying and separate artifactual sources from EEG signal, improving Accuracy	ICA relies on assumption of statistical independence, it may not hold true values for all types of artefacts.

3	Artifactual sources are identified based on Kurtosis value and are rejected.	They help in reconstructing the artefact free EEG	The accuracy construction depends on the choosing of the Wavelets
4	Reconstruct channel wavelet coefficients and inverse wavelet transform is applied	It allows further analysis and interpretation.	The reconstructed signals may still contain Artefacts.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
EEG data, Electrical recording of the Brain	Independent Component Analysis, Wavelet Decomposition, Kurtosis.	The Kurtosis parameters and the SWT.	Wavelet and Artefact filter.

Relationship Among the Above 4 Variables in This article
As the data includes all the artefacts and required signals they are pre-processed and filtered for the required analysis. Then further they are classified into Artefacts and the Signals depending on the Kurtosis and SWT parameters and the required threshold values. Hence, the artefacts are removed and the process is automated by setting the required threshold value and required operating variables.

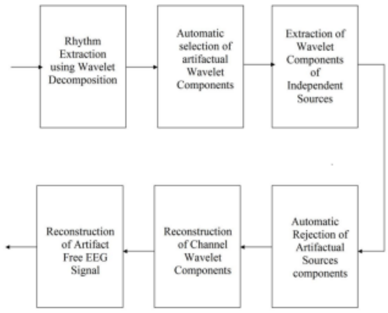
Input and Output	Feature of This Solution	Contribution & The Value of This Work

<table>
<tr>
<td>
<table>
<tr><th>Input</th><th>Output</th></tr>
<tr><td>Multi channelled EEG signal.</td><td>Artefact free channel wavelet component vector.</td></tr>
</table>
</td>
<td>Used to remove artefacts from multichannel signals and automate the removal of artefacts.</td>
<td>It contributes the removal and processing of the signals to automate.
It can also handle a large number of Channels.</td>
</tr>
</table>

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
By extracting rhythmic components and removing artefacts, it improves the quality of signals making them more reliable.	It depends on the Kurtosis parameters, if threshold value is not set accurately it results in rejection of useful information with the artefacts.

Analyze This Work by Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
By using this sequence we can automate the process of Artefact removal which increases the accuracy and also leaves a scope for analysis of various EEG signals for disease detection and mental state analysis.	Kurtosis parameters, ICA, Wavelet Decomposition and Stationary Wavelet Transform.	Abstract I. Introduction II. Process Flow III. Simulation Results IV. Conclusion and Future Scope V. References

Diagram/Flowchart



---End of Paper 18---

19

Reference in APA format	H. Donmez and N. Ozkurt, "Emotion Classification from EEG Signals in Convolutional Neural Networks," 2019 Innovations in Intelligent Systems and Applications Conference (ASYU), Izmir, Turkey, 2019, pp. 1-6, doi: 10.1109/ASYU48272.2019.8946364.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/8946364	Hayriye Donmez, Nalan Ozkurt	EEG, CNN, Deep Learning, Emotion Classification
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Emotion Classification from EEG Signals in Convolutional Neural Networks	To develop an Emotion Classification system using Single-channel EEG	Categorical classification model, EEG Recordings, Signal Segmentation and Spectrogram Calculations, Emotion classification.

	recordings and Spectrogram Analysis.	

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)
1	. It involves the segmentation of EE signals into different emotional states.	It allows for analysis of specific emotion states.	It might be a complex process which might end up he user having pressure on the brain
2	They are further mapped into 2-dimensional functions of frequency and STFT to extract Information.	Using spectrogram calculations helps in providing visual representation of signals energy distribution over time and frequency.	It requires the use of a short -time Fourier transform which is a complex algorithm.
3	The spectrogram which represents the energy distribution of signal over time frequency plane, obtained by squaring the magnitude of STFT.	By mapping into a 2-dimensional function it allows the important and useful information.	As it uses the STFT coefficients and window functions, it requires additional computational resources.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable

Accuracy rate of the emotion classification system.	Use of EEG device and the application of SFTF.	STFT coefficients, which determine the energy distribution.	Spectrogram which represents the energy distribution over time frequency plane.

Relationship Among the Above 4 Variables in This article
As given they are all Interdependent considering each of the variables is required to perform the analysis. Where such the accuracy rate is determined using the EEG device and by using the SFTF coefficients. Here the SFTF coefficients also determine the strength of the relation as they deal with the extraction of required information from the data. Finally the Spectrogram is used as the mediating variable which deals with the output generated from the classification.

Input and Output	**Feature of This Solution**	**Contribution & The Value of This Work**
<table><tr><th>Input</th><th>Output</th></tr><tr><td>Spectrogram images of bran signals from EEG devices.</td><td>Prediction of Emotion state</td></tr></table>	To classify the emotion states into three major emotions such as Fear, Fun and Sadness.	It provides insights about the effectiveness by using the spectrogram to obtain the brain activity and by further using CNN to classify them into the emotion states

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
It helps in classifying the emotional states which can help in disabled people to make action depending on their emotions.	All the action cannot be performed whereas the mechanism used might be complicated for the use in longer durations.

Analyze This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
In this work, resulted by using EEG signals and spectrogram images for emotion classification. The CNN model can achieve an accuracy of about 84.69% in classifying the Emotion States.	The document does not explicitly mention the tools used to access the work, whereas the EEG device is used to analyse the brain activity and SVM, Random forest methods, and deep learning are used to classify them.	Abstract I. Introduction II. Material and Method III. Results and Discuss IV. Conclusion V. References

Diagram/Flowchart

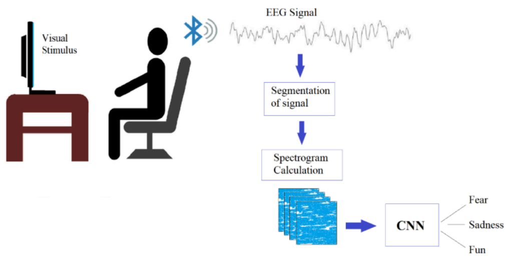


Figure 2. The Flow Chart of an Emotion Classification from EEG signals

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Reference in APA format	T. Nakamura, Y. D. Alqurashi, M. J. Morrell and D. P. Mandic, "Hearables: Automatic Overnight Sleep Monitoring With Standardized In-Ear EEG Sensor," in IEEE Transactions on Biomedical Engineering, vol. 67, no. 1, pp. 203-212, Jan. 2020, doi: 10.1109/TBME.2019.2911423.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/7959059	TAKASHI NAKAMURA , VALENTIN	Wearable EEG, in-ear sensing, ear-EEG, automatic sleep

	GOVERDOVSKY ,MARY J. MORRELL, AND DANILO P. MANDIC	classification, structural complexity analysis.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Automatic Sleep Monitoring using Ear - EEG	Aim to Develop, long-term wearable in-ear sensor for recording the electroencephalogram (ear-EEG).	It includes Ear-EEG sensor(Cloth Electrode, Foam Substance, Scalp - EEG, algorithms like SEF and MSFE, support vector machine (SVM) with a radial basis function (RBF).

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

Performance of Detection of spam in email is evaluated based on different algorithms and constraints. Even though this author compared various results upon validating the test data and trained data using machine learning with all supervised and Lazy learning algorithms.

	Process Steps	Advantage	Disadvantage (Limitation)
1	Data Acquisition	Scalp EEG are recorded using Gold-cup Electrodes, EEG was recorded from left and right ear and the devices to measure are comparatively Feasible.	The electrode needs to be placed inside the ear which may cause discomfort to the User.

2	Sleep Stage Scoring	A passband filter of 1 – 20hz was applied to two bipolar EEG Configuration.	They were manually scored by a clinical expert.
3	Pre – Processing for Automatic Stage Classification	It is fairly compared with automatic Scoring Algorithm fir a single EEG channel, then the data is down sampled.	There is an approximate loss of Data for about 20%
4	Feature Extraction	Further 2 types of features are extracted from each epoch of EEG.	There are Multi-scale entropy calculating structural complexities of time series over multiple temporal scales.
5	Classification	SVM and RBF are used as classifiers for the 30 SEF and MSEF	As they are Normalised to range [0 1], the one – against – one multi – class kernel are used.
6	Performance Evaluation	It evaluates according to the sleep intervals and is calculated for both in Ear EEG and Scalp EEG.	The performance metrics are all class specific sensitivity and precision.
7	Data Acquisition	Scalp EEG are recorded using Gold-cup Electrodes, EEG was recorded from left and right ear and the devices to measure are comparatively Feasible.	The electrode needs to be placed inside the ear which may cause discomfort to the User.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Ear – EEG device and Scalp EEG	Sleep Schedule of the User	The connectivity in between the EEG device to the output representation.	The paper does not mention mediating variables, but Classification algorithms such as SVM and RBF can be considered as the Intervening Variables.

Relationship Among the Above 4 Variables in This article
As the device begins to work it initially collects the user's sleep data which may vary depending on the user's everyday activity. Further this collected data is transmitted to categorise under 30s of duration to record the no. of Epochs to score. They are further classified using SVM and RBF methods to result in the output.

Input and Output	Feature of This Solution	Contribution & The Value of This Work
<table><tr><th>Input</th><th>Output</th></tr><tr><td>Users sleep data.</td><td>If the user is having any trouble and the accuracy of the measurement.</td></tr></table>	To develop a fully functional Ear-EEG device to analyse sleep pattern without involvement of a trained clinical professional.	It plays an important role as to understand about the use of this device and whether it accurately accomplishes all our requirements.

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
It helps in understanding the availability of different measurement devices available and to choose the accurate	As it majorly deals with sleep monitoring it leaves us a major drawback regarding the rest of emotions and users state of mind.

Analyse This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
This work deals with an easily feasible device which can be used even without a trained professional and can also be used for longer duration. It is also improvised in aspects that were not accomplished in previous devices.	Manual scoring guidelines under ICREC	Abstract I. Introduction II. Methods III. Results IV. Discussion and Conclusion

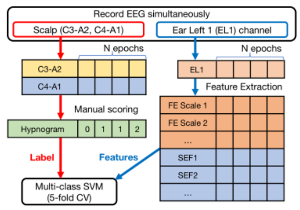
Diagram/Flowchart


FIGURE 4. Flowchart for the sleep stage prediction framework adopted in this study (*Scenario 2*).

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2.2 COMPARISION TABLE:

Author	Year	Approach	Description
M.M.Kodab agi,Mr.Vijay amahantesh S. Kanavi,"	2013	Morphological operation, horizontal and vertical edge	They used morphological, horizontal and vertical operation for extraction, character segmentation

		processing, neural network	was used for labeling component neural network for recognition license plate.
Saravana Kumar.G, Ram Kumar.T, Senthil Kumar.M, Manoj kumar.W	2013	Ycbcr color model and MATLAB	They proposed accurate license plate which used serial operation to localize license plate.
Manoranjan Paul*, Shah M E Haque and Subrata Chakraborty	2013	spatio-temporal filtering techniques and optical flow	They proposed optical flow and spatio-temporal filter techniques and addressed some issue to some extent of fixed object and their motion.
D.Surangsrirat and A. Intarapanich	2014	SVM and optical flow	They proposed method for identifying player motions.
Matko Saric,Hrvo Rozic	2009	Algorithm region growing based, hsv color model, internal contour	They proposed algorithm that used temporal redundancy and increased identification.
Hussein Alawieh, Zaher Dawy, Elias Yaacoub, Nabil Abbas, and Jamil El-Imad	2019	A real-time algorithm for Electrocardiogram (ECG) feature extraction.	They proposed a real-time algorithm for ECG feature extraction, employing frequency analysis and adaptive thresholding to accurately detect and visualize meditation levels.
P. Pandey, J. Rodriguez-Larios, K. P. Miyapuram and D. Lomas	2023	The approach involves using EEG signals and machine learning models to detect moments of distraction during meditation practice and	They proposed a solution using EEG signals and machine learning to detect and alert moments of distraction during meditation, improving the overall meditation experience.

		provide real- time neurofeedback to alert practitioners.	
D. Surangsrirat and A. Intarapanich	2015	The approach involves using a consumer EEG device, Muse, to record and analyze brainwave activity, particularly during meditation, and assessing its potential as an affordable and accessible research tool for studying brain activity.	The paper proposes the utilization of a consumer EEG device, Muse, to record and analyze brainwave activity during activities such as meditation, demonstrating its potential as a cost- effective tool for research in this domain.
H. Hadavi and N. Sho'ouri	2019	Involves introducing soft boundaries and a variable scoring system in neurofeedback training, known as Soft Boundary- based Neurofeedback Training (SBNFT), to control and optimize EEG signal features.	The proposed method, Soft Boundary-based Neurofeedback Training (SBNFT), utilizes fuzzy similarity measures and a variable scoring system to regulate and optimize EEG signal features during neurofeedback training.
W. L. Lim, O. Sourina and	2015	The approach involves developing a	They propose the development of a 3D game, "Multitask In

L. Wang		3D multitasking game with neurofeedback, using the Unreal 3 engine, to test and train cognitive abilities particularly multitasking skills.	Neurofeedback Driving (MIND)," integrating neurofeedback technology for testing and training multitaskingabilities, emphasizing its potential benefits in cognitive skill enhancement.
Bhavna P.Harne,Yog iniBobade, Dr.R.S.Dhek ekar, Dr.AnilHiwa le	2019	Support Vector Machne	This method aims to classify EEG signals using Support Vector Machine (SVM) classification in order to assess the impact of OM Mantra meditation on the brain
Neha Gupta, Neetu Sood, Indu Saini	2018	Statistical Feature Based Comparison of EEG in Meditation for Various Wavelet	Different wavelet functions give different observations in all bands of EEG. The ratio of powers is calculated.
Büşra Ülker, Mehmet Barış Tabakcıoğlu, Hüseyin Çizmeci1, Doruk Ayberkin2	2017	The Neurosky EEG biosensor is used to evaluate students' degrees of attention and meditation.	A program is developed in C# medium. The developed program records raw brainwave data, attention and meditation average while the students are studying.
Laxmi Shaw, Aurobinda Routray	2020	The highest level of consciousness which might be seen in proficient Kriya practitioners.	This study, whose subjects are long-term KY meditation practitioners, offers a topographical method for identifying microstates throughout the whole brain.This study, whose

			subjects are long-term KY meditation practitioners, offers a topographical method for identifying microstates throughout the whole brain.
Ankita Tiwari, Rajinder Tiwari	2017	Matlab	The aim of the author is to concentrate on understanding how mood swings affect EEG waves and how yoga practice. might help avoid these swappings
InungWija yanto	2019	SVM-support vector machine	Provide the test to diagnose and detect epilepsy
Cheng-Yi Chiang, Nai-Fu Chang	2011	Preprocessing of data	train a machine learning model for seizure prediction using a fixed training set in real-time. or near-real-time.
Gupta, S. Bagga	2020	methodology adopted involves the application of Discrete Wavelet Transform (DWT) to EEG signals.	the epileptic seizures is a time consuming process so by using classfiers the model gives the quick and 99.6 accurate output.
Bryan Van Hal Samhita Rhodes	2014	Filter EEG signal into different frequency bands. Compute thresholds based on baseline data.	counting approach and an algorithmic approach to enhance the accuracy of sleep detection
Richa S. Wadekar Prashant V. Kasambe	2017	Butterworth filter of order 6 to enhance the raw EEG signals	To develop a LabVIEW platform for EEG signal analysis

2.3 WORK EVALUATION TABLE:

	Work Goal	System's Components	System's Mechanism	Features /Characteristics	Performance	Advantages	Limitations /Disadvantages	Results
H. Alawieh, Z. Dawy, E. Yaacoub, N. Abbas and J. El-Imad 2019	Developing real-time EEG and ECG feature extraction with VR for meditation enhancement, applicable to cognitive training and neurofeedback.	System components: EEG and ECG sensors, signal processing, VR platform, feedback controller for meditation.	System dynamically optimizes meditation using real-time ECG features and VR feedback.	Features include EEG/ECG pattern analysis, low respiratory rates, stable blood pressure, and motion tracking for enhanced relaxation in VR.	The real-time monitoring capability provides immediate feedback, while integration with virtual reality enhances the immersive nature of meditation training.	Real-time monitoring enables immediate feedback and Integration with virtual reality enhances the immersive nature of meditation training.	Algorithm details lacking for feature extraction; individual variations in meditation experiences not fully addressed.	Algorithm effectively distinguishes meditation states using ECG features, showing increased relaxation levels during Chi meditation.

P. Pandey, J. Rodriguez-Larios, K. P. Miyapuram and D. Lomas 2023	To use machine learning to detect distraction during meditation practice by analyzing EEG signals.	The components of the solution include EEG data collection, feature extraction, machine learning models (supervised and unsupervised), data segregation, and result analysis for detecting moments of distraction during meditation.	The mechanism of this work involves Data Collection and preprocessing, Model learning and Prediction.	Include linear and non-linear features extracted from the EEG data. These features are used to characterize and analyze the EEG signals for the purpose of classifying different meditation states.	By leveraging EEG data and machine learning, the system achieves real-time detection of meditation distractions, providing immediate feedback for enhanced focus, which benefits both beginners and experienced practitioners.	Utilizing EEG data and machine learning enables real-time detection of meditation distractions, offering immediate feedback for enhanced focus. This objective assessment benefits both beginners and experienced practitioners.	Study focused on breath focus meditation; limited exploration of effectiveness for diverse techniques. EEG signals prone to artifacts, data quality issues, external factors affecting accuracy.	The results indicate that machine learning models can successfully identify moments of distraction during breath focus meditation.

D. Surangsrirat and A. Intarapanich 2015	To explore the feasibility of using a consumer EEG device for recording brainwave activity during meditation and various activities.	Muse (Consumer EEG Device), EEG Data	The process of this work involves Data Collection, Data Analysis and Spectral Analysis	Use of a consumer EEG device (Muse) to provide affordable, non-invasive, and wireless EEG data collection, making it accessible for research and spectral analysis of brainwave activity during various activities.	Consumer EEG devices like the Muse offer affordable and accessible data collection with user-friendly dry electrodes, showcasing their viability as research tools for spectral analysis of brainwave activity during various activities, although they may provide less detailed data..	Consumer EEG devices offer affordable and accessible data collection, utilizing user-friendly dry electrodes. The study showcases their viability as research tools, emphasizing their advantages over traditional EEG systems.	Consumer EEG devices, though accessible, may lack detail and accuracy compared to clinical-grade systems, potentially limiting broader research applicability focused on meditation.	It discusses the process, methods, and the potential of using a consumer EEG device (Muse) to record the brainwave activity of Buddhist monks during various activities, including meditation.

H. Hadavi and N. Sho'ouri 2019	Aims to guide subjects in learning how to control specific features of their EEG signals during training while avoiding excessive increases or decreases that may lead to side effects.	Target and preliminary clusters, fuzzy similarity calculation, a threshold, and a variable scoring index.	The SBNFT method, as described in the paper, involves the calculation of fuzzy similarity measures for subjects' training features, comparison of these measures to a threshold, and the use of a variable scoring index to provide feedback to the subjects during training.	Offers controlled neurofeedback training, employing fuzzy similarity measures to evaluate subjects' brain activity in relation to a target cluster. It incorporates a dynamic scoring index and aims to prevent excessive changes in brain activity, ultimately enhancing training outcomes	The SBNFT method ensures safe and effective neurofeedback training by safeguarding against side effects, tailoring feedback with variable scoring for precision, and promoting more effective control of brain signals, although effectiveness relies on accurately defining clusters and fine-tuning thresholds.	The SBNFT method safeguards against side effects, tailors feedback with variable scoring for precision, and ensures safe and effective neurofeedback training.	Effectiveness relies on accurately defining clusters, fine-tuning thresholds, and dealing with added complexity in implementing fuzzy similarity measures.	Increased low beta power in some subjects during training and analyzed fuzzy membership values towards the target cluster, revealing variations among subjects. Subjects showed different trends in obtained scores during online training using FNFT and SBNFT methods, and a comparison of scores between the two methods.

W. L. Lim, O. Sourina and L. Wang 2015	To address and enhance the multitasking abilities of individuals, particularly in scenarios relevant to driving or piloting, such as those in the aviation industry.	A 3D game environment, multiple multitasking tasks, neurofeedback using EEG technology, difficulty levels, a scoring system, various game variants, and a training and testing protocol.	The process combines game-based training, cognitive tasks, and neurofeedback to create an engaging and adaptive environment for users to improve their multitasking abilities.	The solution features a 3D game with neurofeedback to train and test multitasking abilities, addressing a growing interest in improving cognitive skills for tasks like driving and piloting.	The proposed 3D multitasking game, "Multitask In Neurofeedback Driving (MIND)," offers an interactive platform with a quantifiable scoring system and flexible game variants for diverse testing scenarios, aiming to enhance cognitive performance, despite dependencies on EEG headset availability and	Advantages include an interactive platform for multitasking training, a quantifiable scoring system for assessment, and flexible game variants for diverse testing scenarios.	Limitations include the dependency on the availability of the Emotiv EPOC EEG headset, a learning curve for users adapting to multitasking tasks, and the need for high technical expertise in game development and neuroscience for implementation.	The result is a proposed 3D multitasking game, named "Multitask In Neurofeedback Driving (MIND)," designed for training and testing multitasking abilities. The output also includes a scoring system, game variants, and the integration of neurofeedback technology, aiming to enhance cognitive performance.

					technical expertise for implementation.			
Inung Wijayanto	providethe text to diagnose and detect epilepsy	EEG Equipment	SVM-support vector machine	several key features that make it effective for its intended purpose.	Sixty thousand	fast	Depends on input data	A fused image which helps researchers compare and benchmark different methods for medical image fusion, which can lead to further improvements in the field.

Cheng-Yi Chiang, Nai-Fu Chang	train a machine learning model for seizure prediction using a fixed training set in real-time or near-real-time.	EEG Equipment	Preprocessing of data	seizure prediction in epilepsy incorporates several key features that contribute to its effectiveness	Sixty thousand	fast	Depends on input data	Binary segmentation mask that identifies the tumor region in the images.

Gupta, S. Bagga	the epileptic seizures is a time consumi ng process so by using classfiers the model gives the quick and 99.6 accurate output.	EEG Equipmen t	methodol ogy adopted involves the applicatio n of Discrete Wavelet Transform (DWT) to EEG signals.	utilization of Discrete Wavelet Transform (DWT) for the analysis of EEG signals	65 thousand	Fast	Depends on input data	The results of this work show that the fusion process provides more accurate and informative images for clinical diagnosis, which can lead to better patient outcomes and improved healthcare delivery.
Bryan Van Hal Samhita Rhodes	counting approach and an algorith mic approach to enhance the accuracy of sleep detection	EEG Equipmen t	Filter EEG signal into different frequency bands. Compute thresholds based on baseline data.	the presented sleep detection system is its ability to provide real-time detection	65 thousand	Fast	Depends on input data	A fused image

Richa S. Wadekar Prashant V. Kasambe	To develop a LabVIEW platform for EEG signal analysis	Neurosky headset	Butterworth filter of order 6 to enhance the raw EEG signals	focus on providing a cost-effective and accessible platform for EEG signal analysis	70 thousand	Fast	Depens on input data	The fusion results obtained are observed and quantitatively analysed, indicating a favourable hybrid fusion response in combining MRI and CT images of the brain.

Ankitha Tiwari Rajinder Tiwari 2020	Aim of the author is to concentrated on understanding how mood swings affect EEG waves and how yoga practice might help avoid these swappings	EG stands for electrical impulses from the nerves related to actions done . Every source of ideas, actions, and emotions is signaled electrically by the brain's nerves	Data Analysis and Visualization. Customization. Signal processing.	Observing and analyzing EEG signals before and after yoga during depression in the human brain using MATLAB involves various features and components that makes it a comprehensive solution .	-	Observing and analyzing EEG signals before and after yoga during depression in the human brain using MATLAB involves various features and components that makes it a comprehensive solution .	. A wide range of preprocessing methods for EEG data, including feature extraction, noise reduction, and filtering, are available in MATLAB.	Observing and analyzing EEG signals before and after yoga during depression in the human brain using MATLAB involves various features and components that makes it a comprehensive solution.

Bhavna P.Harn, YoginiBobade, Dr.R.S. Dhekekar, Dr.Anil Hiw 2017	This method aims to classify EEG signals using Support Vector Machine (SVM) classification in order to assess the impact of OM Mantra meditation on the brain. Finding out how OM Mantra meditation impacts brain	EEG Data Acquisition, Data Preprocessing , Feature Extraction, Data Labeling, data splitting, SVM Model Selection.	Mean of delta band of EEG before and after OM meditation. Standard deviation of delta band of EEG before and after OM meditation. Variance of EEG signal for before and after OM meditation.	SVM excels in handling high-dimensional data, making it suitable for processing the complex information extracted from EEG signals during OM Mantra meditation.		A quantitative way to assess changes in this particular frequency range is by calculating the mean of the delta band	The standard deviation alone does not provide specific information about the underlying neural processes that may be altered during meditation.	. This work mainly focused on the method having high computational accuracy with less complexity and less computational time with the SVM classifier.

			IQR of EEG signal for before and after OM meditation.	The solution provides a robust and accurate classification, offering insights into how brain activity changes during meditation					
Neha Gupta Neetu Sood Indu Saini 2018	Different wavelet functions give different observations in all bands of EEG. The ratio of powers is calculated.	EEG Data	Data collection. Preprocessing, Wavelet Processing, Feature Extraction	The solution involves statistical analysis of EEG data, indicating a quantitative and rigorous approach to studying brainwave patterns during meditation.	-	The approach allows for the identification of patterns or trends in EEG signals that may not be immediately apparent.	Collaboration between experts in statistics, neuroscience, and signal processing is necessary, posing challenges in interdisciplinary research..	. It implies that Haar wavelet gives better performance than other wavelet function.

Büşra Ülker Mehmet Barış Tabakcıoğlu Hüseyin Çizmeci 1 Doruk Ayberkin2 2017	A program is developed in C# medium. The developed program records raw brainwave data, attention and meditation on average while the students are studying	Attention Measurements, Meditation level Assesment, psychological factor.	Get Brainwave Information, This level of concentration and meditation might be raised by altering the color scheme of the space.	Uses a special brain sensor called Neurosky Mindwave to measure how focused and relaxed students are. Not just for education—can be used in other areas like making driving safer or developing technology for people with disabilities..	-	Determining individual differences in meditation and attention spans can help with the creation of tailored learning strategies.	Focusing too much on brain factors may oversimplify the many influences on learning.	Since the students' levels of focus and concentration are sufficiently high, it is acknowledged that they are learning the course material. Students have worse exam marks because they meditate and pay less attention on

Laxmi Shaw Aurobinda Routray 2020	This study, whose subjects are long-term KY meditation practitioners, offers a topographical method for identifying microstates throughout the whole brain	Band pass filtering, Notch filtering, Baseline removal, Wavelet thresholding	Experimentation and data collection, Region of Interest(ROI) selection, EEG Microstate detection using global field power (GFP) and topographical representation	Microstates refer to short-lived, quasi-stable, topographical brain patterns. EEG (Electroencephalogram) is used to trace these microstates, capturing the electrical activity of the brain.	-	.Provides a clear, measurable view of brain activity, which is crucial for studying meditation.	Interpreting EEG data is complex and requires specialized knowledge.	the initial microstate activation of frontal-right temporal lobe brain states remained stable for a few milliseconds before rapidly evolving into another quasi-stable microstate.

N. Murali Krishna, Kaushik Sekaran, Annepu Venkata Naga Vamsi, G. S. Pradeep Ghantasala, P. Chandana, Seifedine Kadry, Tomas Blažauskas, and Robertas Damaševičius.	To provide a method of communication for people suffering from Physical Health Conditions through Emotion Recognition using EEG	8 – channel EEG device, Generalized mixture distribution Model.	The device is used to collect the user data through the 8 – channel Electrodes. The collected data is pre-processed and classified through MFCC, further by classifying them into the band depending on the Range and rhythm.	The paper focuses on establishing a method of communication for physically challenged people using EEG to identify and classify the Emotions.	The emotion recognition for Happiness was (99.3%), Sadness (83.4%), Boredom (78.9%), Neutral (98.4%).	For people suffering from disabilities like Parkinson's or such other, this gives a mean to communicate with them.	It may affect the generalizability of the results when compared to a larger population. The effectiveness may differ upon specific events.	It is shown to give a total accuracy of 89.1%

Raja Majid Mehmood, Ruoyu Du, and Hyo Jong Lee.	To classify human emotions using various Hjorth. Parameters based optimal feature selection and classifiers including Deep Learning, KNN, SVM	Emotiv-EPOC with a 14 channel electrodes to record 128 samples each second. WEKA Machine Learning system which includes the classifiers used for Emotion Recognition.	Using the EPOC device the EEG signals are collected and they are sent for pre processing. Using one – way Anova, KNN, SVM as classifiers they are further separated.	In this paper with regard to the previous workings such as Khalili at al, chanel et al and other various methods the proposed method includes deep leaning, svm, knn methods for the classification which helps in achieving better emotion detection.	Considering 2 sessions of 45 instances with 4 emotions, it gives a total of 360 instances.	Using Auto-WEKA Libraries helps in selection of the top classifiers, which finally provides the classification for the instances occurred.	The hardware requirement may not be feasible for daily use. While considering for a large or Complex Data sets it requires specialized hardware.	It is shown to give a total accuracy of 76.6%

Anusha Zachariah , Jinu Jai, Geevarghese Titus	This paper represents research on accurately analysis of required Critical EEG Rhythms and Artifact Removal	EEG Device, Matlab	Artifact removal from multichannel EEG. Wavelets correspond to each rhythm for separately stored channels. Artifactual sources are identified based on Kurtosis value and are rejected. Reconstruct channel wavelet coefficients and inverse wavelet transform	Used to remove artifacts from multichannel signals and automate the removal of artifacts.	The different categories of classifications are further measured.	It helps in extracting different frequency components for better analysis and removal of artifacts.	It increases redundancy of signals, may sometimes may result in rejection of useful data.	Artifact free channel wavelet component vector.

Hayriye Donmez , Nalan Ozkurt	To develop an Emotion Classification system using Single-channel EEG recordings and Spectrogram Analysis.	Categorical classification model, EEG Recordings, Signal Segmentation and Spectrogram Calculations, Emotion classification.	It involves the segmentation of EE signals into different emotional sate. They are further mapped into 2-dimensional function of frequency and STFT to extract Information. obtained by squaring the magnitude of STFT.	To classify the emotion states in to three major emotions such as Fear, Fun and Sadness.	The accuracy to measure the emotions are comparatively exponential with respect to the existing models.	It allows for analysis of specific emotion state.	It might be a complex process which might end up he user having pressure on the brain	Prediction of Emotion state.

T. Nakamura, Y. D. Alqurashi, M. J. Morrell and D. P. Mandic	Aim to Develop, long-term wearable in-ear sensor for recording the electroencephalogram (ear-EEG).	Ear-EEG sensor	Data Acquisition, Pre – Processing for Automatic Stage Classification, Feature Extraction, Classification, Performance Evaluation	a fully functional Ear-EEG device to analyse sleep pattern with out involvement of a trained clinical professional.	The emotion recognition for various are recorded with greater accuracy	It evaluates according to the sleep intervals and is calculated for both in Ear EEG and Scalp EEG.	It increases redundancy of signals, may sometimes may result in rejection of useful data.	Prediction of Emotion state.

CHAPTER 3

PROPOSED SYSTEM

3.1 PROPOSED SYSTEM

The proposed approach is focused on the creation of a user oriented web application making use of neurofeedback advanced technologies to exemplify an improved mental wellness through individual meditation. The users will be allowed to simply manually enter numeric values showing brain wave patterns. As the application analyse the data in real time, it will provide auditory guidance during the sessions of meditation where they are tailored to meet an individual needs, promoting mindfulness and relaxation. Also, the system will resolve mental health disorders that highly probable to occur by using EEG data that provided by users and offer representation of brainwave patterns and allow users to interact with their data directly to better understand their mental health issues.

3.2 OBJECTIVES OF PROPOSED SYSTEM

The objectives of the proposed system include the following:

- Predicting mental health disorders through EEG signal analysis.
- Providing personalized meditation recommendations based on neurofeedback data analysis.
- Offering real-time audio guidance during meditation sessions.
- Providing visualization feedback of EEG data to track meditation progress.
- Ensuring accessibility to individuals seeking mental well-being improvement.
- Integrating technologies to promote mental wellness through meditation.

3.3 ADVANTAGES OF PROPOSED SYSTEM

The proposed system has the following advantages:

- Personalized Meditation Recommendations: Tailored meditation suggestions based on individual EEG data analysis.

- Real-Time Audio Guidance: Providing immediate audio support during meditation for enhanced relaxation.
- Visualization Feedback: Visual tracking of meditation progress through EEG data visualization.
- Effective Distraction Identification: Identifying distractions during meditation to improve focus.
- Prediction of Mental Health Disorders: Early detection and prediction of potential mental health disorders.
- Global Accessibility: Accessible platform for mental well-being improvement worldwide.
- Integration of Advanced Technologies: Leveraging cutting-edge technologies for innovative mental wellness solutions.

3.4 SYSTEM REQUIREMENTS

The system requirements for the development and deployment of the project Neurofeedback Meditation Web Application, is described in this section. These system requirements concentrate on complete implementation beyond user viewing environments and support to various devices.

3.4.1 SOFTWARE REQUIREMENTS

Below are the software requirements for application development:

1. Python environment with Streamlit library for frontend development.
2. Editor for Python scripting such as VS Code or Jupyter Notebook.
3. Machine learning libraries including Scikit-learn for model training.
4. Libraries for data visualization like Matplotlib and Seaborn.
5. Streamlit-compatible web browsers for testing and deployment.

3.4.2 HARDWARE REQUIREMENTS

Hardware requirements for application development are as follows:

1. CPU: Intel Core i5 or higher for efficient processing.
2. RAM: 8 GB or higher to handle data processing and model training.
3. Storage: Sufficient disk space for storing datasets and model files.
4. Internet connection: Required for accessing EEG datasets and deploying web application.

3.4.3 FUNCTIONAL REQUIREMENTS

1. Input: Users should be able to input EEG data containing measurements of brainwave activity across various frequency bands (alpha, beta, delta, theta, high beta, gamma waves).
2. Data Preprocessing: Implement preprocessing steps such as handling missing values, standardizing channel names, and categorizing mental health disorders for analysis.
3. Feature Engineering: Extract meaningful features from EEG signals, including metrics like mean band power for different mental health disorders.
4. Model Training: Train machine learning models (e.g., MLP) to predict mental health disorders based on extracted EEG data features.
5. Personalized Recommendations: Provide personalized meditation recommendations and audio guidance based on the predicted mental health disorder.
6. Visualization Feedback: Display visual feedback on EEG data to allow users to track their meditation progress over time, empowering active management of mental well-being.

3.4.4 NON-FUNCTIONAL REQUIREMENTS

1. Security: Ensure robust measures to protect user privacy and confidentiality, especially regarding the handling of sensitive EEG data.
2. Performance: Optimize system performance to deliver real-time audio guidance and visualization feedback seamlessly, without delays or lag.

3. Usability: Design an intuitive and user-friendly interface accessible across various devices, ensuring ease of navigation and interaction for users of all levels.

4. Reliability: Ensure the system operates reliably without frequent downtime or interruptions, particularly during meditation sessions.

3.5 IMPLEMENTATION TECHNOLOGIES

3.5.1 NeuroFeedback:

Neurofeedback, also known as EEG biofeedback or neurotherapy, is a form of brain training that aims to regulate brainwave patterns to improve cognitive functions and emotional well-being. It involves monitoring a person's brainwave activity, typically using electroencephalography (EEG), and providing real-time feedback to help individuals learn to self-regulate their brain activity. This feedback is often presented visually or audibly, allowing individuals to observe changes in their brainwave patterns and adjust their mental state accordingly. Neurofeedback has been used to treat various conditions, including attention deficit hyperactivity disorder (ADHD), anxiety, depression, and insomnia, by promoting relaxation, focus, and emotional balance.

EEG Data Analysis:

The system is based on the advanced analytical techniques in EEG data extraction to generate essential information out of the raw EEG signals. This includes elimination of noises and artifacts from the data and feature extraction to identify the significance of the features related to integrated mental health conditions. After the individual features are extracted, these are used to train the machine learning models for those prediction and recommendation purposes.

3.5.2 Multilayer Perceptron:

MLP stands for Multilayer Perceptron, which is a type of artificial neural network architecture. It is a class of feedforward neural networks consisting of multiple layers of nodes, or neurons, organized in a hierarchical manner. In an MLP, information flows from the input layer through one or more hidden layers to the output layer. Each layer is fully connected to the next layer, with each connection having an associated weight. MLPs are capable of learning complex patterns in data and are widely used for various machine learning tasks, including classification, regression, and pattern recognition. They can approximate nonlinear functions and capture intricate relationships between input and output variables. The training of MLPs typically involves techniques like backpropagation, where the network adjusts its weights based on the error between predicted and actual outputs, in order to minimize the loss function.

MLPs have been successfully applied in diverse domains such as image recognition, natural language processing, and financial forecasting. They are known for their flexibility, scalability, and ability to model complex datasets, making them a popular choice for many machine learning applications.

Data Processing:

Pythons pandas imports help with data loading, manipulation, and preprocessing. scikit-learn for standardization of features and encoding categorical variables. MNE (MNE-Python) could be used to process EEG data requiring analysis and simulation with shareable models, visualization, and feature extraction.

Feature engineering and Model Training:

Feature engineering is a critical step in analyzing EEG data for mental health disorder prediction. It involves extracting informative features from raw EEG signals to capture relevant patterns indicative of different mental states. This process includes visualizing EEG signals to understand their characteristics, calculating metrics such as mean band power for various frequency bands, stratifying the dataset based on mental health disorders, and restructuring the data for analysis. These engineered features serve as input for machine learning models, enabling them to learn and predict mental health disorders accurately. Model training involves optimizing and selecting the best-performing algorithm based on evaluation metrics such as accuracy, precision, recall, and F1-score, ensuring the effectiveness of the prediction model in the NeuroFeedback Meditation Web App.

3.5.2 Python:

The backend for the system is developed using Python programming language (Jupyter Notebook). Python gives a generous set of libraries and frameworks for machine learning, data analysis, and web development, therefore, it is good for constructing the complicated and dynamic applications. With its readability and ease of use, Python adds to the efficiency and maintainability of the system's code base.

Streamlit:

Streamlit is an open-source Python library that simplifies the process of creating web applications for data science and machine learning projects. It allows developers to build interactive web apps directly from Python scripts, without needing to write HTML, CSS, or JavaScript code. With Streamlit, developers can quickly prototype and deploy data-driven applications, visualize data, and share insights with others. It provides a straightforward and intuitive interface for creating user interfaces, incorporating widgets for input controls, data visualization, and interactivity. Streamlit's simplicity and flexibility make it an ideal tool for creating web-based applications for data exploration, model prototyping, and showcasing machine learning models.

CHAPTER 4

SYSTEM DESIGN

4.1 PROPOSED SYSTEM ARCHITECTURE

The proposed system involves the possible use the user interaction for data inputting where the data undergoes a preprocessing procedure and moves on to analyze it with advanced machine learning models like MLP in order to predict mental health disorders. Later, a system will generate personalized recommendations and audio mentoring during meditation sessions, additionally EEG data visualization will be provided in order to reinforce users in controlling their mental health effectively.

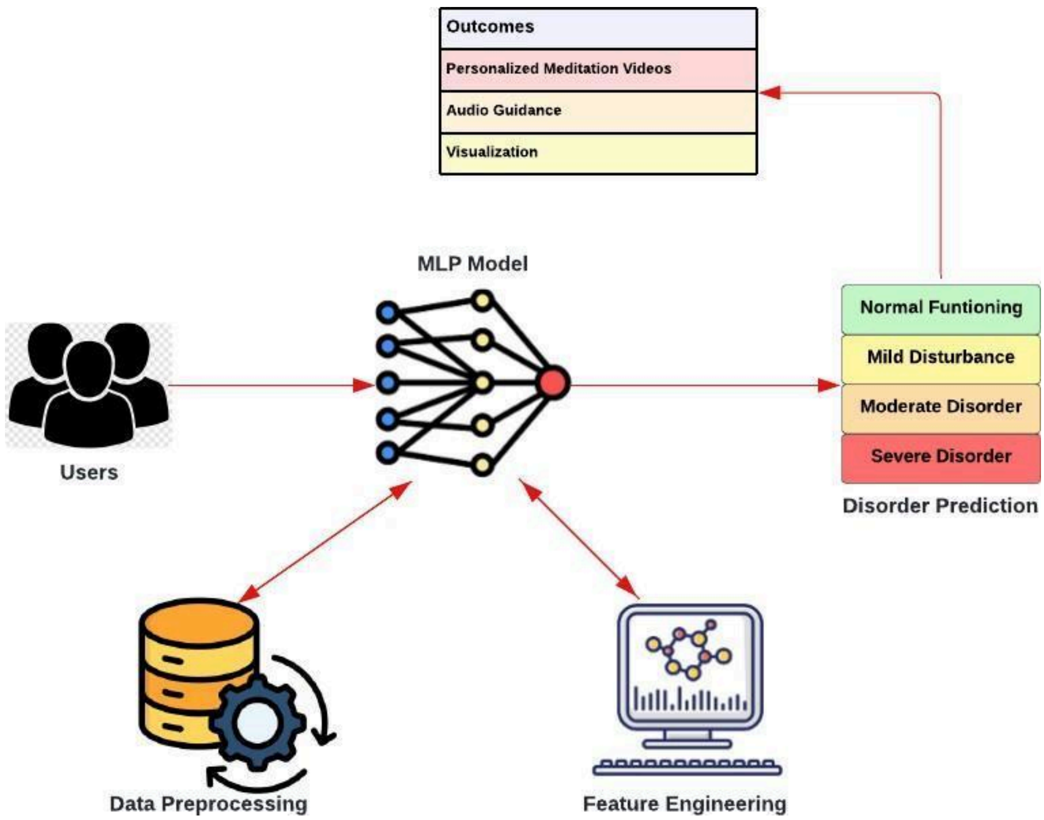

Figure 1: Proposed Architecture

4.2 APPLICATION MODULES

The application on an overall involves three main modules, i.e, Data Acquisition and Preprocessing, Feature Engineering, and Model Training. This software incorporates algorithms to handle incoming EEG data, isolates important parameters, and uses

Multi-Layer Perceptron (MLP) classifier to teach the computer to tell mental illnesses from healthy conditions.

4.2.1 Data Acquisition and Preprocessing Module

The Data Acquisition and Preprocessing module is the first building block in this system that helps to make EEG-based mental health disorder monitoring. This vital stage starts with data acquisition from a reliable diagnostic center, famous with specialists in conducting neurological and psychological assessments, that will share data. The pick of this source will present the data in a reliable and pertinent way, allowing it to be used as the basis for further analysis. Simultaneously, the EEG recordings themselves are inseparable in the process; also, metadata, describing demographics and recording conditions, are acquired. The supplement provides the required additional contextual information which helps to give the dataset a significant enhancement for a better understanding of the underlying mental health and brain signals. Data collection from sources is carried out to follow with careful data preprocessing that aims to ensure the standardization and consistency of the dataset. The main preprocessing steps incorporate dealing with missing values, and to that end you need to be cautious about handling any voids in the data set by means of appropriate procedures to maintain data consistency and eliminate biases. Besides, the standardization of channel names is also prudent for the sake of depicting a uniform representation in the data set and further easing the investigation and comprehension. On the other hand, the data are divided according to the mental disorders, making a sorting task of the later stages of the classification process possible. Python stands out not only with the aid of a favorable resource library of Pandas and MNE, but these facilitate preprocessing making it easy for even beginner programmers to load, manipulate, and visualize data easily. In order to achieve that through meticulous attention to detail the preprocessing after all the dataset in structured and refined and ready for the depth of analysis and modeling to select mental disorders from EEG data.

4.2.2 Feature Engineering Module

To begin with, in the EEG pre-processing, the Feature Engineering section is the crucial part to derive the discriminatory features for boosting the capacity to predict mental health disorders. This phase starts with a complete review of the EEG channels dynamics involving both time and frequency domain, displaying their distinctive patterns of response. Their role is to help the researchers understand the dynamics behind different kinds of mental health problems, and thus arrive at the way the brain activity is controlled. The next stage, namely feature engineering, rakes up statistics, including one named band power or the average EEG signal energy distribution, being frequency specific. Calculation of the measures such as mean band power exactly pick up the characteristic groupings which underline the specific states of mental health disorders. Data, varying with respect to the features mentioned above, could also be stratified to identify underlying, fine-grained patterns in the EEG signals which correlate with particular disorders. This operation is meant to transform the data into a format suited for generating the final models and analysis-training process. Python libraries such as Scikit-learn and some of the new modules developed, especially, the ones for the feature extraction and transformation are essential tools that are used in this lesson to make it interesting and simple to follow. Through this library, researchers can easily perform complicated calculations and sensible normalizer feature sets in order to thus be able to match the algorithms used for machine learning. The module is designed to give the researchers access to the numerous libraries available thereby unlocking the potentials of Scikit-learn that can eventually enhance the features of EEG data and increase the prediction accuracy of the system that can be used to predict mental health disorders.

4.2.3 Model Training Module

The Model Training module of the given system comprises the application of machine learning algorithms, which are essential for accurately predicting mental health disorders from extracted features of EEG data. This module encompasses the evaluation and optimization of three distinct models: such as Random Forest Classifier, Support Vector Machine (SVM), and Multilayer Perceptron (MLP).

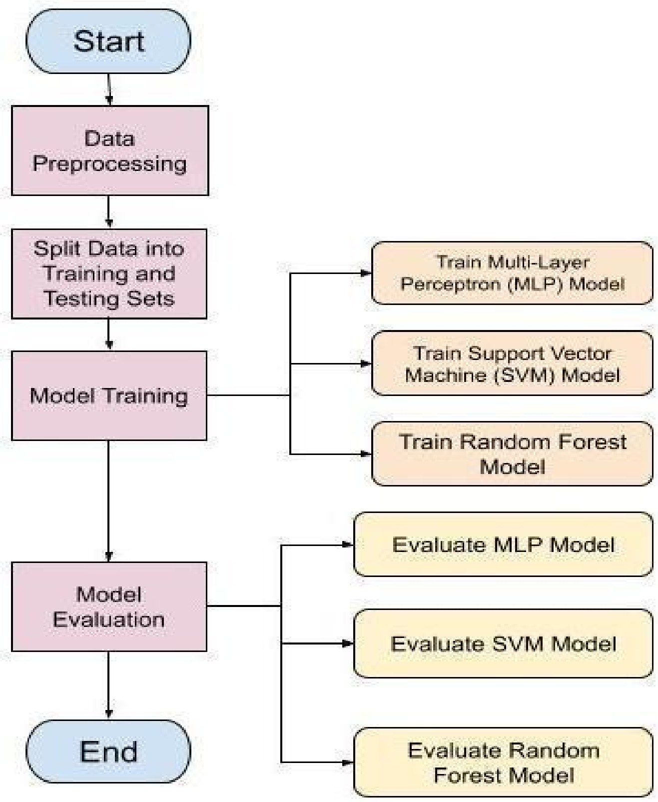

Figure 2: Implementation of the model.

By using stringent criteria, it turns out that among all possible options, the MLP model emerges to be the best candidate; it demonstrates better ability in discerning the regularities in EEG unlike the rest that aren't sensitive enough to the imprints of the mind activities associated with different mental disorders. The training process is composed of several iterative steps for the right parameter optimization and achieving a better accuracy level. Initially the model is trained using the training dataset supplying necessary datasets for learning the feature relationships and underlying patterns between EEG features and mental health disorders. Over the entire period of training, the model's performance is periodically evaluated by using a different but separate testing dataset to make sure that the generalizability and robustness are held on high. Measures such as accuracy, precision, recall, and F1 (F-Score) score, that are computed in an automated manner, are relied on to quantitatively establish the extent to which the model can classify the electrical patterns corresponding to different mental health disorders. The metrics represent a set of the valuable information about the model’s pros and cons, and these data enable the informed approval of the model for use or for the possible improvements of it. Model Training in turn is the base of building a predictive system which uses diverse machine learning techniques for accurate and repeated forecast of the mental health problem according to the EEG information. By performing a detailed and upgraded variant of its algorithm, the MLP model uncovers itself as a superb approach to improve the strategies of mental health diagnosis and treatment.

4.3 UML Diagrams

UML stands for Unified Modelling Language. UML is a standardized fashionable-cause modelling language in the subject of object-oriented software engineering. In its modern shape, UML comprises of two essential components: a Meta-model and a notation. The Unified Modelling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software program machine, in addition to for commercial enterprise modelling and other non-software systems. The UML uses more often than not graphical notations to express the design of software program projects.

4.3.1 Use Case Diagram

In the Unified Modeling Language (UML), a use case diagram is a behavioral diagram that stems from use-case analysis. Its number one objective is to provide a visual summary of a gadget's capability, showcasing actors, their objectives (portrayed as use cases), and any relationships amongst those use cases. The fundamental aim of a use case diagram is to demonstrate which device capabilities are accomplished for each actor worried, while additionally illustrating the jobs played via these actors within the gadget.

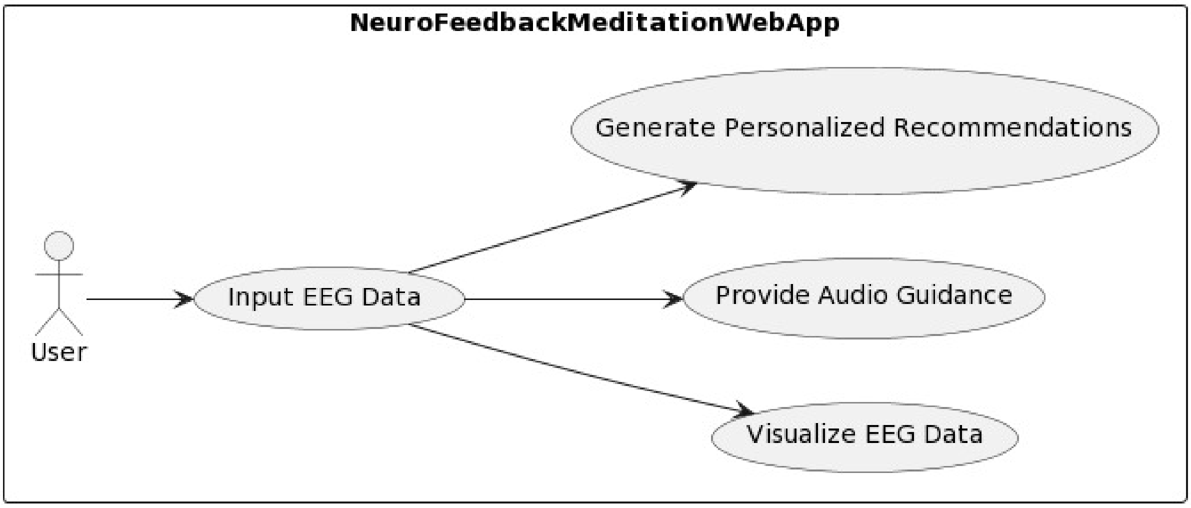

Figure 3: Use case Diagram

4.3.2 Class Diagram

In software engineering, a class diagram within the Unified Modeling Language (UML) is a static shape diagram that delineates the architecture of a machine. It achieves this by using illustrating the training within the gadget, inclusive of their attributes, operations (or techniques), and the connections between those classes. This diagram elucidates the distribution of statistics among lessons and clarifies which elegance is responsible for housing unique records.

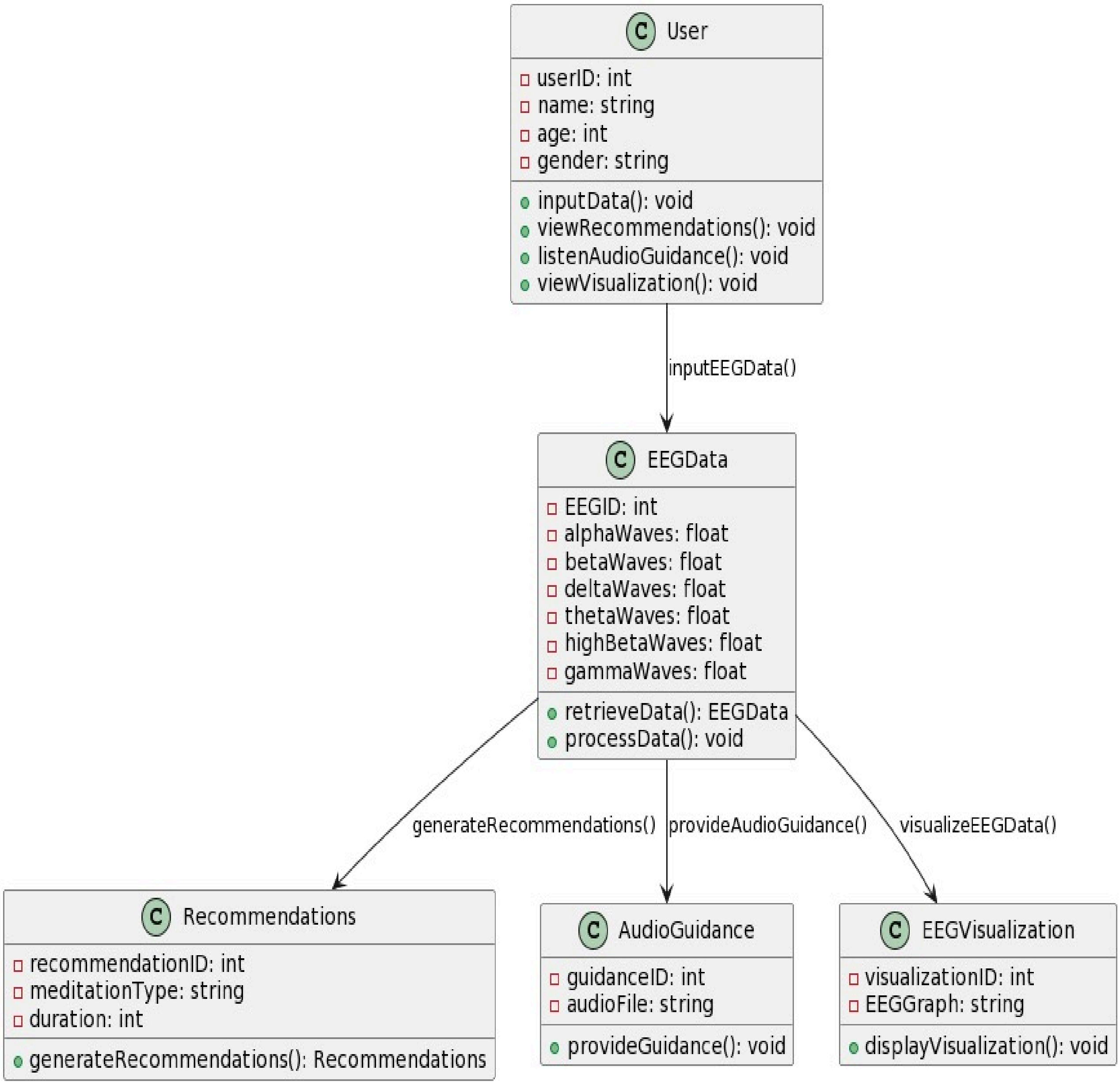

Figure 4: Class Diagram

4.3.3 Sequence Diagram

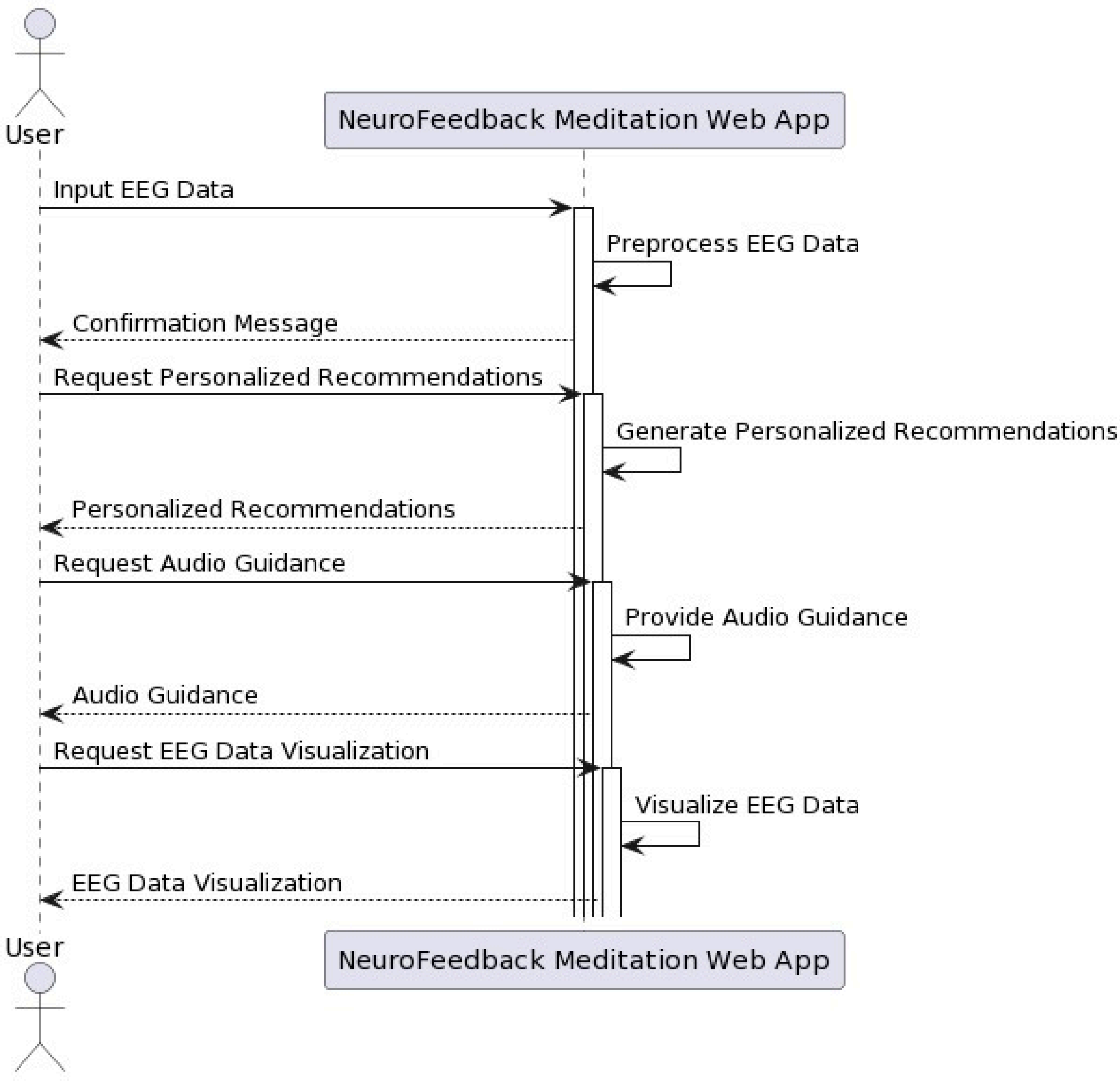

Figure 5: Sequence Diagram

4.3.4 Activity Diagram

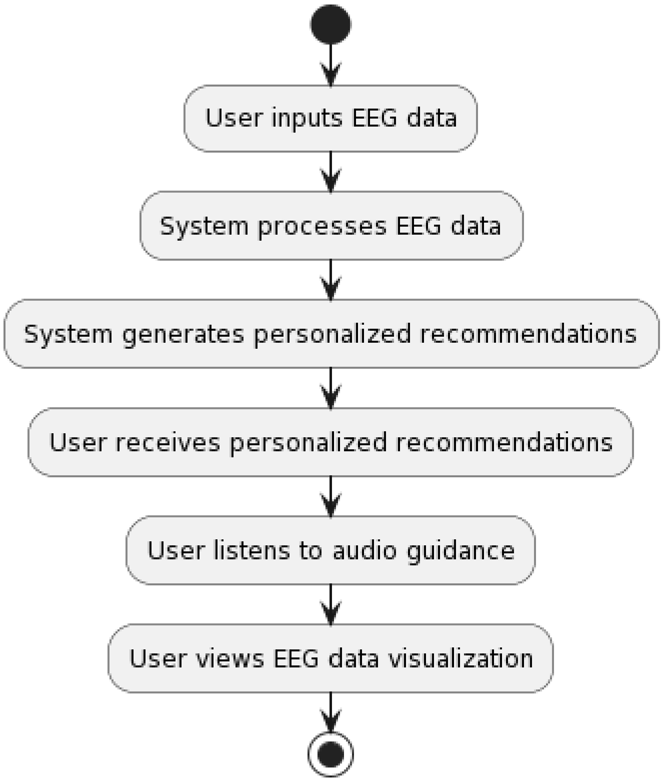

Figure 6: Sequence Diagram

CHAPTER 5

IMPLEMENTATION

This subsection is responsible for processing and analyzing EEG (electroencephalogram) data provided by users.

no.	sex	age	eeg.date	education	IQ	main.disorder	specific.di sorder	(EEG Channels and Values)
1	M	32	2012.9.10	16	113	Addictive disorder	Alcohol use disorder	29.942, 27.545, 17.150, ...
2	F	19.2	2013.8.5	12	NA	Trauma and stress-related disorder	Acute stress disorder	11.907, 9.707, 12.455, ...
3	F	32.8	2015.9.21	16	108	Mood disorder	Depressive disorder	12.404, 9.777, 13.007, …
4	F	34.1	2018.6.29	18	119	Healthy control	Healthy control	72.431, 68.233, …
5	M	18	2012.9.27	10	124	Addictive disorder	Behavioral addiction disorder	33.001, 34.567, …
6	M	37	2015.6.24	14	113	Obsessive-compulsive disorder	Obsessive compulsitve disorder	26.786, 29.345, …
7	M	29.2	2012.1.11	16	102	Schizophrenia	Schizophre nia	13.533, 14,265, …
8	M	34.4	2016.3.28	10	89	Anxiety disorder	Panic disorder	8.806, 8.002, …
9	M	19.1	2011.1.17	12	122	Anxiety disorder	Social anxiety disorder	14.234, 16.913, …
10	F	36.6	2011.1.28	12	99	Trauma and stress-related disorder	Posttrauma tic stress disorder	21.714, 19.580, 18.522, ...
11	M	23.2	2011.3.17	12	98	Mood disorder	Bipolar disorder	8.974, 9.421, 7.995, ...

Table 3: Demographic and Clinical Characteristics of EEG Dataset Participants

The provided above table is EEG dataset contains various demographic and clinical characteristics of participants along with EEG channel values. Each row represents a participant, and the columns represent attributes such as sex, age, EEG date, education, IQ, main disorder, specific disorder, and EEG channels with their corresponding values.

- **Sex:** Indicates the gender of the participant (M for male, F for female).
- **Age:** Represents the age of the participant at the time of EEG recording.
- **EEG Date:** Specifies the date when the EEG recording was conducted.
- **Education:** Indicates the level of education of the participant.
- **IQ:** Represents the intelligence quotient of the participant.
- **Main Disorder:** Denotes the main mental health disorder diagnosed for the participant.
- **Specific Disorder:** Provides additional specificity regarding the mental health disorder, if applicable.
- **EEG Channels and Values:** Lists the EEG channel names along with their corresponding values recorded during the EEG session.

In this dataset all data fields of each participant are presented in order to be used by analysts. These data are the basis of developing machine learning models to classify mental health disorders through EEG data as well as demographic and clinical parameters.

In our described model, users need to enter these data aforementioned as: alpha, beta, delta, theta, high beta, and gamma waves that got extracted from their EEG readings. Amongst these values are also parameters such as sex, age, education, and IQ that all together become an input dataset for the prediction of mental health problems. The system incorporates the use of machine learning algorithms that are being trained on a medical dataset, obtained from a reputable diagnostic centre focused on neurological and psychological evaluations. This dataset involves EEG channel values and attributes along with the patient's clinical condition. We take utmost care to guarantee that they are accurate and confidential. With a deep machine learning, the system scan the EEG data and associated feature can predict possible mental disorders related to addictive disorders, mood disorders, anxiety disorders, trauma-related disorders, and others by executing the deep machine learning. Through the power of data-driven algorithms, the system offers an individual the insights on their mental health measured by their EEG. Also, the privacy and confidentiality of the data are strictly followed due to the fact that the data is originally given by the reliable testing center which has a longstanding protocols for data security and privacy.

5.1 SOURCE CODE

index.py

```
import streamlit as st
import os.path as op
import numpy as np
import matplotlib.pyplot as plt
import mne
import pandas as pd
import joblib
import os
mlp_model = joblib.load('mlp_model.joblib')
scaler = joblib.load('scaler.joblib')
le_disorder = joblib.load('le_disorder.joblib')

suggest_df = pd.read_csv("suggest.csv")
music_folder_path = "music"

yoga_df = pd.read_csv("yoga.csv")
mental_health_yoga_df = pd.read_csv("mental_health_yoga.csv")

dss_flat = pd.read_csv("dss_flat.csv")

raw_file_path = op.join(mne.datasets.sample.data_path(), 'MEG', 'sample',
'sample_audvis_raw.fif')

raw = mne.io.read_raw_fif(raw_file_path, preload=True)

evoked_file_path = op.join(mne.datasets.sample.data_path(), 'MEG', 'sample',
'sample_audvis-ave.fif')
evoked = mne.read_evokeds(evoked_file_path, baseline=(None, 0), proj=True)

if not evoked:
    st.error("No evoked data loaded. Check the file path and content.")
else:
    evoked_l_aud = evoked[0]
    evoked_r_aud = evoked[1]
    evoked_l_vis = evoked[2]
    evoked_r_vis = evoked[3]

st.markdown("""
    <style>
```

```
        body {
            background-color: #f4f4f4;
            font-family: 'Arial', sans-serif;
        }
        .header {
            background-color: #3498db;
            color: #ffffff;
            padding: 10px;
            text-align: center;
            font-size: 36px;
        }
    </style>
""", unsafe_allow_html=True)

st.markdown("<div class='header'>NeuroFeedback Meditation Web App 🧠</div>",
unsafe_allow_html=True)

menu = ["Home", "Prediction",  "About", "Contact"]
choice = st.sidebar.selectbox("Navigation", menu)

if choice == "Home":
    st.subheader("Welcome to the EEG Disorder Prediction App")
    st.markdown("This web app uses machine learning to predict specific disorders based on
EEG data. "
                "Enter your EEG data in the form, and we will provide predictions along with
helpful suggestions.")
    st.image("your_logo.png", caption="EEG BASED COMPUTATION PROGRAM",
use_column_width=True)

elif choice == "Prediction":
    st.header("Enter EEG Data:")

    with st.form(key='user_input_form'):
        col1, col2, col3 = st.columns(3)
        with col1:
            channel = st.text_input("Channel:", "")
        with col2:
            delta = st.text_input("Delta:", "")
            theta = st.text_input("Theta:", "")
        with col3:
            alpha = st.text_input("Alpha:", "")
            beta = st.text_input("Beta:", "")
            highbeta = st.text_input("High Beta:", "")
```

```
            gamma = st.text_input("Gamma:", "")

        predict_button = st.form_submit_button("Predict")

    eeg_data_placeholder = st.empty()

    if predict_button:
        custom_input = pd.DataFrame([[channel, delta, theta, alpha, beta, highbeta, gamma]],
                               columns=['channel', 'delta', 'theta', 'alpha', 'beta', 'highbeta', 'gamma'])

        encoded_channel = pd.concat([dss_flat['channel'].astype(str),
custom_input['channel']]).astype(int).iloc[-1]
        custom_input['channel'] = encoded_channel
        custom_input['specific.disorder'] = 0  # Use the same value used during training

        custom_input_scaled = scaler.transform(custom_input.drop(['specific.disorder'],
axis=1))

        custom_prediction = mlp_model.predict(custom_input_scaled)

        # Get the predicted class name
        predicted_class_name = le_disorder.inverse_transform(custom_prediction)[0]

        # Display the result
        if predicted_class_name == "Healthy Control":
            st.success("You are Healthy Control.")
        else:
            st.success(f"Predicted Class: {predicted_class_name}")
            st.subheader(f"We suggest you follow this video and audio procedure to manage your
{predicted_class_name}.")

            video_match = suggest_df[suggest_df.apply(lambda row:
predicted_class_name.lower() in row['class'].lower(), axis=1)]

            if not video_match.empty:
                video_url = video_match['url'].values[0]
                st.video(video_url)

                yoga_suggestion = yoga_df[yoga_df.apply(lambda row:
predicted_class_name.lower() in row['class'].lower(), axis=1)]['url'].values[0]
                meditation_suggestion =
mental_health_yoga_df[mental_health_yoga_df.apply(lambda row:
predicted_class_name.lower() in row['class'].lower(), axis=1)]['Yoga'].values[0]
```

```
            st.subheader("Yoga Suggestion:")
            st.markdown(f"[{predicted_class_name} Yoga Video]({yoga_suggestion})")
            st.video(yoga_suggestion)

            st.subheader("Meditation & Music Therpy Suggestion:")
            st.markdown(f"{meditation_suggestion}")

            st.markdown(meditation_suggestion)

        else:
            st.warning("No matching video URL found for the predicted class. Showing a
default message or action.")
        audio_filename = f"{predicted_class_name.lower()}.mp3"
        audio_path = os.path.join(music_folder_path, audio_filename)

        if not os.path.exists(audio_path):
            audio_filename = f"{predicted_class_name.capitalize()}.mp3"
            audio_path = os.path.join(music_folder_path, audio_filename)

        if os.path.exists(audio_path):
            st.audio(audio_path, format="audio/mp3", start_time=0)
        else:
            st.warning(f"No matching audio file found for the predicted class
({audio_filename}). Showing a default message or action.")
        col1, col2 = st.columns(2)

        with col1:
            fig, ax = plt.subplots()
            frequencies = ['delta', 'theta', 'alpha', 'beta', 'highbeta', 'gamma']
            spectrum_values = [float(custom_input[frequency]) for frequency in frequencies]
            ax.bar(frequencies, spectrum_values, color='blue')
            ax.set_title('EEG Spectrum')
            ax.set_xlabel('Frequency Bands')
            ax.set_ylabel('Power/Frequency')
            st.pyplot(fig)

        with col2:
            fig, ax = plt.subplots()
            ax.plot(frequencies, spectrum_values, marker='o', linestyle='-', color='green')
            ax.set_title('Custom EEG Plot')
            ax.set_xlabel('Frequency Bands')
            ax.set_ylabel('Power/Frequency')
```

```
        st.pyplot(fig)
        from mne_plot import generate_mne_plot

    def eeg_data_page_content():
        st.header("EEG Data Visualization")

        st.subheader("Evoked Data")
        evoked_plot = evoked_l_aud.plot(exclude=())
        st.pyplot(evoked_plot)

        picks = mne.pick_types(evoked_l_aud.info, meg=True, eeg=False, eog=False)

        st.subheader("Evoked Data with Spatial Colors and GFP")
        evoked_spatial_plot = evoked_l_aud.plot(spatial_colors=True, gfp=True,
picks=picks)
        st.pyplot(evoked_spatial_plot)

        st.subheader("Topomaps")
        st.write("Left Auditory Topomap:")
        left_aud_topomap = evoked_l_aud.plot_topomap(times=0.1, show=False)
        st.pyplot(left_aud_topomap)

        st.write("Right Auditory Topomap:")
        right_aud_topomap = evoked_r_aud.plot_topomap(times=0.1, ch_type='mag',
show=False)
        st.pyplot(right_aud_topomap)

        st.subheader("Topomaps in Subplots")
        fig, ax = plt.subplots(1, 4)

        ax_topo_1 = ax[0].inset_axes([0, 0, 0.45, 1])
        ax_topo_2 = ax[0].inset_axes([0.55, 0, 0.45, 1])
        evoked_l_aud.plot_topomap(times=0.1, axes=[ax_topo_1, ax_topo_2],
show=False)
        st.pyplot(fig)

        st.subheader("Make Field Map")
                subjects_dir = op.join(mne.datasets.sample.data_path(), 'subjects')
        trans_fname = op.join(mne.datasets.sample.data_path(), 'MEG', 'sample',
'sample_audvis_raw-trans.fif')
        maps = mne.make_field_map(evoked_l_aud, trans=trans_fname, subject='sample',
subjects_dir=subjects_dir, n_jobs=1)
```

```
            st.write("Field Map at 0.1s")
            field_map_plot = evoked_l_aud.plot_field(maps, time=0.1)
            st.pyplot(field_map_plot)

        eeg_data_page_content()


elif choice == "About":
    st.subheader("About This Project")
    st.markdown("This web application is designed for predicting specific disorders based on
EEG data using machine learning. "
                "It provides users with insights into their EEG spectrum and suggests procedures to
manage predicted disorders.")

    st.markdown("### Key Features:")
    st.markdown("- EEG data prediction using a pre-trained machine learning model.")
    st.markdown("- Visualization of EEG spectrum with customizable plots.")
    st.markdown("- Personalized suggestions for managing predicted disorders.")

    st.markdown("### Technologies Used:")
    st.markdown("- Python (Streamlit for web app development)")
    st.markdown("- Machine Learning (MLP model for disorder prediction)")
    st.markdown("- Data Preprocessing (Pandas, joblib for model and scaler loading)")

elif choice == "Contact":
    st.subheader("Contact Us")
    st.markdown("If you have any questions, suggestions, or feedback, feel free to contact
us.")


st.sidebar.markdown("Page navigation")

st.markdown("""
    <style>
        footer {
            position: fixed;
            bottom: 0;
                left: 0;
            width: 100%;
            background-color: #f1f1f1;
            text-align: center;
            padding: 10px;
        }
```

```
    </style>
    """, unsafe_allow_html=True)

footer = """
    <div class="footer">
        <p>2024 @COPYRIGHTS Team-8 CSM</p>
    </div>
    """

st.markdown(footer, unsafe_allow_html=True)
```

mne_plot.py

```
import mne
import numpy as np
import matplotlib.pyplot as plt
import streamlit as st

def generate_mne_plot(raw_eeg):
    fig, ax = plt.subplots(figsize=(10, 4))
    raw_eeg.plot_psd(ax=ax, fmax=50, spatial_colors=False, show=False)
    ax.set_title('EEG Power Spectral Density')
    ax.grid(True)

    st.pyplot(fig)

raw = mne.io.read_raw_fif(str(mne.datasets.sample.data_path() / 'MEG' / 'sample' / 'sample_audvis_raw.fif'), preload=True)

picks = mne.pick_types(raw.info, eeg=True)

picks = np.array(picks, dtype=int)

info = mne.create_info(ch_names=[raw.ch_names[i] for i in picks], sfreq=raw.info['sfreq'], ch_types='eeg')

raw_eeg = mne.io.RawArray(raw.get_data(picks), info)

generate_mne_plot(raw_eeg)
```

backend.ipynb

```
#!/usr/bin/env python
# coding: utf-8
```

```python
# In[1]:


import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import mne
df = pd.read_csv("EEG.machinelearing_data_BRMH.csv")


# In[2]:


chs = {'FP1': [-0.03, 0.08],
       'FP2': [0.03, 0.08],
       'F7': [-0.073, 0.047],
       'F3': [-0.04, 0.041],
       'Fz': [0, 0.038],
       'F4': [0.04, 0.041],
       'F8': [0.073, 0.047],
       'T3': [-0.085, 0],
       'C3': [-0.045, 0],
       'Cz': [0, 0],
       'C4': [0.045, 0],
       'T4': [0.085, 0],
       'T5': [-0.073, -0.047],
       'P3': [-0.04, -0.041],
       'Pz': [0, -0.038],
       'P4': [0.04, -0.041],
       'T6': [0.07, -0.047],
       'O1': [-0.03, -0.08],
       'O2': [0.03, -0.08]}
channels = pd.DataFrame(chs).transpose()
channels


# In[3]:


for key in chs.keys():
    chs[key]+=[0]
```

```
chs


# In[4]:


mont = mne.channels.make_dig_montage(chs)
mont.plot()
plt.show()


# In[5]:


def plot_eeg(levels, positions, axes, fig, ch_names=None, cmap='Spectral_r', cb_pos=(0.9,
0.1),
             cb_width=0.04, cb_height=0.9, marker=None, marker_style=None, vmin=None,
vmax=None, **kwargs):
    """
    Function visulises processed EEG data in a simple way. Based on mne.viz.plot_topomap.


    :param levels: numpy.array, shape (n_chan,)
        data values to plot.
    :param positions: numpy.array, shape (n_chan, 2)|instance of mne.Info
        Location information for the data points(/channels). If an array, for each data point,
        the x and y coordinates. If an Info object, it must contain only one data type and exactly
        len(data) data channels, and the x/y coordinates will be inferred from the montage
applied
        to the Info object.
    :param axes: matplotlib.axes.Axes
        The axes to plot to.
    :param fig: matplotlib.figure.Figure
        The figure to create colorbar on.
    :param ch_names: list | None
        List of channel names. If None, channel names are not plotted.
    :param cmap: matplotlib colormap | None
        Colormap to use. If None, ‘Reds’ is used for all positive data, otherwise defaults to
‘RdBu_r’.
        Default value is 'Spectral_r'
    :param cb_pos: tuple/list of floats
        Coordinates of color bar
    :param cb_width: float
```

```
        Width of colorbar
    :param cb_height: float
        Height of colorbar
    :param marker: numpy.array of bool, shape (n_channels,) | None
        Array indicating channel(s) to highlight with a distinct plotting style.
        Array elements set to True will be plotted with the parameters given in mask_params.
        Defaults to None, equivalent to an array of all False elements.
    :param marker_style: dict | None
        Additional plotting parameters for plotting significant sensors. Default (None) equals:
        dict(marker='o', markerfacecolor='w', markeredgecolor='k', linewidth=0, markersize=4)
    :param vmin, vmax: float | callable() | None
        Lower and upper bounds of the colormap, in the same units as the data.
        If vmin and vmax are both None, they are set at ± the maximum absolute value
        of the data (yielding a colormap with midpoint at 0). If only one of vmin, vmax is None,
        will use min(data) or max(data), respectively. If callable, should accept a NumPy array
        of data and return a float.
    :param kwargs:
        any other parameter used in mne.viz.plot_topomap
    :return im: matplotlib.image.AxesImage
        The interpolated data.
    :return cn: matplotlib.contour.ContourSet
        The fieldlines.
    """
    if 'mask' not in kwargs:
        mask = np.ones(levels.shape[0], dtype='bool')
    else:
        mask = None
    im, cm = mne.viz.plot_topomap(levels, positions, axes=axes, names=ch_names,
vmin=vmin, vmax=vmax,
                              cmap=cmap, mask=mask, mask_params=marker_style, show=False,
**kwargs)

    cbar_ax = fig.add_axes([cb_pos[0], cb_pos[1], cb_width, cb_height])
    clb = axes.figure.colorbar(im, cax=cbar_ax)
    return im, cm


# In[6]:


mis = df.isna().sum()
sep_col = mis[mis == df.shape[0]].index[0]
df = df.loc[:, 'main.disorder':sep_col].drop(sep_col, axis=1)
```

```
df


# In[7]:


def reformat_name(name):
    '''
    reformat from XX.X.band.x.channel to band.channel
    '''
    _, _, band, _, channel = name.split(sep='.')
    return f'{band}.{channel}'

reformat_vect = np.vectorize(reformat_name)
new_colnames = np.concatenate((df.columns[:2],
                               reformat_vect(df.columns[2:])))
df.columns = new_colnames

print(df.columns)


# In[8]:


df


# In[9]:


df['main.disorder'] = pd.Categorical(df['main.disorder'])


# In[10]:


df['main.disorder'].dtype


# In[11]:


import pandas as pd
```

```
df['main.disorder'] = pd.Categorical(df['main.disorder'])

numeric_columns = df.select_dtypes(include='number').columns
main_mean = df.groupby('main.disorder')[numeric_columns].mean().reset_index()

bands = ['delta', 'theta', 'alpha', 'beta', 'highbeta', 'gamma']

main_mean = pd.wide_to_long(main_mean, bands, ['main.disorder'], 'channel', sep='.',
suffix='\w+')

print(main_mean)


# In[12]:


main_mean


# In[13]:


import pandas as pd

df['main.disorder'] = pd.Categorical(df['main.disorder'])
df['specific.disorder'] = pd.Categorical(df['specific.disorder'])
main_numeric_columns = df.select_dtypes(include='number').columns
main_mean = df.groupby('main.disorder')[main_numeric_columns].mean().reset_index()

spec_numeric_columns = df.select_dtypes(include='number').columns
spec_mean = df.groupby('specific.disorder')[spec_numeric_columns].mean().reset_index()

bands = ['delta', 'theta', 'alpha', 'beta', 'highbeta', 'gamma']

main_mean = pd.wide_to_long(main_mean, bands, ['main.disorder'], 'channel', sep='.',
suffix='\w+')

spec_mean = pd.wide_to_long(spec_mean, bands, ['specific.disorder'], 'channel', sep='.',
suffix='\w+')

print(main_mean)
print(spec_mean)
```

In[14]:

```
spec_mean
```

In[15]:

```
columns = df.columns.to_frame(index=False).astype(str).agg('_'.join, axis=1)
df.columns = columns
print(df.columns)
```

In[16]:

```
dss = spec_mean
```

In[17]:

```
dss.loc['Schizophrenia', :]
```

In[18]:

```
import mne
import matplotlib.pyplot as plt
import numpy as np

def plot_eeg(levels, positions, axes, fig, ch_names=None, cmap='viridis', cb_pos=None,
cb_width=None, cb_height=None, marker='o', marker_style=None, **kwargs):
    marker_style = marker_style or {'markersize': 6, 'facecolors': 'black', 'edgecolors': 'black'}

    im, cm = mne.viz.plot_topomap(levels, pos=positions, axes=axes, names=ch_names,
cmap=cmap, show=False, **kwargs)

    if cb_pos is not None and cb_width is not None and cb_height is not None:
```

```
        cbar_ax = fig.add_axes([cb_pos[0], cb_pos[1], cb_width, cb_height])
        clb = plt.colorbar(im, cax=cbar_ax)
    else:
        clb = None

    if positions is not None:
        x, y = positions.T
        axes.scatter(x, y, marker=marker, s=marker_style['markersize'],
c=marker_style['facecolors'], edgecolors=marker_style['edgecolors'])


    return im, cm, clb

test = main_mean.loc['Schizophrenia', 'delta']

channels = np.array(test.index.get_level_values('channel'))

positions = np.random.rand(len(channels), 2)

fig, ax = plt.subplots()
plot_eeg(test, positions, ax, fig, marker_style={'markersize': 6, 'facecolors': 'black',
'edgecolors': 'black'})
plt.show()


# In[19]:


dss


# In[20]:


df = main_mean


# In[21]:


from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
```

```
from sklearn.preprocessing import LabelEncoder

dss_reset = dss.reset_index()


# In[22]:


dss_reset


# In[23]:


le = LabelEncoder()
dss_reset['channel'] = le.fit_transform(dss_reset['channel'])

dss_reset = dss_reset.set_index(['specific.disorder', 'channel'])


# In[24]:


dss_reset = dss_reset.reset_index()


# In[25]:


dss_reset


# In[26]:


X = dss_reset.drop(['specific.disorder'], axis=1)
y = dss_reset['specific.disorder']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)
```

```
y_pred = model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))


# In[27]:


from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report
from sklearn.preprocessing import LabelEncoder

dss_flat = dss.reset_index()

le = LabelEncoder()
dss_flat['channel'] = le.fit_transform(dss_flat['channel'])

X = dss_flat.drop(['specific.disorder'], axis=1)
y = dss_flat['specific.disorder']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

svm_model = SVC(kernel='linear', random_state=42)
svm_model.fit(X_train, y_train)

y_pred_svm = svm_model.predict(X_test)
print("SVM Accuracy:", accuracy_score(y_test, y_pred_svm))
print("SVM Classification Report:\n", classification_report(y_test, y_pred_svm))


# In[28]:


from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
from sklearn.preprocessing import LabelEncoder, StandardScaler

dss_flat = dss.reset_index()

le_disorder = LabelEncoder()
dss_flat['specific.disorder'] = le_disorder.fit_transform(dss_flat['specific.disorder'])
```

```
le_channel = LabelEncoder()
dss_flat['channel'] = le_channel.fit_transform(dss_flat['channel'])

X = dss_flat.drop(['specific.disorder'], axis=1)
y = dss_flat['specific.disorder']

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,
random_state=42)

mlp_model = MLPClassifier(hidden_layer_sizes=(100,), max_iter=1000, random_state=42)
mlp_model.fit(X_train, y_train)

y_pred_mlp = mlp_model.predict(X_test)
print("MLP Accuracy:", accuracy_score(y_test, y_pred_mlp))
print("MLP Classification Report:\n", classification_report(y_test, y_pred_mlp))


# In[29]:


import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test, y_pred_mlp)

plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='g', cmap='Blues', xticklabels=le_disorder.classes_,
yticklabels=le_disorder.classes_)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - MLP Model')
plt.show()

print("MLP Classification Report:\n", classification_report(y_test, y_pred_mlp))

accuracy = accuracy_score(y_test, y_pred_mlp)
print("MLP Accuracy:", accuracy)

plt.figure(figsize=(12, 6))
```

```
plt.plot(y_test.values, label='Actual', linestyle='dashed')
plt.plot(y_pred_mlp, label='Predicted', linestyle='solid')
plt.title('Actual vs Predicted Values - MLP Model')
plt.xlabel('Sample Index')
plt.ylabel('Disorder Type')
plt.legend()
plt.show()


# In[30]:


plt.figure(figsize=(12, 6))
plt.plot(y_test, label='Actual', linestyle='dashed')
plt.plot(y_pred_mlp, label='Predicted', linestyle='solid')
plt.title('Actual vs Predicted Values - MLP Model')
plt.xlabel('Sample Index')
plt.ylabel('Disorder Type')
plt.legend()
plt.show()


# In[31]:


from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
from sklearn.preprocessing import LabelEncoder, StandardScaler
import matplotlib.pyplot as plt

dss_flat = dss.reset_index()

le_disorder = LabelEncoder()
dss_flat['specific.disorder'] = le_disorder.fit_transform(dss_flat['specific.disorder'])
le_channel = LabelEncoder()
dss_flat['channel'] = le_channel.fit_transform(dss_flat['channel'])

X = dss_flat.drop(['specific.disorder'], axis=1)
y = dss_flat['specific.disorder']

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,
random_state=42)

mlp_model = MLPClassifier(hidden_layer_sizes=(100,), max_iter=1000, random_state=42)

history = mlp_model.fit(X_train, y_train)

y_pred_mlp = mlp_model.predict(X_test)
print("MLP Accuracy:", accuracy_score(y_test, y_pred_mlp))
print("MLP Classification Report:\n", classification_report(y_test, y_pred_mlp))

plt.figure(figsize=(12, 6))
plt.plot(history.loss_curve_, label='Training Loss')
plt.title('Training History - MLP Model')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()


# In[32]:



from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report, roc_curve, auc
from sklearn.preprocessing import LabelEncoder, StandardScaler
import matplotlib.pyplot as plt
import numpy as np

dss_flat = dss.reset_index()

le_disorder = LabelEncoder()
dss_flat['specific.disorder'] = le_disorder.fit_transform(dss_flat['specific.disorder'])
le_channel = LabelEncoder()
dss_flat['channel'] = le_channel.fit_transform(dss_flat['channel'])

X = dss_flat.drop(['specific.disorder'], axis=1)
y = dss_flat['specific.disorder']

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,
random_state=42)

mlp_model = MLPClassifier(hidden_layer_sizes=(100,), max_iter=1000, random_state=42)
mlp_model.fit(X_train, y_train)

y_pred_mlp = mlp_model.predict(X_test)
print("MLP Accuracy:", accuracy_score(y_test, y_pred_mlp))
print("MLP Classification Report:\n", classification_report(y_test, y_pred_mlp))

y_prob = mlp_model.predict_proba(X_test)

n_classes = len(np.unique(y))
fpr = dict()
tpr = dict()
roc_auc = dict()

for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve((y_test == i).astype(int), y_prob[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

plt.figure(figsize=(10, 6))
for i in range(n_classes):
    plt.plot(fpr[i], tpr[i], label=f'Class {i} (AUC = {roc_auc[i]:.2f})')

plt.plot([0, 1], [0, 1], 'k--', label='Random')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - MLP Model')
plt.legend()
plt.show()


# In[33]:


X_test


# In[55]:
```

```
custom_input_scaled = [6, 1.08239692, 2.40995626, 1.70194018, 2.54830192, 0.88309089,
1.03565913]

custom_input_scaled_reshaped = [custom_input_scaled]

custom_prediction = mlp_model.predict(custom_input_scaled_reshaped)

print("Predicted Class:", custom_prediction[0])


# In[53]:


dss_flat.to_csv('dss_flat.csv', index=False)


# In[54]:


import joblib

joblib.dump(le_channel, 'le_channel.joblib')
joblib.dump(le_disorder, 'le_disorder.joblib')
joblib.dump(scaler, 'scaler.joblib')
```

CHAPTER 6

RESULTS

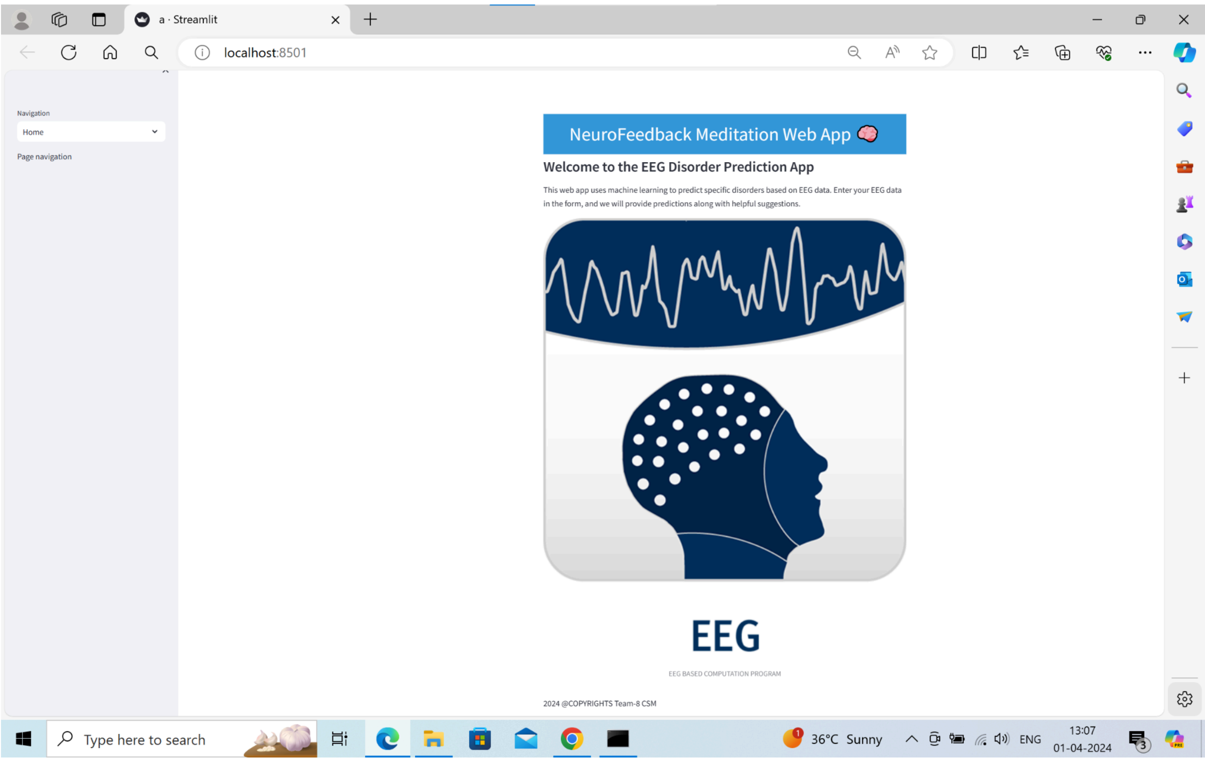

Figure 7: Website Home page

To ensure the best performance of the NeuroFeedback Meditation Web App, users are asked to fill the values indicated. This data set mainly includes EEG (Electroencephalography) measures, which are related to the measurements of brainwave activity in alpha, beta, delta, theta bands and high beta, and gamma waves frequencies.

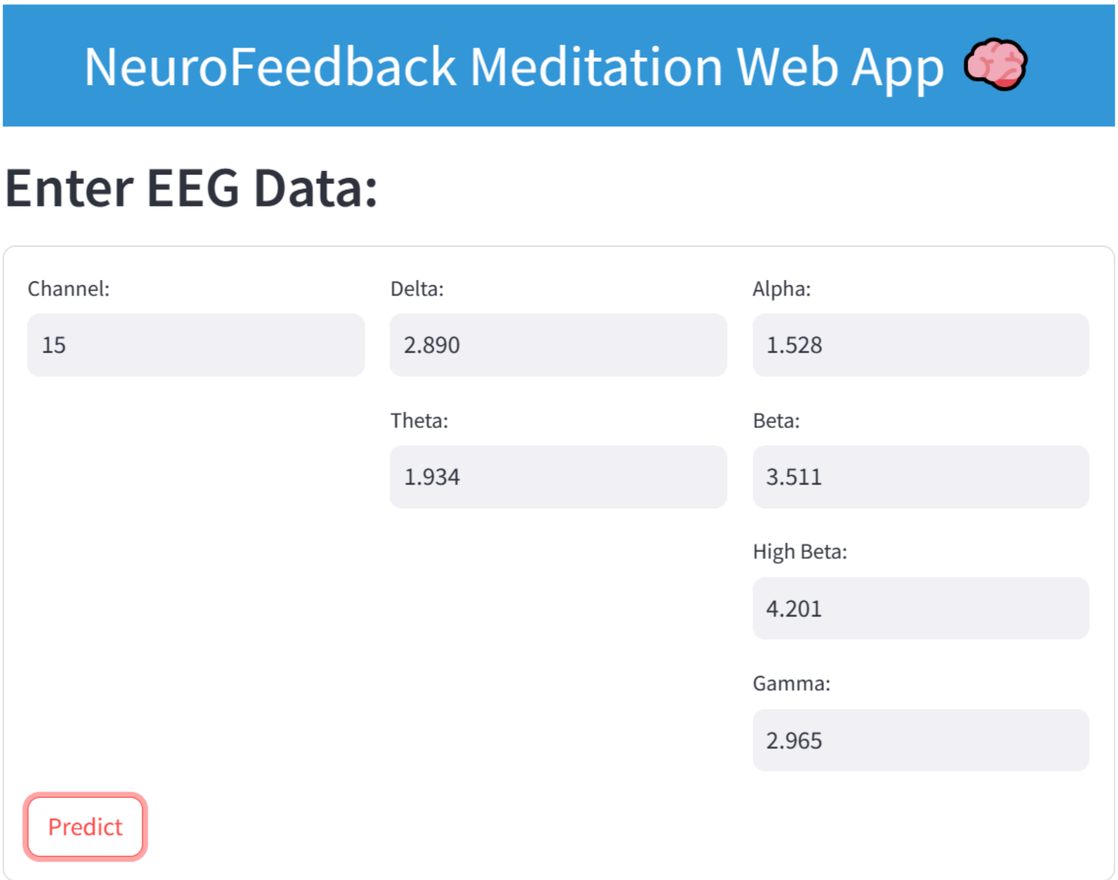

Figure 8: Interface for Entering EEG Data

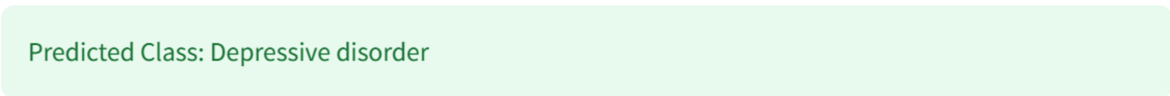

Figure 9: Prediction of Mental Health Disorder

We suggest you follow this video and audio procedure to manage your Depressive disorder.

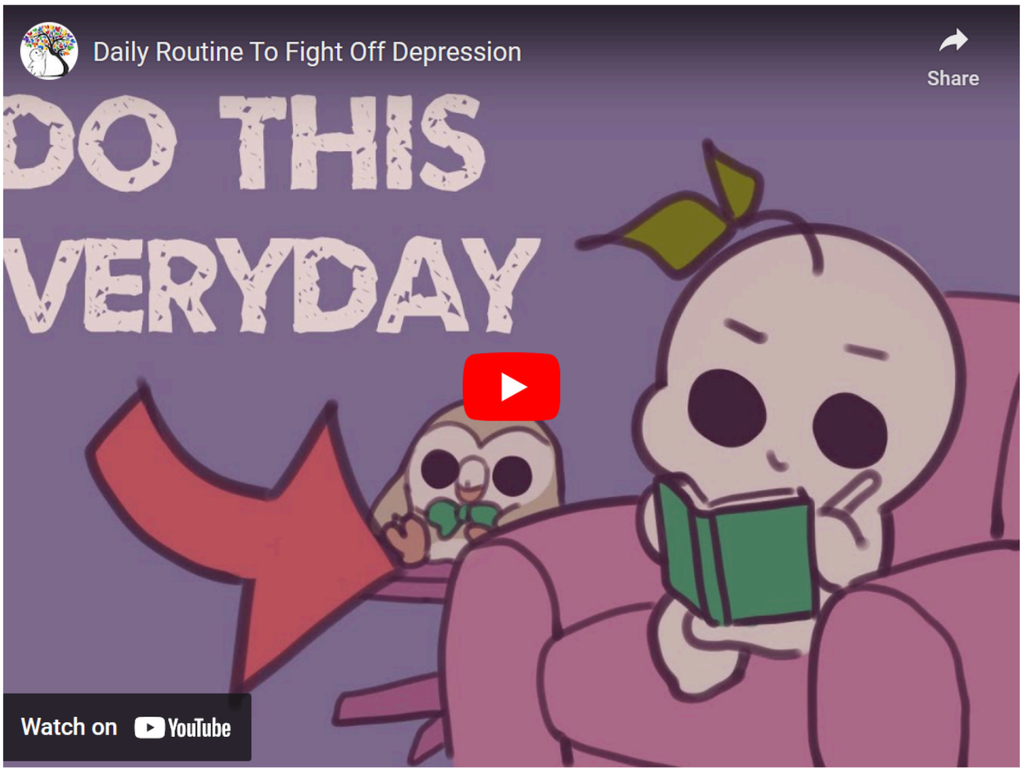

Figure 10: Personalized Programs

Yoga Suggestion:

[Depressive disorder Yoga Video]

Figure 11: Customized Meditation Recommendations

Meditation & Music Therpy Suggestion:

Sun salutations and gentle yoga sequences can contribute to an improved mood. Backbends and heart-opening poses can be particularly beneficial for uplifting the spirit.

Sun salutations and gentle yoga sequences can contribute to an improved mood. Backbends and heart-opening poses can be particularly beneficial for uplifting the spirit.

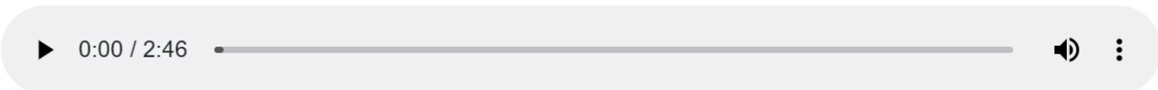

Figure 12: Audio Guidance

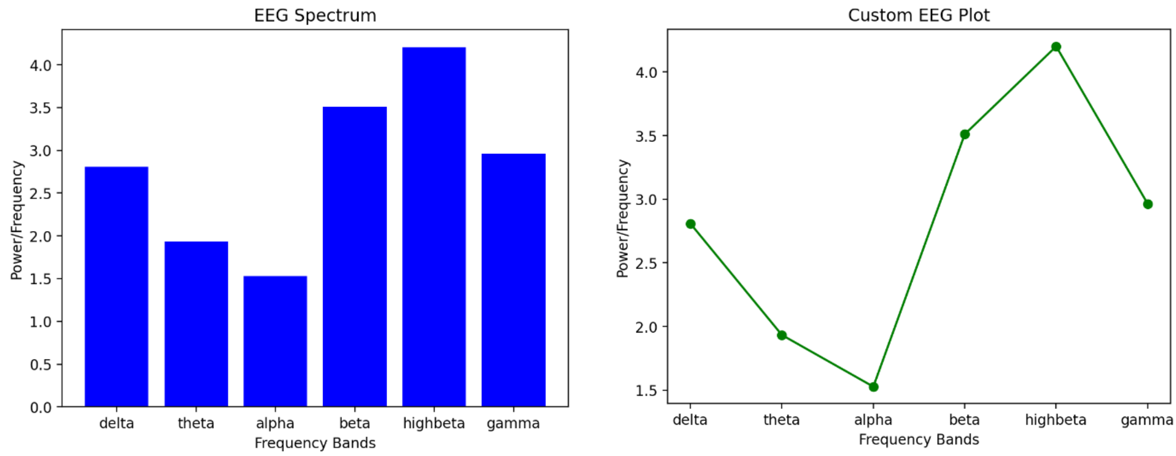

Figure 13: Visualizations of EEG Data

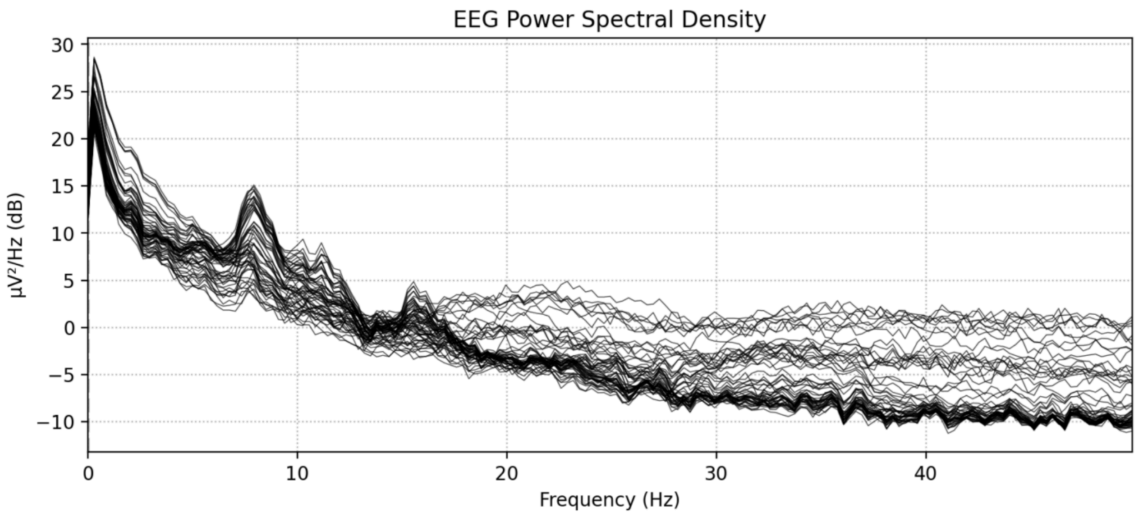

Figure 14: Power Spectral Density (PSD) Analysis

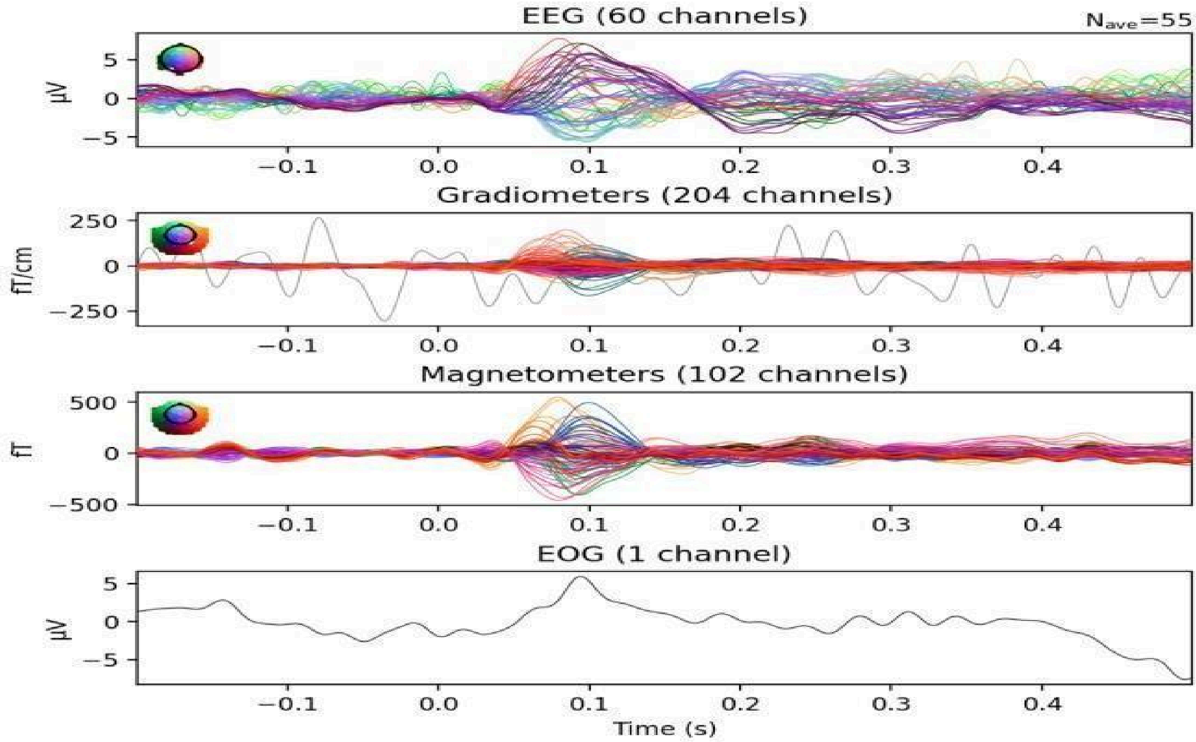

Figure 15: Evoked EEG Data Visualization

MLP Accuracy: 0.6956521739130435

MLP Classification Report:

	precision	recall	f1-score	support
0	1.00	0.88	0.93	8
1	0.00	0.00	0.00	3
2	1.00	1.00	1.00	1
3	1.00	0.50	0.67	4
4	1.00	1.00	1.00	3
5	0.57	0.67	0.62	6
6	0.67	0.80	0.73	5
7	0.50	0.67	0.57	3
8	0.67	0.67	0.67	3
9	0.75	0.75	0.75	4
10	0.67	0.67	0.67	3
11	0.40	0.67	0.50	3
accuracy			0.70	46
macro avg	0.69	0.69	0.67	46

Figure 16: MLP Model Performance Evaluation

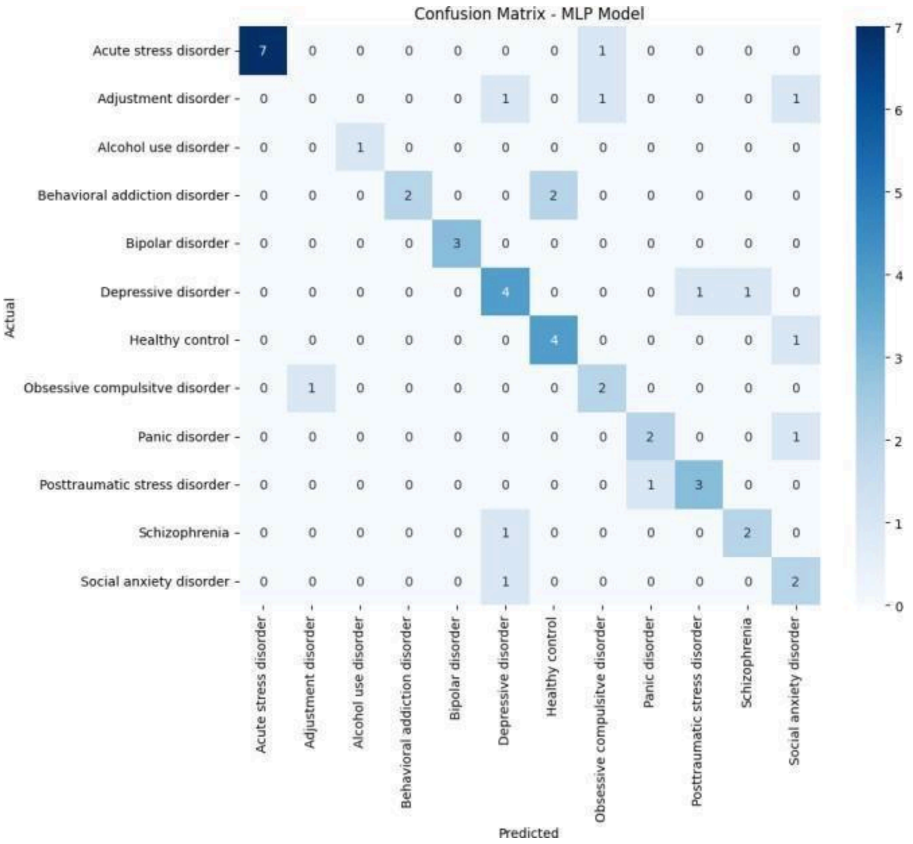

Figure 17: Confusion Matrix of MLP Model

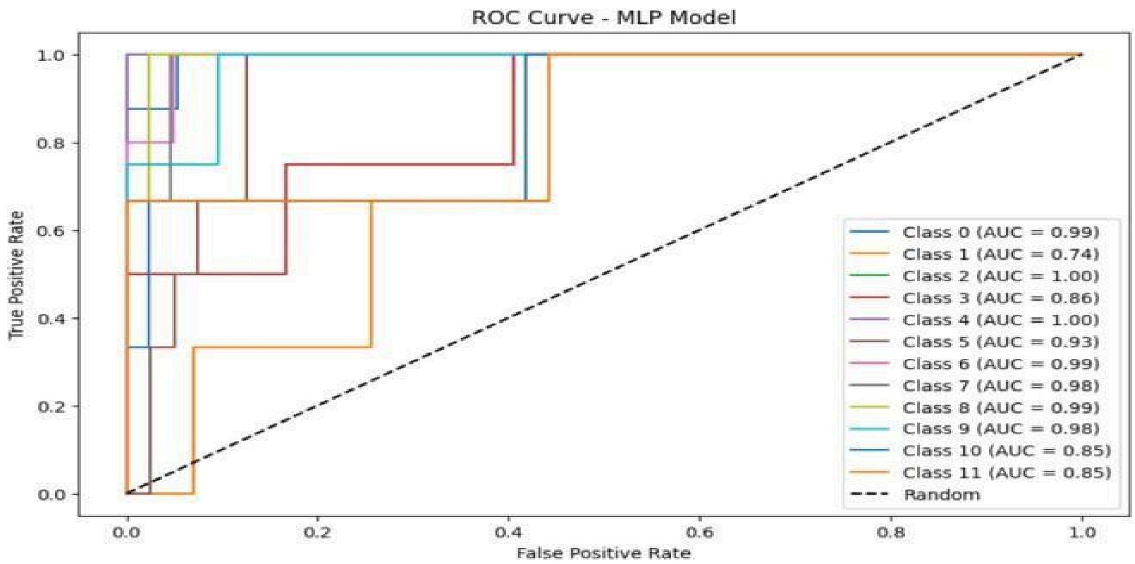

Figure 18: ROC Curve of MLP Model

CHAPTER 7

CONCLUSION

In Conclusion, the developed NeuroFeedback Meditation Web App, on the other hand, is a major leap in the field of mental health care since it integrates the latest technologies in neurofeedback with an individual‘s personal well-being support. Utilizing labeling of machine algorithms children are able to accurately predict particular disorders and they are having customized interventions. The interactive interface, along with advanced analytics, is both accessible and engaging, this way stimulates cooperation and allows for an effective resolution of mental health issues. Onward journey, the gaining which was done through this study makes a way for the research and development in the field of digital mental health interventions, which possibly can make a turnaround in the way we understand and treat mental health problems.

FUTURE ENHANCEMENTS AND DISCUSSIONS

The NeuroFeedback Meditation Web App has many future prospects, which range from expansion to improvement. First of all, the research process will concentrate on improving the accuracy and specificity of disease predictions, by applying the best machine learning algorithms and larger datasets. Moreover, real-time EEG data processing abilities will be incorporated so that the app can give users immediate feedback and intervention suggestion during meditation sessions. Furthermore, the incorporation of EEG wearable devices and mobile interfaces will increase the scope of the application, empowering continuous monitoring and custom-tailored assistance beyond traditional facilities. Collaborating with mental health professionals and researchers will contribute to the verification and optimization of the app's predictive models, hence making the tool accurate and functional for people from different backgrounds. The NeuroFeedback Meditation Web App, finally, may radically transform mental health care services, offering a solution that is scalable and accessible for individuals wishing to receive pre-emptive support in managing their mental health.