Empowering Mental Health Well-being: Advancements in Personalized Well-being through the NeuroFeedback Meditation Web Application

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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.

KEYWORDS

NeuroFeedback, EEG Data, Multi-Layer Perceptron, Mental Health Disorder, Personalized Recommendations

1. INTRODUCTION

With the constantly changing context of today's digital era, taking into account how we can appropriately thrive in this critical domain has become an indisputable priority. People are increasingly turning to digital platforms for mental health help now that technology is pervasively integrated in almost all aspects of life thus this demand for innovative solutions capable of forecasting and supplying effective remedies of the mental health problems is rising more and more. This study captures various details of the Neurofeedback Meditation Web app deployment scheme, a groundbreaking project that rests on three pillars: advanced machine learning technology, neurofeedback devices, and audio-based system of therapeutic guiding. In other words, the Neurofeedback Meditation web application marks a bold step towards the application of machine learning for the prediction of some mental health problems by processing and interpreting the Electroencephalograph (EEG) data. EEG data integration, the most significant innovation here, serves as a major tool in exposing the mystery of neural behavior, and is thus, opening doors to the renaissance of healthcare. An increase in mental health conditions, from addiction to emotional disorders includes great struggles that can be overcome only by an effective and innovative scheme. While we are steadfast in standing out as a bay for technological advancement, the project targets proactive mental health care technique innovations that promote overall wellness. The main function of the app is built on two pillars: EEG signals as a primary data source and a precisely trained MLP network model. It is this model that describes how modern machine learning methodologies merge with the complexity of interpreting brain activities. Streamlit, the open-source framework for creating webpages that brings all together in one place, i.e., both the easy access by the users and the engagement. On the other hand, the backend elegantly drills on data processing, representation, and machine learning model training. It does this in a collaborative manner, and the user is oblivious of the happening. The application makes a unique splash in the market and gives the users something different. Besides the audio instructions, the application involves the use of peaceful tones. This is the deliberate diversification that we tailored as a way of improving therapeutic results, and thus user satisfaction.

This implementation of EEG data is not an arbitrary decision, from which it derives its essence, rather it is deliberate, which reflects the abundance of important information that is contained within the electrical activity in the brain. We have put together a large amount of channel data and a band power vector that contains a lot of details to form the perfect foundation for our web application. Our team is, therefore, studying these neurophysiological features from the roots and branches, which include but not limited to the delta and theta waves, alpha, beta, high beta and gamma waves that constructively add up to an understanding of the holistic neural dynamics. The web app reaches beyond mere prescient tendency, paying attention to a myriad of tactics to bring about the desired action. This suite of interventions consists of the video or audio special training, further moving to yoga and meditation among other therapeutic modalities. In that respect, the Neurofeedback Meditation Web App is not just a tool for prediction, but it is a comprehensive environmental sustainability platform.

Weaving technological tools indiscriminately into healthcare would be great; this service provides its users with a detailed and personalized mental health approach. As technology moves forward, this initiative becomes yet another demonstration that technological innovation can be a life changer once coupled with kindness and that the day when proactive mental health care is not only a remote possibility but a real presence on the horizon may be not so far away anymore.

2. EXISTING PROBLEMS

One of the most significant issues that our computational EEG-based website addresses well is early identification and intervention at an early stage in mental illnesses. By using brain scan data as well as machine learning algorithms, the app gives a dependable tool for diagnosing some mental health disorders. This is because it helps to enable timely intervention and care which greatly improves overall prognosis and quality of life among patients with mental health problems. The lack of access to EEG machines and their unaffordability is another serious problem solved by our application. Many individuals face challenges while trying to acquire personal EEG machines due to their high costs or unavailability. To overcome this, we have developed a web app that allows users to provide perceived EEG recordings based on what they think are accompanying psychological states. This friendly and low- cost approach can help everyone learn about their own minds in ways that circumvent economic restrictions stemming from owning an EEG device. Our application, among other things, solves the problem of traditional mental health assessment with subjective approaches. Diagnostic approaches done in traditional settings tend to lean on opinions and self-reports that have possible prejudices and inaccuracies. It uses EEG data to get a clear, absolute view of what is going on in our brains. This calls for more objectivity when it comes to measuring mental health because it enhances validity and reliability, unlike the traditional way that relied heavily on subjective assessments which only lead to wrong diagnoses many times over.

3. IMPLEMENTATION

The solution to the present problem in the mental health sector can be achieved through the implementation of an EEG-based computation web app designed to classify mental health states into [2] multiple levels.

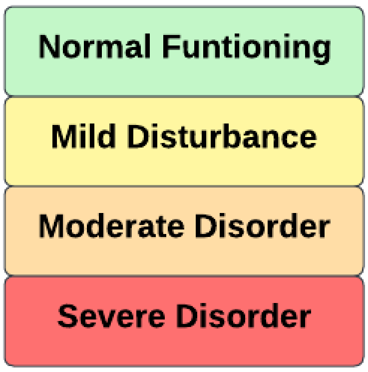

Figure.1: Multi-level Framework for Mental Health

The above figure is the proposed multi-level classification.

The classification of mental health information is crucial for personalized insights and interventions.

Table 1: Description of Multiple Levels of Mental Health Data

Level	Description	Type of data
Normal Functioning	Represents a baseline mental health state.	Standard EEG patterns associated with normal cognitive functioning.
Mild Disturbance	Indicates mild deviations from normal patterns.	EEG variations linked to stress, mild anxiety, or temporary disruptions.
Moderate Disorder	Represents a more pronounced deviation from normalcy.	EEG patterns associated with moderate mental health disorders, such as depression or attention related issues.
Severe Disorder	Signifies a significant departure from normal mental health.	EEG patterns are indicative of severe mental health disorders, such as schizophrenia or severe anxiety.

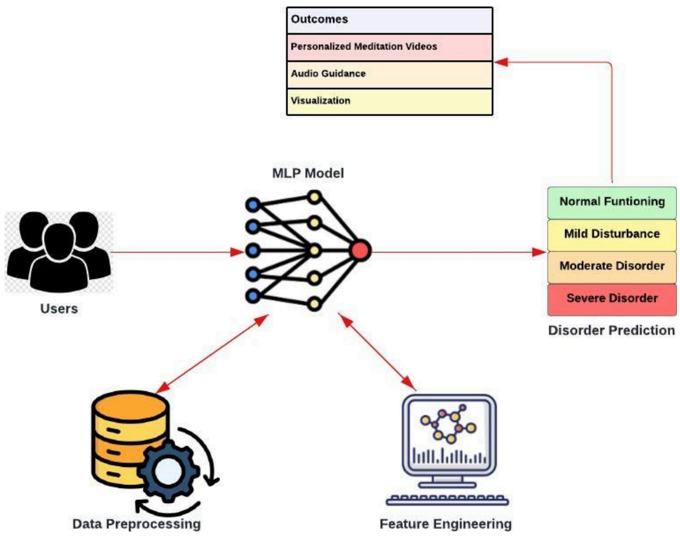

Figure.2: Architecture

The above figure show the The NeuroFeedback Meditation Web App core framework is present in the architectural diagram that is centered on mental health support and user engagement. Users interact with the system to input EEG data that then undergoes preprocessing, feature extraction, and disorder prediction. Models such as Multi-Layer Perceptron (MLP) are applied in analyzing EEG signals for the purpose of predicting mental health disorders. As a result, personalized recommendations are given by the system, audio guidance during meditation is provided while EEG data is visualized in order for users to succeed in actively managing their mental well-being.

4. SOLUTION TO THE PROBLEM

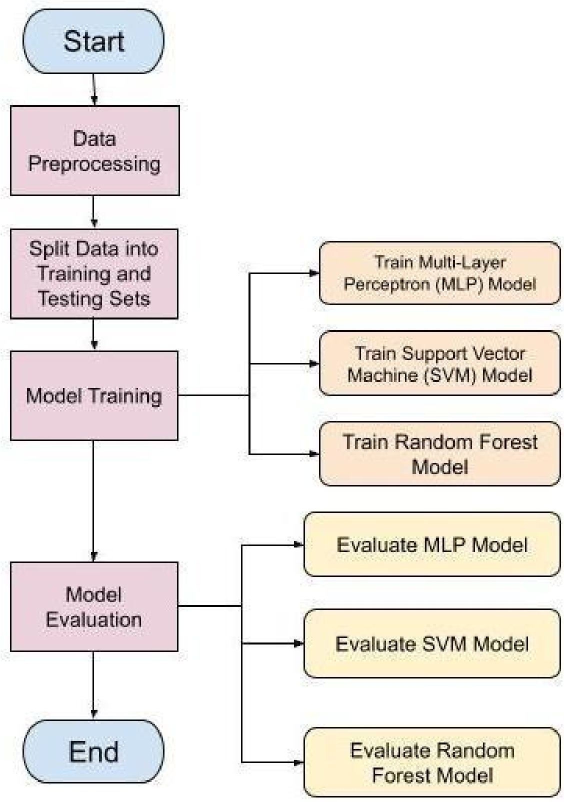

Figure.3: Implementation of Model

A. Data Acquisition and Preprocessing

The EEG data used for the training and assessment of machine learning models is obtained from a renowned diagnostic center that concentrates on neurology and psychological health evaluations. The data set contains EEG channels that provide an accurate representation of the electrical activity in the brain from different regions. The EEG channels are properly positioned on the scalp to pick up the signals from specific brain regions. Such a diversity in channels increases the depth and accuracy of EEG data, a more precise representation of brain activity. Furthermore, the dataset comprises EEG recordings along with vital metadata. Such metadata is about the recording conditions, participant demographics, and context upon which the data is produced. The additional descriptions are part of a better understanding of the EEG data and help analysts to make better analyses.

Table 2: Demographic and Clinical Characteristics of EEG Dataset Participants

no.	sex	age	eeg.date	education	IQ	main.disorder	specific.disorder	(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 compulsive disorder	26.786, 29.345, …
7	M	29.2	2012.1.11	16	102	Schizophrenia	Schizophrenia	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	Posttraumatic 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, ...

The above table summarizes the EEG dataset, reflecting on such patient background factors as age, gender, years of education, and eight longitudinal EEG channels specific to each participant. The ellipsis (...) in the table indicates the continuation of the EEG channels and their respective values. Here each row represents the demographics of an individual participant, and this includes the health education, intelligence quotient (IQ), and mental health condition of the person. The EEG channels are AB.A.delta.a.FP1, AB.A.delta.b.FP2, ..., AB.C.alpha.b.FP2 and other International 10-20 System channels; their values are denoted. The dataset presented here is an excerpt from the current research paper is illustrated with. The full data is more diverse and intricate and is utilized to develop and test machine learning algorithms. In the process of designing a machine learning system for EEG data analysis, a reproducible and robust data pre-processing pipeline was implemented to ensure the quality and consistency of the dataset. The steps involved were handling missing values, reshaping names of channels, categorizing mental health disorders, and visualization of EEG topographic maps. In the first stage of preprocessing, the data was loaded structured formula using the Pandas package. We only identified and removed columns with complete missing values to keep the dataset original and consistent. Locating channels of EEG supports the EEG analysis process. To get this done, a predefined dictionary was used, which linked EEG channel names to the coordinated 2D space by pixels. The python-based MNE library was used in the development of custom digitized montage including visualization and interpretation of EEG spatial distribution.

Pseudo code

1. Import necessary libraries (e.g., pandas, matplotlib)
2. Read EEG data from a file (csv file)
3. Define channel locations for EEG data
4. Create a data structure to store channel locations
5. Create a montage object based on the channel locations
6. Visualize the montage structure
7. Check for missing values in the data
8. Separate data and target variables based on a specific delimiter
9. Define a function to reformat column names
10. Convert the target variable to a categorical format
11. Group data by the target variable
12. Calculate mean values for numerical features within each group
13. Convert the data from long format to wide format based on predefined categories
14. Save the preprocessed data to a new file

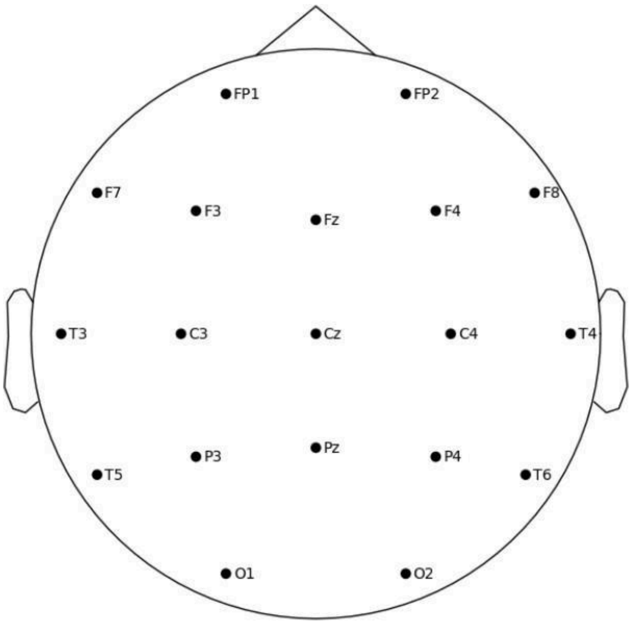

Figure.2: Channel Location Specification

B. Feature Engineering

Initially, in view to grasp the data, (the function) plot_eeg was used to plot each channel (one by one). The component allowed for the readout of time series and spectrograms since the package had both the time and frequency domain features of each channel. For the unification of a standardized representation, the method by which EEG channels were given the names was reformed. The naming approach which consisted of frequency bands and specific channels, was replaced with a simpler mechanism, which contains only an indication of channel and frequency band. Thus, the main purpose of the study was to explore the influence of mental health disorders on EEG patterns. Feature engineering involves the approach of finding and plotting the mean band power for various mental health problems. The datasets were stratified according to disorder and band with mean power calculated by design. This approach was performed through applying the wide_to_long function which restructures the data in a form suitable for the next phase of analysis. This discriminant analysis was based on the category type variable 'main.disorder' which was transformed into a categorical data type. This forms a major raw material later used for insightful subgroup analysis. The EEG dataset was divided into different classes of mental illness episode by episode and then the mean value of the different EEG features both in the frequency and time domain were calculated. This stage provided us the ability to build an EEG features compressed summary based on modalities for each mental health disorder.

Pseudo code

1. Import necessary libraries (e.g., pandas, scikit-learn)
2. Load preprocessed data from a file (format not specified)
3. Separate features (independent variables) from the target variable (dependent variable)
4. Create an object to standardize features (e.g., standardization)
5. Apply standardization to the features
6. Save the standardized features to a new file

C. Model Training

In our endeavor to develop an accurate predictive model for identifying mental health disorders specifically based on EEG site data a complex model training pipeline was employed. The dataset was sensor preprocessed to ensure it was reliable and consistent and it was split into training and testing using the train_test_split function from the scikit- learn library. Three distinct machine learning models were employed for comparative analysis: The models we have evaluated are Random Forest Classifier, Support Vector Machine with a linear kernel function, and Multilayer Perceptron Neural Network.

Random Forest Classifier

The Random Forest Classifier, a robust ensemble learning algorithm, was used since it can efficiently handle complex datasets as well as reduce overfitting. The training process was started by converting the category labels in the dataset into numerical representations which was done by using the label encoder. More precisely, the 'channel' variable was subjected to this process to maintain the model compatibility. The next step included the instantiation of the RandomForestClassifier from Scikit-learn, the default hyperparameters were used, and the classifier was trained on the prepared training set. The conjunction of decision trees was able to leverage the model's capability to distinguish intricate patterns within EEG data associated with different mental health disorders. After training, the model was evaluated on the retained testing set. Measures like accuracy and a detailed report of classification scores were computed to obtain information about the model's performance across different disorder types.

Support Vector Machine (SVM)

The Support Vector Machine, a versatile algorithm that performs both classification and regression, the linear kernel was used to differentiate between linear EEG signals. In the same way that the Random Forest Workflow was implemented, the "channel" variable was also label encoded. Next, the Support Vectors Classification(SVC) model [1] was implemented, trained on the encoded training set, and was then evaluated on the testing set. The discriminative function of SVM provides it with the ability to find optimal hyperplanes that divide distinct mental health disorder classes. As expected, the accuracy and classification report gave us clear-cut metrics which enabled us to make a more informed judgment about the proficiency of the SVM model in differentiating fine-grained EEG signals associated with certain disorders. The figure.3 represents report that gives the accuracy rate of 63.04% which shows that in general the SVM model is satisfying. On the contrast side, the precision, recall, and F1-score metrics are detailed for each mental health disorder to apprehending the robustness of SVM model for the discriminatory purpose.

SVM Accuracy: 0.6304347826086957

SVM Classification Report:

	precision	recall	f1-score	support
Acute stress disorder	1.00	0.88	0.93	8
Adjustment disorder	0.00	0.00	0.00	3
Alcohol use disorder	0.25	1.00	0.40	1
Behavioral addiction disorder	1.00	0.50	0.67	4
Bipolar disorder	0.60	1.00	0.75	3
Depressive disorder	0.50	0.50	0.50	6
Healthy control	0.67	0.80	0.73	5
Obsessive compulsitve disorder	0.67	0.67	0.67	3
Panic disorder	0.50	0.67	0.57	3
Posttraumatic stress disorder	0.67	0.50	0.57	4
Schizophrenia	0.50	0.67	0.57	3
Social anxiety disorder	1.00	0.33	0.50	3
accuracy			0.63	46
macro avg	0.61	0.63	0.57	46
weighted avg	0.68	0.63	0.62	46

Figure.3: SVM Model Performance Evaluation

Multi-Layer Perceptron (MLP)

An MLP (Multilayer Perception) neural network, which may be used for detecting hidden patterns and discriminating mental disorder types, was used. The MLP model was used by classifier from the scikit-learn module (MLPClassifier). This type of Neural Network had a single hidden layer of 100 neurons. As for the training, it was iterated more than thousand times. Determination of MLP model is based on the fact that the given model can make complex EEG representations with yet unmapped relationships sometimes associated with mental disorders. Standardized feature sets can be obtained using the StandardScaler function, with an equal scale being presented to all the channels or frequency bands. Also, this approach eliminates the possibility of "learning" larger scale features over the others by the neural network as large features would prevail in the network learning processes. The training consisted of the MLP model formation as well as the testing of the network by using the fit method. Also, for a complete evaluation the model's performance was compared with the test set and metrics like accuracy, precision, recall and F1 score was curated. The figure 4 above is schematic of the Multilayer Perceptron classifiers in our mental health classifier framework based upon EEG records. The figure illustrates the different layers and the connections between them. And this so proves that the model is efficient by having the accuracy score of 70%, among others. The inference of course is that it is now a respected and important voice. Another indispensable aspect of the model development has been the implementation of additional interpretability and application properties achieved by using different dataset subsets. For example, in some cases it has been possible to restrict only certain frequency bands.

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.4: MLP Model Performance Evaluation

Furthermore, in addition to confusion matrix and Receiver Operating Characteristic (ROC), the curve was also made accessible for the view of the model's classification ability.

The plotted matrix above provides visual representation of actual and predicted disorder binary variables frequencies. The matrix shows to which diseases the model learns to assign instances, and provides insights into the model's accuracy. Predicted labels and actual labels are x-axis and y-axis respectively, and the color intensity represents how many times the points are in each category. Within a heatmap, annotations presents raw counts and this makes for a precise understanding of how many situations are recorded for each category. TP, TN, FP and FN counts can be derived, thus enabling us to calculate evaluation metrics, precision, recall and the F1 score.

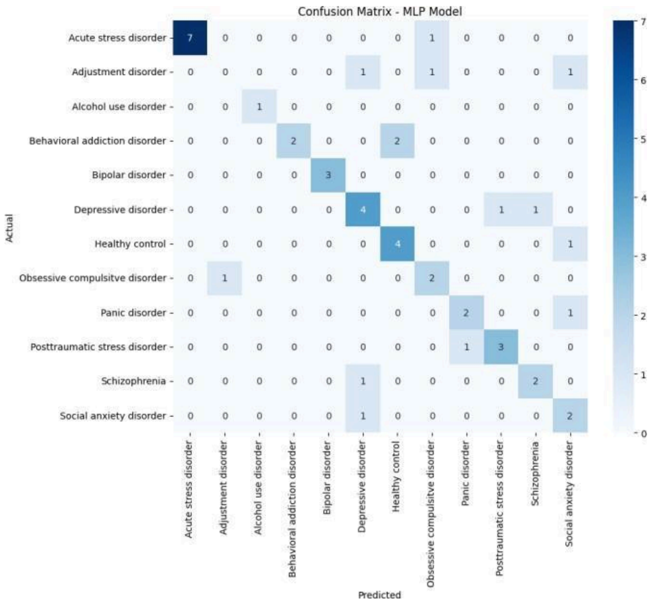

Figure.5: Confusion Matrix of MLP Model

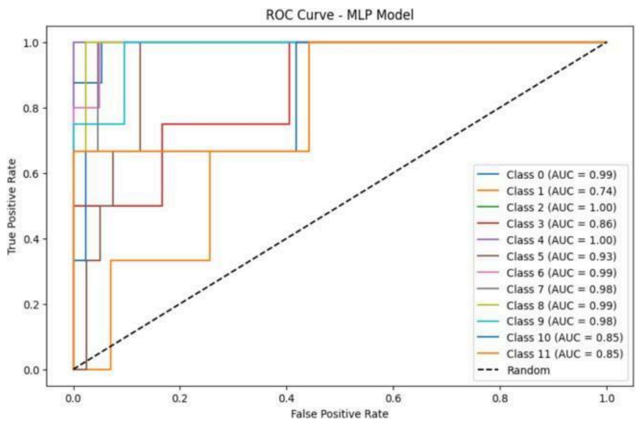

Figure.6: ROC Curve of MLP Model

The above figure represents a Receiver Operating Characteristic (ROC) curve, which indicates the level of distinction of the MLP model's output across various types of mental health conditions. ROC curve is a graphical representation of the how the true positive rate alters with the false positive rate of the different classification thresholds. In this case, each point on the curve related to a specific mental health condition (from Class 0 to 11) and the Area Under Curve (AUC) coefficients verified if the model could discriminate between the mental disorders. The AUC is a holistic score of the model's general performance, where higher AUC values indicate a better distinction of the true positive and false positive samples. This is what ROC curve actually is. It is a great tool for assessing the model's sensitivity and specificity, identifying for how effective it is to differentiate mental health conditions. Adding this curve improves the understandability of what MLP can do in decision-making; thus, it significantly contributes to the overall evaluation of the MLP performance. Finally, model was saved using joblib for its future use; and especially the meticulously planned out steps taken in the phase of training explain how the power of neural networks is used to classify the mental health disorders from the perspective of EEG data.

Pseudo code

1. Import necessary libraries (e.g., scikit-learn, matplotlib)
2. Preprocess data (assumed to be completed beforehand)
    - Encode categorical variables (e.g., target variable, channels)
    - Split data into training and testing sets
    - Standardize features
3. Define a Multi-Layer Perceptron (MLP) classifier model
    - Set hyperparameters (e.g., hidden layer size, maximum iterations)
4. Train the MLP model on the training data
5. Evaluate the model on the testing data
    - Calculate accuracy score
    - Generate classification report
    - Plot Receiver Operating Characteristic (ROC) curve for multi-class classification
6. Make predictions on a new, unseen data point (custom input)
7. Save the preprocessing encoders (LabelEncoders) and scaler for future use

5. RESULT ANALYSIS

In this section, is the all-important part where we step into painstaking investigations to identify all the outcomes and exhaustively examine the far-reaching implications obtained from the novel NeuroFeedback Meditation Web App. Lodged between the sophisticated ploy of machine learning disciplines and the transformative realm of neurofeedback technology, our application is unique. It is not merely a predictive tool that identifies mental disorder, but it pushes the boundaries of personalized mental health care through a revolutionary shift. The interface is skillfully created to accept any EEG signals, there is no need for a specialized EEG device. This intentional design preference extends the app's scope, and therefore it becomes available to more people, and consequently, it becomes more inclusive and accessible for a bigger audience. This user-oriented approach is based on the use of a sophisticated tool Streamlit that simplifies the interdisciplinary complexity of neurofeedback and reduces it to a seamless user experience. Streamlit increases the level of clarity in this process by means of an interactive visualizing that allows a user to provide values which correspond to different brain waves. Users are being encouraged to share their own cognitive markers by feeding their EEG data into the system. This interactivity which is enabled by an easily-navigated interface necessitates the user to feed in important EEG channel values that indicate different features of the brain's electrical activity. This in turn highlights the user's active involvement in designing their neurofeedback journey. On the other hand, our application is not limited only to the analysis but also provides the guided meditation and yoga videos which respond to different personal need. Such curated resources become vital components in the armory of the end-users to be pro-actively in charge of their mental fitness and protect themselves against the development of disorders. Besides that, the introduction of melody mediation music in the app is an extra feature that increases the level of the user experience to a peaceful and quiet place where one can be comfortable. Therefore, these personalized inputs combined with an advanced analytics driven by a pre-trained model result in the app displaying neurofeedback visualization.

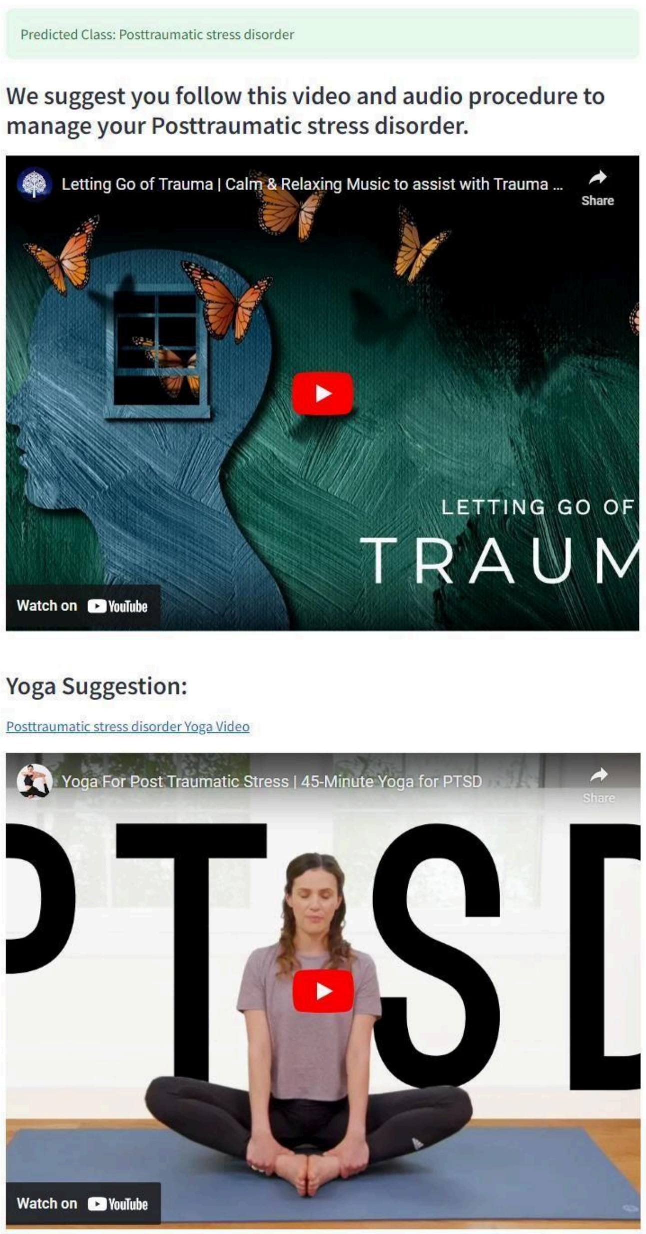

Figure.7: Personalized Meditation Videos

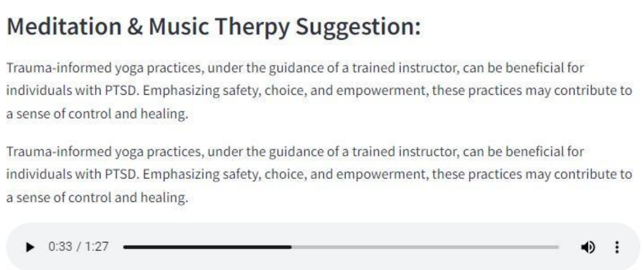

Figure.8: Audio Guidance

The above figures 7 and 8 represents the outcomes of our objectives which are personalized meditation videos and audio guidance. These visualizations are a customized auto-recommendation system based on the processing of user EEG data. The meditation videos set up a person for a relaxation and mental wellness through guiding, while the audio cues support a person during meditation sessions.

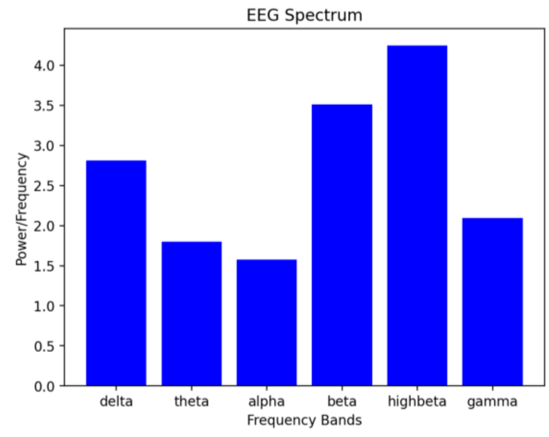

Figure.9: EEG Spectrum Analysis for Depressive Disorder

The above figure presents the EEG spectra in light of the amplitudes of the diverse brainwave frequencies. For example in a state of depression, the visualization suggests that there is high activity of delta and beta waves which are known to signify introspection, emotional processing, and rumination. Empirically, similar trend with past research literature on EEG biomarkers of depression seem to show an unbalance in neural oscillation that can potentially gives rise to depressive symptoms. In addition, the chart helps users to do comparative analysis of EEG spectra across different brain regions that result in not only understanding overall neural activity, but also localized activity. By identifying areas of the brain that show deviated brainwaves, the users will be able to gain the knowledge on neurobiological basis of their depression.

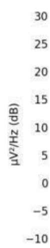

Figure.10: Power Spectral Density (PSD) Analysis

The above figure is a graphical depiction of the power spectral density (PSD), which stands for the proportionality of the neural activity within the brain for the different frequency bands. Through this image, the horizontal axis showing the range of brainwave frequencies and the vertical one indicate their power (μV or dB). Interpreting this PSD in the context of depression, it is essential to consider the segmentation of the graph into distinct frequency bands: these include delta, theta, alpha, beta, and high beta the gamma. Research recently indicates that depressed individuals might present changes in these EEG bands. For example, as theta and alpha activity increases with a drop in the beta band activity, this has been linked to a decrease in mood. On the other hand, it is intellectually honest to remark that these patterns may not be the same for all individuals. The intensity of depression, the co-presence of other conditions and the physiology of the brain are some of the factors which can change the observed EEG patterns. Thus, even though such an imaging type can contribute essential information on possible neurophysiological markers in depression, clinical evaluations and individual assessments are crucial when accurately diagnosing and developing a personalized treatment.

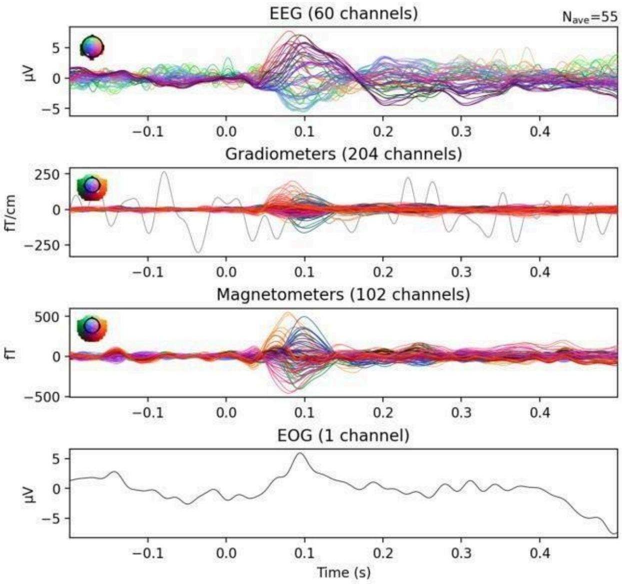

Figure.11: Evoked EEG Data Visualization

The demonstration of the above figure is electromechanical activity of the brain in the form of EEG from electrical recordings of 60 waveforms acquired independently from areas of brain offers a view of head neurological processes in action. Applied at a given point of time, the activity of channel averaging reflects shown and calls through Nave=55. Magnetometers (102)/(gradiometers 204)/ physiological feedback loop to detect magnetic fields with high precision, while an EOG channel records eye movement artifacts. Measurements to be performed will have unit fT/cm for magnetic field strength and µV for electrical potential respectively to have the same measure. The time axis indicates the energy metabolism of the brain throughout the seconds. The plot shows multi-lines, with different colours for various type of sensor, and represents the activity patterns, which reflect the level of neural engagement. On the other hand understanding these snapshots helps to consider the neural activities providing the necessary information with regards to cognition and behavior. Ultimately, the visualization as a whole is one of those necessary tools for a better understanding of how the brain works, and it leads to better cognition and behavior through a serious review of the brain activities.

6. CONCLUSION AND FURTHER SCOPE

The Neurofeedback Meditation Web App symbolizes a remarkable endeavor to develop specialized neurofeedback technology within the cyber-enabled mental health care niche. Unlike other used approaches that only offer general ideas, our application relies on the latest machine learning and neurofeedback technologies to give you precise prognosis with regard to the specific mental health disorder you are suffering and also provide customised advices for meditation, yoga practices and another calming audio content. Hence, the combination of superior analytics, user- relevant design, and proactive mental health management makes our project stand out compared to the rest of the projects since it targets real-world problems comprehensively and globally. From now on we will be directing our attention to improving the precision of the models along with total amount of the interventions and searching for valuable feedback from professionals of our model in order to make it valid and useful. Moreover, EEG devices of wearable type and mobile platform would help bringing the app into use, allowing users to control their psychological state and keep track of their emotions regardless of place. Through these approaches, our initiative is able to revolutionize the way of handling/managing mental issues as well as provide people with a better well- being and quality life.

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