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BCI Project 3

Introduction

This project aims to establish a brain-computer interface (BCI) capable of determining the anxious state of individuals in real-time without needing a psychoanalyst. The idea is to collect cerebral cortex brain wave activity using a commercially available Electroencephalography (EEG) electrode headset from subjects with known anxiety levels. The key to this BCI application is developing a classifier that can accurately predict anxiety levels.

Upon the classifier's maturity, the end user can use a headset and an iPhone app to obtain an anxiety level reading. Such a BCI would allow healthcare providers to monitor the anxiety levels of individuals unable to communicate their anxious state. Another application is the screening of grade-school-aged students.

Methods

a. Dataset Selection

With the paradigm that induced anxiety will result in changes to brain activity, we choose a dataset called 'Database for Anxious States, which is based on Psychological Stimulation' (DASPS), to investigate and potentially support our BCI application. This database aims to show that anxiety/stress recognition features can be derived from EEG signals [1][2].

b. Experimental Protocol

23 Subjects were subjected to Exposure Therapy stimulation to elicit tolerable levels of anxiety. The stimulation was performed in two phases for each situation. In the first phase, the psychotherapist recited a stressful event to the subject, followed by a second phase where the psychotherapist prompted the subject to recall this event. This process is repeated for five more situations, resulting in twelve 15-second trials. Brain activity was acquired using the Emotiv Epoc headset consisting of 14 electrodes (+2 references) using System International 10-20 placement at locations AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4. The electrode data was down-sampled and recorded at 128 Hz, with a +/- 4.18 mV dynamic range. Gyroscope and accelerometer channels are also included in the data.

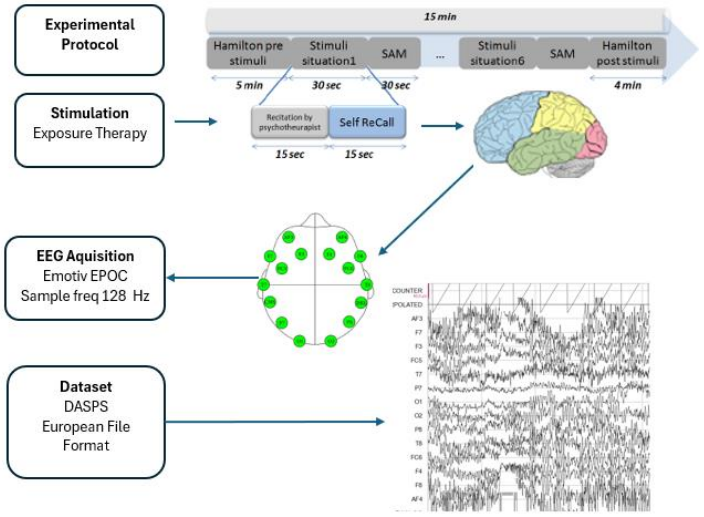

Figure 1: Experimental protocol and methods to collect the EEG signals for this dataset.

Labeling of the data is performed using two methods of anxiety evaluation. Before the start of the protocol, a psychotherapist evaluates the subject's anxiety level using a Hamilton Anxiety Rating (HAM-A)[4]. HAM-A rates the subject's anxiety levels in 14 areas on a scale from 0 to 4, for a total score from 0 to 56. A score below 17 indicates mild severity, 18-24 mild to moderate severity, and 25-30 moderate to severe. After each situation, the subject performs a Self-Assessment Manikin (SAM)[5], indicating their feelings during the situation. The SAM used in this protocol measures two parameters, Valence and Arousal, using a scale from

1 to 9. After the six situations, the psychotherapist performs a post-HAM evaluation. The timing for this protocol is pre-stimulus Hamilton anxiety rating scale HAM-A (5 min) and six trials of exposure therapy, each consisting of two 15-second EEG recorded phases (recital and recall). Post-stimulus HAM-A

c. Model Brain Activity

Brain action associated with anxiety is a mixture of emotional and cognitive activity. The emotion portion originates deep within the brain, in the amygdala region. The cognitive portion is associated with an area in the frontal lobe called the dorsal anterior cingulate cortex (dACC). When anxious patients are shown pictures of fearful faces, the dACC and amygdala (amongst other brain regions) ramp up their chatter, producing palpable anxiety. People without anxiety show little to no response [6].

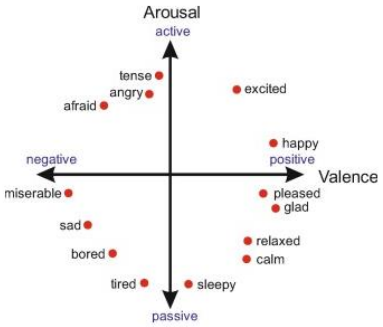

Figure 2: Arousal measures excitement, while Valence measures the subject's attitude.

Studies suggest that EEG data collected from electrodes placed on the frontal lobe (FP1, F3, F7, FP2, F4, and F8) showed a decrease in the PSD band below 20 Hz [7].

d. Pre-processing of Data (part of the public dataset [1])

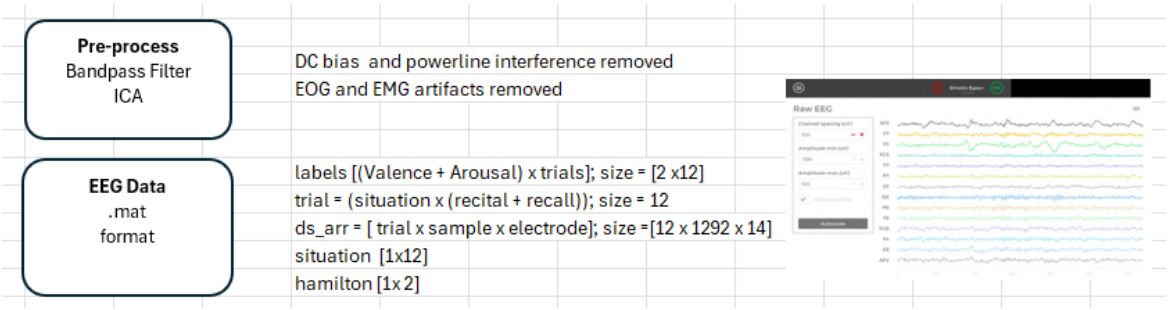

Figure 3: Pre-processing of .edf file to .mat file - Raw EEG was pre-processed to remove artifacts using ICA, and A FIR bandpass filter (4- 45 Hz) was used to remove low-frequency components and power line interference.

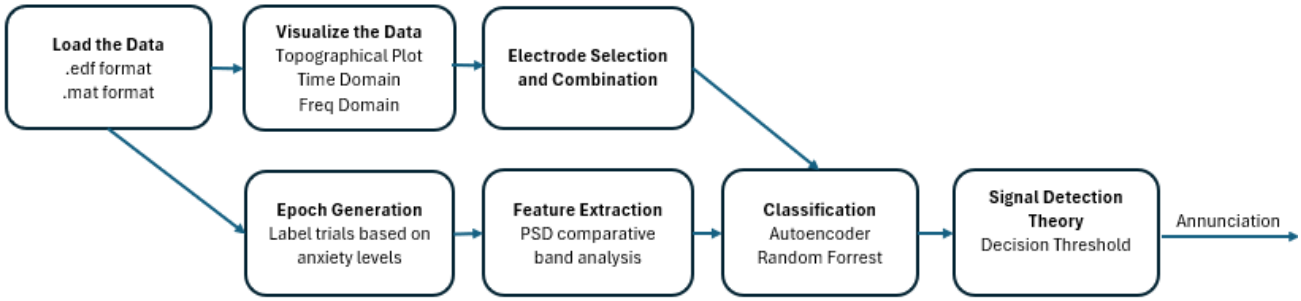

Figure 4: Block Diagram - Methods to develop and analyze exposure therapy classifier BCI performance.

e. Analyzing the Data

Figure 4 indicates the methods used to translate physiological brain signals, as recorded in the DASDPS data set, into an actionable output to the user.

The first step is to validate the information contained in the dataset. A set of Python utility functions allows the examination and visualization of EEG data in different domains. These functions are :

- **loadedf:** This function loads EEG data from .edf files using MNE (a Python package for EEG/MEG data analysis). It returns the raw EEG data, channel names, and metadata.
- **plot_edf_data**: This function plots EEG data in both time and frequency domains. It inputs raw EEG data and plots time-domain signals for each channel and their corresponding Power Spectral Density (PSD) in the frequency domain.
- **plot_scalp_map:** This function plots scalp maps of EEG data, showing the spatial distribution of neural activity. It inputs subject information, electrode names, EEG data, and other parameters and plots the scalp map based on the specified domain (either time or frequency).
- **clear_all_figures:** This function clears all existing figures from the current Matplotlib session. It helps clear the plotting environment before generating new plots.

These utility functions enabled the examination of brain activity characteristics of the recorded EEG signals in the temporal, spectral, and spatial domains.

f. Epoch Generation

Recall from Figure 1 that the recorded EEG signals are associated with 23 subjects, six situations, and 2 phases for a total of 276 (15-second) trials. The purpose of the experimental protocol is to invoke brain activity using Therapy Exposure. Labeling categorizes each trial into levels of anxiety based on Self-Assessment Manikin (SAM) scores. The definition of anxiety levels is provided by [1] and consists of five categories: Normal – not anxious, Severe Anxiety, Moderate Anxiety, Light Anxiety, and Normal Anxiety.

labelling: This function labels EEG data trials based on SAM scores by :

- Inputting two parameters, EGG **data**, and **labels containing** SAM Valence and Arousal scores associated with each trial.
- Creates a DataFrame by vertically stacked EEG data.
- Iterates through the indices of the DataFrame, assigning labels based on the SAM scores.
- The anxiety label thresholds are shown in Figure 5[1].
- Keeping track of the count for each category
- Returning a labeled DataFrame and a tuple containing the counts for each anxiety leve.
- Note : we found an error in the flow chart from [1]. The first decision block should be if Valence <= 5 & Arousal >= 5. Making this change resulted in consistent counting of anxiety levels.

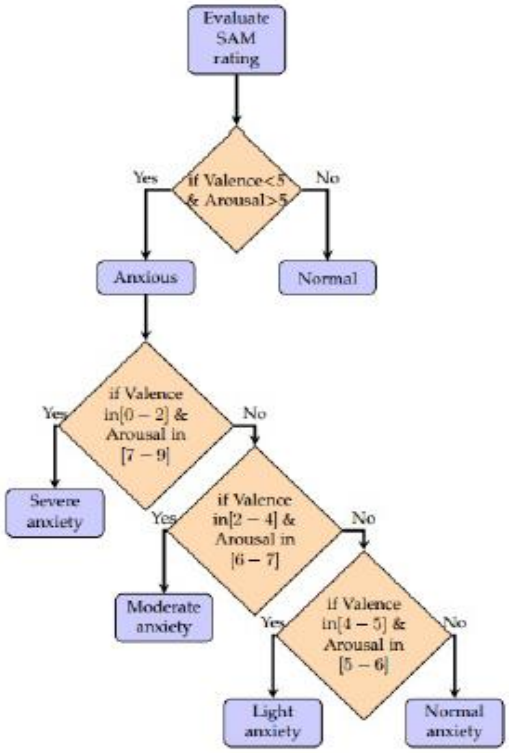

Figure 5: Flow Chart of Labeling Process [1]

g. Feature Extraction

Functions to generate features :

transformations : Pre-processes EEG data and generates features for classification using either an autoencoder (unsupervised learning) or a random forest (supervised learning)model. A summary of functionality is :

- Inputs a DataFrame containing EEG data and labels, the type of model, and parameters for data splitting and batch size.
- Initializes transforms for EEG data feature extraction of :
    - Band Power Spectral Density: alpha band 8-14 Hz, beta band 14-31 Hz, and gamma band 31-49 Hz.
    - Band Differential Entropy. In information theory, Entropy represents the amount of uncertainty. Signals with low Entropy are more predictable. Band Differential Entropy indicates the randomness of EEG signals within frequency bands (alpha, beta, and gamma bands).
    - The EEG data is normalized for each trial in the DataFrame, and band powers and differential entropies are computed.
    - Concatenates the extracted features with the anxiety level labels.
    - Formats the features and labels appropriately for the model and splits the data into training and testing sets.
    - Returns arrays consisting of data and labels for training and testing.

h. Classification

Three different models were used for classification :

- **Autoencoder** - unsupervised learning consists of an encoder that compresses the input data to a lower dimensional representation and a decoder network that reconstructs the input data from this representation. The autoencoder attempts to minimize the reconstruction error by learning a meaningful data representation. Classes developed that encapsulate this functionality with the data :
    - **Encoder:** Defines the structure of a neural network responsible for encoding input data into a latent space representation
    - **Decoder:** Defines the structure of a neural network responsible for decoding latent representations back into the original data space
    - **Classifier:** Backpropagation neural network designed for classification tasks
    - **VAE**: encapsulates the structure and functionality of a Variational Autoencoder (VAE).
        - Initializes the VAE with an encoder, classifier, and decoder.
        - It uses the forward pass of the VAE
        - Passes the input tensor through the encoder to obtain latent variables
        - Latent variable **z** passed into the classifier to obtain prediction **output**
        - Latent variable **z** passed through the decoder to reconstruct the input data
    - **loss:** Implements various loss functions used in training a VAE
    - **train:** Manage the setup of different loss components essential for tuning a VAE.
- **Random Forest** - supervised learning based upon classifying the EEG data features based on labeled training data.
    - **Regular randomforest:** Performs hyperparameter tuning using GridSearchCV
        - Initializes the random forest classifier with specified parameters
        - Performs hyperparameter tuning using GridSearchCV
        - Conducts training and evaluation on the random forest model by fitting the GridSearch object to the training data to find the best estimator.
        - Once the estimator is found, it makes predictions on the test data.
        - Then, it scores the predicted labels against the actual labels and returns the best estimator.
    - **Latent randomforest :** Uses the best estimator returned by the regular randomforest
        - It is trained on the latent features extracted from the encoder
        - It then makes predictons on the train and test data.

- **Support Vector Classifier -** It is a supervised learning algorithm used for classifying the EEG data features based on the labeled data.
    - **Regular SVC :** A Support Vector Classifier is trained on the features of the EEG data.
        - It then predicts the classes using the training data and test data.
    - **Latent SVC :** The SVC classifier is trained on the latent data extraced by the encoder.
        - It then makes predictions on the test data.

i. **Signal Detection Theory**:

BCI Requirements :

- For our BCI application, speed of response is not a concern, so Information Transfer Rates were not calculated.
- Considering the cost of making an incorrect decision, we selected Specivity as the most pertinent to our BCI application.

- Confusion Matrix
    - Accuracy = (TP + TN)/(TP + TN + FP + FN); calculates the proportion of correctly predicted instances (both positive and negative) out of the total cases.
    - Precision = TP/(TP+FP); the proportion of correctly predicted positive instances.
    - Specificity = TN/(TN+FP); True negative rate, the proportion of correctly predicted negative instances. When the cost of false positives is high, it is essential to identify true negatives correctly.
    - Sensitivity = TP/(TP + FN); True positive rate, the proportion of actual positive instances that are correctly identified.

Results

No exact methodology is described in the paper for mapping the scalp electrodes to the recorded EEG data. Meaning there are 14 columns mapped to 14 unknown electrodes. Case 1, Displayed in Figure 5 uses the general electrode list from the base Emotiv EPOC EEG headset. Case 2 in Figure 5 uses electrode mapping based on the ordering provided by Frarah Muhammand's work[3]. Case 3 in Figure 5 is based on our intuition for which voltages should be expected throughout these trials. We generated Figures 6 and 7 to visualize the data and ensure we could load and process it appropriately.

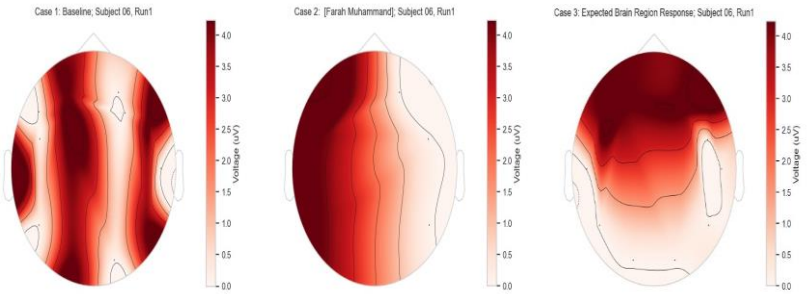

Figure 5: Plot Topo Spatial Maps of Voltage Distribution Across the Scalp for Subject 6 Trial 1 using Three Different electrode maps.

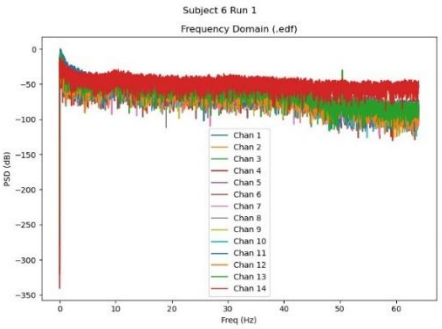

Figure 6. Frequency Domain Of Subject 6 Trial 1

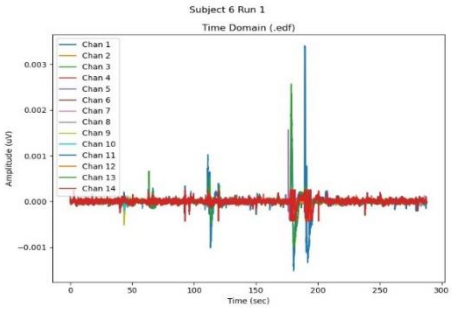

Figure 7. Time Domain of Subject 6 Trial 1

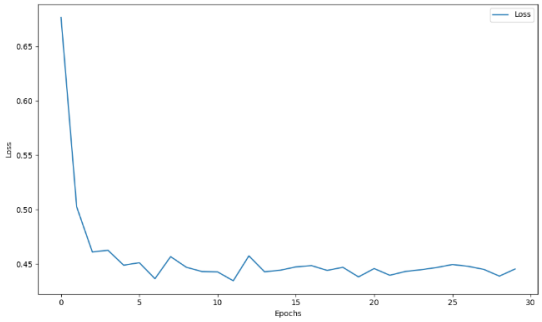

Figure 8. Training Loss of the classifier

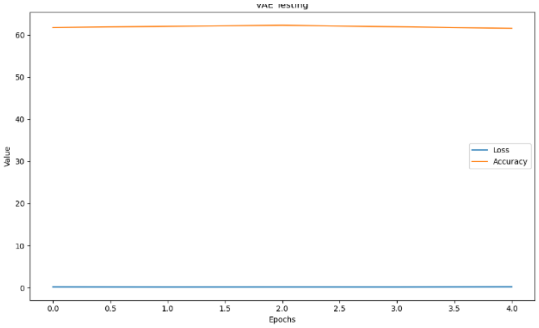

Figure 9. Testing accuracy and loss of autoencoder

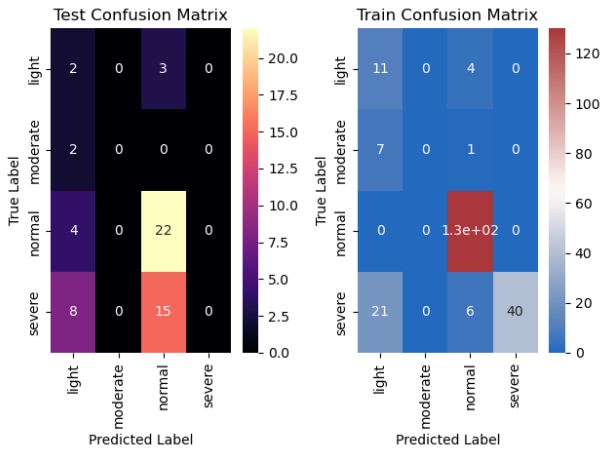

Figure 10. Confusion Matrices of regular random forest

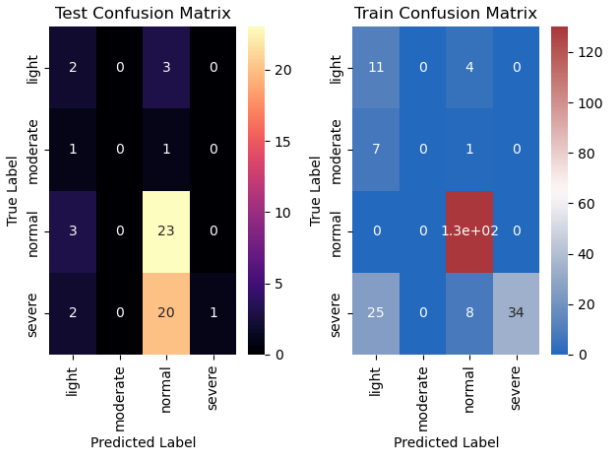

Figure 11. Confusion Matrices of latent random forest

Model	Specificity (%)			
	Normal Anxiety	**Light Anxiety**	**Moderate Anxiety**	**Server Anxiety**
Regular Random Forest	66.6	87.2	96.4	58.9
Latent Random Forest	66.6	89.3	96.4	58.9
Regular Support Vector Classifier	1	89.2	96.4	60
Latent Support Vector Classifier	nan	89.2	96.4	58.9

Table 1: Specificity results for the various classifiers.

Discussion

The needs of the BCI user are to have an easily donned headset and the ability to monitor anxiety without the need for specialists. Users can use relatively inexpensive wireless electrode headsets to run the BCI as an iPhone app. The user protocol would be the same as the experimental protocol discussed above, except a psychotherapist would not need to make professional scores for the HAM-A assessment. Nor would there be a need to perform the SAM assessment. Our proposed method correlates brain signal activity with anxiety levels. Clearly, the Specificity performance of the system, based on a limited training data set, is inadequate. The way forward to improve the Specificity results is by collecting additional data. With the right amount of data, the variational autoencoder we trained can be used to train a classifier for classifying anxiety into different degrees in the following way : If the reconstruction loss between the encoded and decoded brain signals is too low, it would imply that a person is feeling anxious.

Conclusion and Challenges

The accuracy of our classifier in predicting severe anxiety was no better than that of other studies[3].

Technical challenges, in priority order :

1. Lack of trials/data. Neural networks take massive amounts of data to train and tune appropriately. Our dataset contained only 23 subjects in 12 trials. Of these 276 epochs, only 90 were trials associated with Severe Anxiety.
2. Lack of confidence in electrode location to EEG data index mapping hindered us from using only the frontal electrodes, which, according to studies, provide the most information. We chose to use all the electrodes, feeling that our sample size would be increased to 3864 and we would not have to worry about the mapping issue.
3. A review of the technical literature indicates that detecting emotional states in general and anxiety, specifically from brain activity, is highly challenging [8].

Ethical challenges :

- BCI's for anxiety detection should be accessible for all individuals who may benefit from them regardless of socioeconomic status or geographical location. Developers must strive to minimize costs and barriers to access to ensure equitable technology distribution.
- The use of an anxiety-detection BCI may also contribute to the stigmatization and discrimination against individuals with anxiety disorders. Healthcare providers must avoid labeling or stereotyping individuals based on their neurological data and promote understanding and empathy for those experiencing anxiety.

Contributions of authors :

Luke: Attempted PCA, code review, added comments and docstrings, development of results/discussion/conclusion.

Varshney : Written the code for extracting the features, labelling the data, neural networks and classifers and added docstrings for different classes and functions related to Machine Learning.

Jim: Dataset definition, development of methods.

References

[1] Asma Baghdadi, Yassine Aribi, Rahma Fourati, Najla Halouani, Patrick Siarry, Adel M. Alimi, January 6, 2021, "DASPS database ", IEEE Dataport, doi: https://dx.doi.org/10.21227/barx-we60.
Commentary: This reference provides a basic description of the dataset and the experimental protocol used to collect the EEG data and associative anxiety levels.

[2] Asma Baghdadi, Yassine Aribi, Rahma Fourati, Najla Halouani, Patrick Siarry, and Adel M. Alimi. "DASPS: A Database for Anxious States based on a Psychological Stimulation." arXiv preprint arXiv:1901.02942 (2019).
Commentary: This paper details the protocol used to record, pre-process, and analyze the dataset.

[3] Muhammad, F., & Al-Ahmadi, S. (2022). Human state anxiety classification framework using EEG signals in response to exposure therapy. PloS one, 17(3), e0265679. https://doi.org/10.1371/journal.pone.0265679
Commentary: The second source uses the same DASPS dataset. This study selected electrodes and performed frequency domain feature extraction. The frequency bands used were theta and beta bands.

[4] Hamilton M. The assessment of anxiety states by rating. Br J Med Psychol 1959; 32:50–55.
Commentary: Provides a description of how HAM-A evaluation is conducted and the meaning of the test scores.

[5] Self-Assessment Manikin. (2023, September 13). In *Wikipedia*. ttps://en.wikipedia.org/wiki/Self-Assessment_Manikin
Commentary: Define the self-assessment scales for valence and arousal and how the assessment is performed.

[6] Levi Gadye, What Part of the Brain Deals With Anxiety? What Can Brains Affected by Anxiety Tell Us?, Jun 2018, BrainFacts.org
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[7] Chae Chen et al, EEG-Based Anxious States Classification Using Affective BCI-Based Closed Neurofeedback System, Journal of Medical and Biological Engineering (2012)
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Commentary: Diminished alpha wave activity is found in anxiety disorders; however, in studies of patients in categories { Anxiety, OCD Mood disorders}, consistent patterns have not yet been discerned.