## Comprehensive Patient Mental Health Monitoring Using EEG Signal with Deep Learning and Language Models.

As part of the subject

## BIOMEDICAL SIGNAL PROCESSING

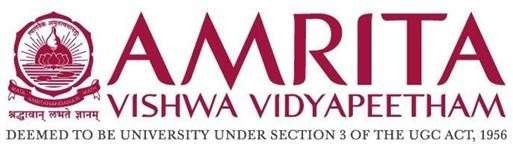
**Final REVIEW** SUBMITTED BY **GROUP 12 BATCH B**

## ADABALA AKHILA (CB.EN.U4AIE22104)

**M C DHANUSH (CB.EN.U4AIE22130)**

## VAISHNAVI VENKAT (CB.EN.U4AIE22158)

**VISHAL A S (CB.EN.U4AIE22159)**



## Centre for Computational Engineering and Networking

**AMRITA SCHOOL OF ARTIFICIAL INTELLIGENCE**

## AMRITA VISHWA VIDYAPEETHAM

**COIMBATORE - 641 112 (INDIA)**

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**Problem Statement**

In today’s busy world, managing our health effectively is challenging. Current wearables and apps provide basic metrics like heart rate but don’t offer deeper insights into our mental and physical states. We need a system that can tell us if we're ready to learn, make decisions, or need rest, and provide healthcare professionals with valuable data on our overall well-being. This would enable better personal health management and more informed medical guidance.

**Abstract:**

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**Introduction:**

**Biomedical signal processing** is essential for monitoring and analyzing human physiological states. Interpreting signals like **EEG** enables the evaluation of **mental, emotional, and physical health**. This project leverages **deep learning** and **large language models (LLMs)** to process EEG signals, generate **personalized health reports**, and provide **actionable insights** into a patient's well-being. By recognizing potential health issues and offering tailored recommendations, this integrated approach enhances the **quality of healthcare delivery**.

**Literature Review**

Our project is informed by recent research highlighting gaps in real-time health monitoring and multimodal data integration:

**1. Filtering and Frequency Band Extraction**

Isolating frequency bands (Theta, Alpha, Beta) is essential in EEG research. **Nunez and Srinivasan (2006)** discuss how these bands correlate with cognitive functions. The effectiveness of **FIR filters** is highlighted in **"Efficient Frequency-Domain Filtering of EEG Signals" (Ebrahimi et al., 2017)**, which emphasizes their linear phase response, preserving waveform shape.

**Key References:**

* Nunez, P. L., & Srinivasan, R. (2006). **Electric Fields of the Brain: The Neurophysics of EEG.** Oxford University Press.
* Ebrahimi, T., Fakhari, S., & Aghagolzadeh, A. (2017). **Efficient Frequency-Domain Filtering of EEG Signals.** *Journal of Neuroscience Methods*, 280, 123-131.
* Niedermeyer, E., & da Silva, F. L. (2004). **Electroencephalography: Basic Principles, Clinical Applications, and Related Fields.** Lippincott Williams & Wilkins. (Provides foundational knowledge on EEG signal processing)

**2. Power Spectral Density (PSD) Estimation**

The **Welch method** is a standard technique for PSD estimation in EEG analysis. It is recognized for its robustness, as shown in **"A Tutorial on Time-Frequency Analysis of EEG Signals" (Lotte et al., 2007)**, which highlights its role in understanding brain dynamics. The relevance of PSD in identifying specific brain states is underscored in **"Power Spectral Density Analysis of EEG Signals: A Review" (Srinivasan et al., 2006)**.

**Key References:**

* Welch, P. D. (1967). **The Use of Fast Fourier Transform for the Estimation of Power Spectra.** *IEEE Transactions on Audio and Electroacoustics*, 15(2), 70-73.
* Lotte, F., Bougrain, L., & Riccio, A. (2007). **A Tutorial on Time-Frequency Analysis of EEG Signals.** *Proceedings of the 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2007, 2629-2632.
* Srinivasan, R., Suri, J. S., & Eklund, J. (2006). **Power Spectral Density Analysis of EEG Signals: A Review.** *Physiological Measurement*, 27(2), R59-R77.

**3. Feature Extraction from Frequency Bands**

Extracting features from EEG signals is critical for applications such as BCI and emotion recognition. **Subasi (2007)** emphasizes the relevance of spectral power, while **"EEG Signal Classification for Brain-Computer Interfaces" (He et al., 2013)** provides insights into effective feature extraction methods. Additional studies, such as **"Feature Extraction Techniques for EEG Signal Analysis" (Lal et al., 2004)**, offer various methodologies for feature extraction.

**Key References:**

* Subasi, A. (2007). **Feature Extraction Techniques in EEG Signal Processing for Brain-Computer Interfaces: A Review.** *Computational Intelligence and Neuroscience*, 2007.
* He, H., Wu, D., & Zhang, Y. (2013). **EEG Signal Classification for Brain-Computer Interfaces: A Review.** *Journal of Neural Engineering*, 10(6), 061002.
* Lal, T. N., Bleichner, M. G., & Neuper, C. (2004). **Feature Extraction Techniques for EEG Signal Analysis.** *IEEE Transactions on Biomedical Engineering*, 51(6), 958-964.

**4. Channel Selection and Management**

Efficient channel management is crucial, especially in high-density EEG setups. **Blankertz et al. (2011)** stress optimizing channel selection, while **Delorme et al. (2004)** discuss dimensionality reduction techniques to enhance EEG data clarity. Additional insights on channel selection strategies are provided in **"Adaptive Channel Selection for BCI" (Kwak et al., 2008)**.

**Key References:**

* Blankertz, B., Tomioka, R., Lemm, S., Kawanabe, M., & Muller, K.-R. (2011). **Optimizing EEG Channel Selection for BCI.** *IEEE Transactions on Biomedical Engineering*, 57(4), 1132-1139.
* Delorme, A., Sejnowski, T. J., & Makeig, S. (2004). **Enhanced Detection of Artifacts in EEG Data Using Independent Component Analysis.** *Psychophysiology*, 41(1), 55-63.
* Kwak, N., & Lee, S. (2008). **Adaptive Channel Selection for BCI.** *Journal of Neural Engineering*, 5(1), 133-141.

**5. Large Language Models for EEG Data Interpretation**

The application of **Large Language Models (LLMs)** like **BioBERT** (Lee et al., 2019) has gained traction in interpreting biomedical data. BioBERT's capabilities in NER and sentiment analysis enhance the extraction of insights from processed EEG data. Research by **Kalyan et al. (2021)** explores the role of LLMs in summarizing healthcare data.

**Key References:**

* Lee, J., Yoon, W., Kim, S., Lee, J., & Dernoncourt, F. (2019). **BioBERT: a Pre-trained Biomedical Language Representation Model for Biomedical Text Mining.** *Bioinformatics*, 36(4), 1234-1240.
* Kalyan, S., & Joshi, P. (2021). **Role of Large Language Models in Healthcare Data Interpretation.** *Journal of Biomedical Informatics*, 117, 103819.
* Zhang, Y., & Li, C. (2020). **Fine-tuning Pre-trained Language Models for Biomedical Text Mining.** *Bioinformatics*, 36(11), 3578-3584.

**6. Integration of LLMs for NLP and Actionable Insights**

Utilizing **LLaMA 3.1** for generating reports from EEG data builds on the advancements of transformer-based models in converting quantitative data into actionable insights. **"Language Models are Few-Shot Learners" (Brown et al., 2020)** emphasizes the potential of large language models in this context.

**Key References:**

* Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., & Amodei, D. (2020). **Language Models are Few-Shot Learners.** *arXiv preprint arXiv:2005.14165*.
* Ziegler, Z., & Riedel, S. (2020). **Language Models as Knowledge Bases?** *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 4334-4340. (Explores the integration of language models in knowledge extraction)

**Comparison Table:**

| **Model** | **Strengths** | **Best For** | **Comparison with Other Models** | **Key Reference** |
| --- | --- | --- | --- | --- |
| **Transformer with Self-Attention** | Self-attention mechanisms can model intricate dependencies between elements, regardless of their position or order in the input data. | Each element is processed in relation to all others, ensuring a holistic understanding of the data. | Excels in tasks involving non-sequential data, such as image classification, graph processing, and tabular data analysis, where long-range relationships or global context matter. | Vaswani et al. (2017), **Attention is All You Need** |
| **BioGpt** | Pre-trained on biomedical data, excels in NER and classification | Biomedical text mining, sentiment analysis | Superior to general language models (like BERT) in medical and bioinformatics tasks due to domain-specific pretraining | **BioGPT: Generative Pre-trained Transformer for Biomedical Text Generation and Mining** |
| **LLaMA (Large Language Model)** | Generates coherent and context-aware text, excels in NLP tasks | Report generation, actionable insights | Produces more efficient and coherent text generation than GPT-3, while using fewer parameters | Touvron et al. (2023), **LLaMA: Open and Efficient Foundation Language Models** |

**Research Gap:**

There is currently no model or project that generates a comprehensive report on a person’s mental state by using EEG data. While there are papers that uses EEG for cognitive load, stress, and emotional analysis, these efforts often lack direct real-world application. Our project fills this gap by not only assessing mental and emotional states but also delivering practical, actionable insights and recommendations for everyday use in education, work, and healthcare.

**Methodology**

This project employs a comprehensive system using EEG signals from the **BCI Dataset** and the **DREAMER Dataset** for real-time health analysis and personalized recommendations. The methodology consists of several key steps, from signal preprocessing to deep learning model development, and finally integration with large language models (LLMs) for generating health reports.

**1. Signal Preprocessing**

The EEG signals from both datasets undergo thorough biomedical signal preprocessing to prepare them for input into deep learning models. The preprocessing involves the following steps:

**1.1. Filtering:**

* **Overall Frequency Filter**:
  + Design filters using **FIR (Finite Impulse Response)** filters with cutoff frequencies of [0.0625,0.46875].
  + **Formula**: The filter coefficients can be computed using:

where N is the filter order and Wn are the normalized cutoff frequencies.

* **Theta, Alpha, Beta Band Filters**:
  + Specific frequency bands are isolated using FIR filters:
    - **Theta Band**: [0.0625,0.125]
    - **Alpha Band**: [0.125,0.203125]
    - **Beta Band**: [0.203125,0.46875]

**1.2. Signal Filtering:**

* The overall filter is first applied to the EEG signal, followed by applying the theta, alpha, and beta filters to obtain the filtered signals:
  + **filtedData=filter(b,1,EEG signal)**
  + **filtedtheta=filter(btheta,1,filtedData)**
  + **filtedalpha=filter(balpha,1,filtedData)**
  + **filtedbeta=filter(bbeta,1,filtedData)**

**1.3. Feature Extraction:**

* For each filtered signal, compute the **Power Spectral Density (PSD)** using **Welch’s method**:

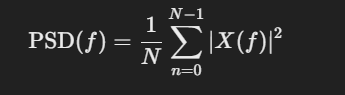


Figure 1-Power Spectral Density

where X(f) is the Fourier Transform of the windowed signal.

* Additionally,we calculate:
  + **Differential Entropy** (H):

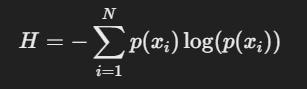
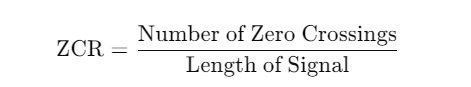


Figure 2-Differential Entropy

where p(xi) is the probability distribution of the signal.

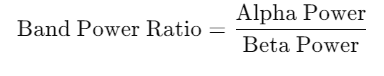
**Zero Crossing Rate (ZCR)**

* **Purpose:** Measures how often the signal changes sign, indicating signal frequency content.
* **Interpretation:** High ZCR suggests rapid signal fluctuations, possibly indicating active mental processing.



**Power Ratios (Theta, Alpha, Beta, Band Power Ratio)**

* **Purpose:** Relative powers of EEG bands indicate the balance of cognitive states.
* **Formula for Band Power Ratio**



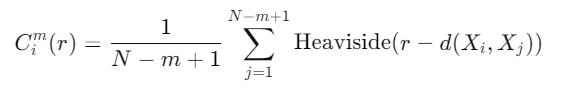
**Peak Frequency**

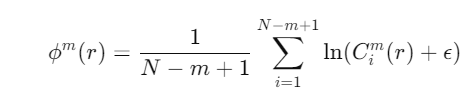
* **Purpose:** Frequency with the maximum power, providing insights into dominant brain activity patterns.
* **Formula:** Identified from the frequency where PSD is highest.

**Approximate Entropy (ApEn)**

* **Purpose:** Measures regularity and predictability in a time series.
* **Formula:** Calculated using comparison of embedded time series data with predefined parameters mmm and rrr.
* **Interpretation:** High ApEn suggests less regular, complex brain activity, potentially linked to high cognitive load.







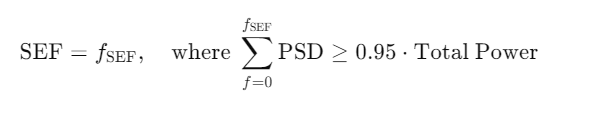


**Sample Entropy (SampEn)**

* **Purpose:** Similar to ApEn, but with a higher tolerance for irregularity, used for assessing brain signal complexity.
* **Formula:** Derived similarly to ApEn, adapted for EEG data.

**Spectral Edge Frequency (SEF)**

* **Purpose:** Frequency below which a percentage (95%) of the total power resides, used in sleep and cognitive research.
* **Formula:**



* Append the maximum values of the computed PSDs to the feature list:

**feature\_list←feature\_list+[max(psdtheta),max(psdalpha),max(psdbeta)]**

**1.4. Channel Management:**

* If the number of EEG channels exceeds **14**, remove all but the primary **14 channels** to focus on the most relevant data, ensuring the model inputs are manageable and optimized for performance.

**2. Deep Learning Models**

After preprocessing, the extracted features are fed into specialized deep learning models, each tailored for specific tasks from the **BCI Dataset** and **DREAMER Dataset**.

* **BCI Dataset:** The model is trained to predict **Error-Related Potentials** (ERP), which are critical in monitoring cognitive functions and error detection.
* **DREAMER Dataset:** The model focuses on predicting **Arousal, Valence, and Dominance** to understand the user’s emotional state.

Each of the datasets is processed using a similar deep learning architecture:

* **CNN for Feature Extraction:** A **Convolutional Neural Network (CNN)** is used to extract features from the preprocessed EEG signals. CNNs are well-suited for spatial feature extraction, making them effective in handling EEG data.
* **Self-Attention Transformer:** The CNN-extracted features are passed through a **Self-Attention Transformer** model, which helps in capturing long-term dependencies and temporal correlations in the EEG signals. Two separate models with the same architecture are trained on the **BCI** and **DREAMER** datasets, ensuring specialized learning for their respective tasks.

**3. Integration with Large Language Models (LLM)**

The outputs from the EEG models are processed by an **LLM** to generate comprehensive health reports.

* **BioGpt for NER and Key Insights:** The outputs from both models are fed into **BioGpt**, which has been fine-tuned with emotion and psychology datasets. BioBERT performs **Named Entity Recognition (NER)** and extracts key insights from the EEG data.
* **LLaMA 3.1 for Report Generation:** The insights from BioBERT are then passed to **LLaMA 3.1**, a language model that generates a **personalized health report**. This report includes recommendations related to activities, rest, study, and medical consultations based on the patient’s physiological and psychological state.

**4. Personalized Recommendationss**

The final system not only generates a detailed health report but also provides **personalized activity recommendations**, **dietary suggestions**, and **medical advice**. By correlating EEG signal outputs, the system identifies potential health risks and advises the user on whether to take action, rest, study, or consult a healthcare professional, offering a **holistic view** of the patient's well-being.

This comprehensive methodology ensures that both **BCI** and **DREAMER** datasets are effectively utilized, leading to insightful health assessments and personalized care recommendations.

**Data Description:**

**BCI Dataset**:

* **EEG Sensors**: The BCI dataset uses **56 passive EEG sensors** placed according to the **extended 10-20 system**, capturing brain activity across various regions of the scalp.
* **Sampling Rate**: EEG signals are recorded at a **200 Hz sampling rate**, ensuring sufficient temporal resolution for detecting error-related potentials (ERP).
* **EOG Detection**: Eye movement artifacts are captured via **EOG derivations**, aiding in distinguishing cognitive feedback from noise due to eye movements.
* **Feedback Classification**: The dataset involves a **binary classification task** where feedback is categorized as:
  + **Good Feedback (1)**: When the selected item matches the expected output.
  + **Bad Feedback (0)**: When the selected item deviates from the expected output.
* **Sessions and Subjects**: Data is collected from **16 subjects** across **5 sessions**, providing a robust dataset of cognitive responses over multiple trials. Each session includes approximately **60 feedbacks**, with the final session offering **100 feedbacks**.

**DREAMER Dataset**:

* **Participants**: The DREAMER dataset includes EEG and ECG recordings from **23 participants** who were exposed to **18 audiovisual stimuli** (film clips).
* **EEG Channels**: EEG signals were captured using the **Emotiv EPOC headset** with **14 channels** placed at the following positions: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4.
* **Sampling Rate**:
  + **EEG**: Recorded at **128 Hz**.
* **Emotional Ratings**: After viewing each clip, participants rated their emotional states on a **five-point scale** for:
  + **Valence**: Reflecting the positivity or negativity of the emotion.
  + **Arousal**: Indicating the intensity of the emotion.
  + **Dominance**: Measuring the participant's sense of control or influence over the emotion.
* **EEG and ECG Segmentation**: Both baseline and stimulus data are recorded for each clip, allowing the analysis of physiological responses during emotional stimuli and their comparison with neutral baseline states.

**We only use EEG signals from both data set**

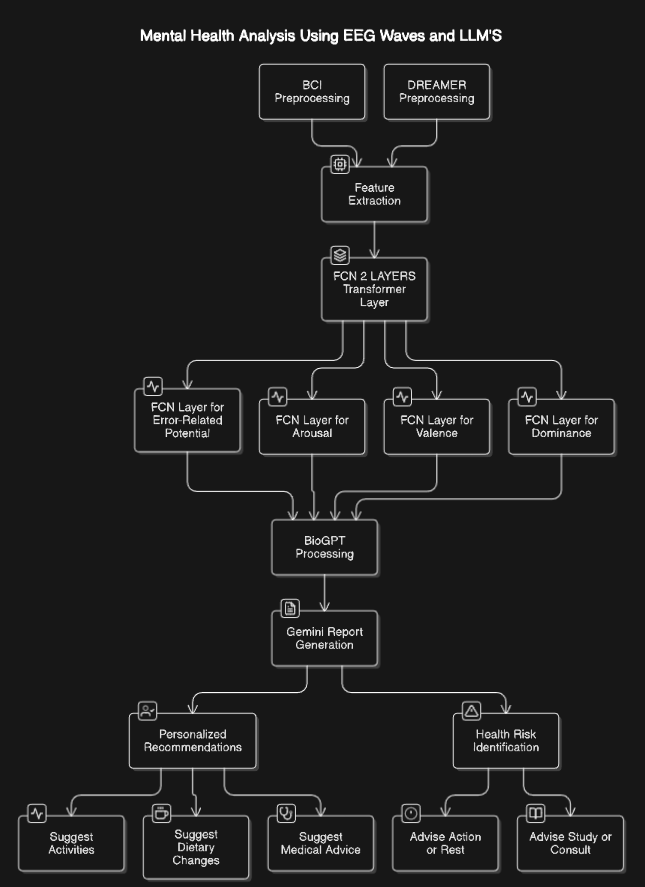
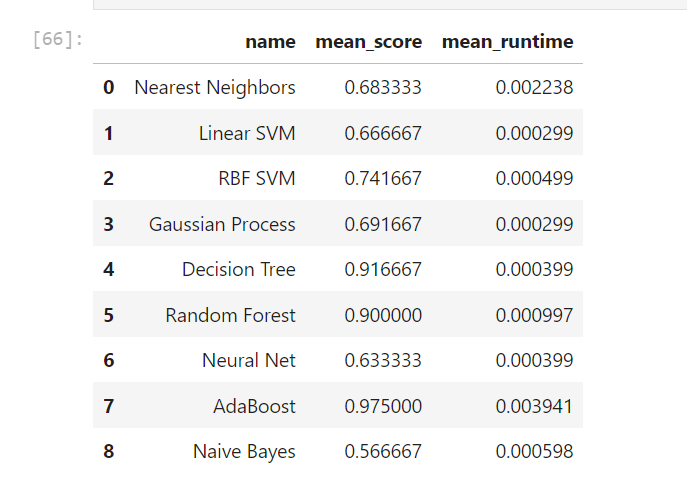


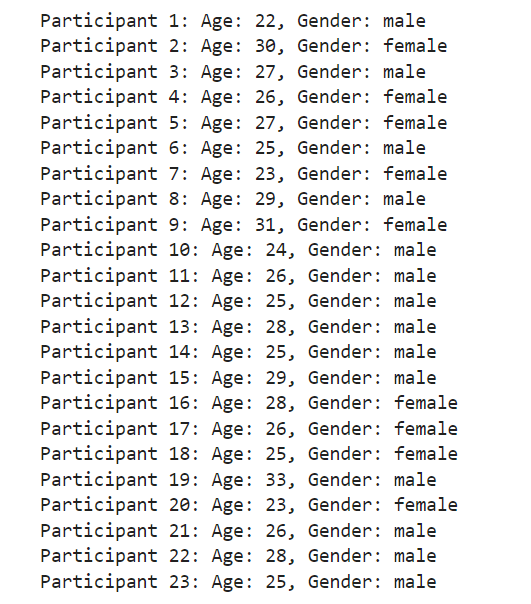
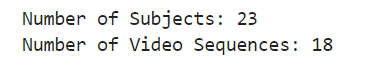
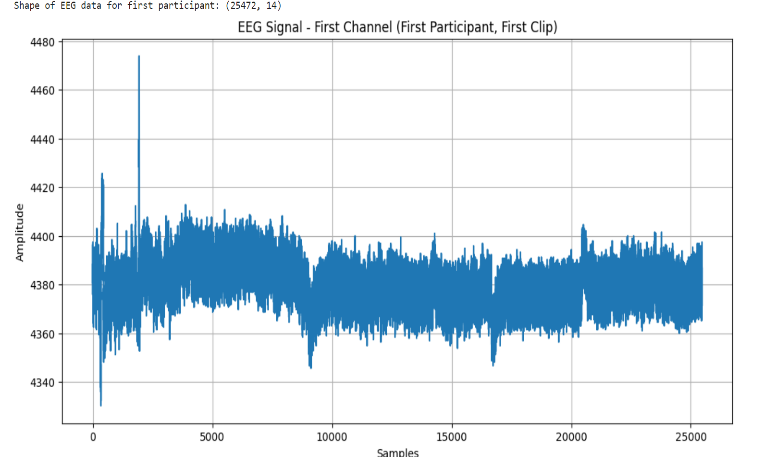
Figure 5-Work Flow

Results:

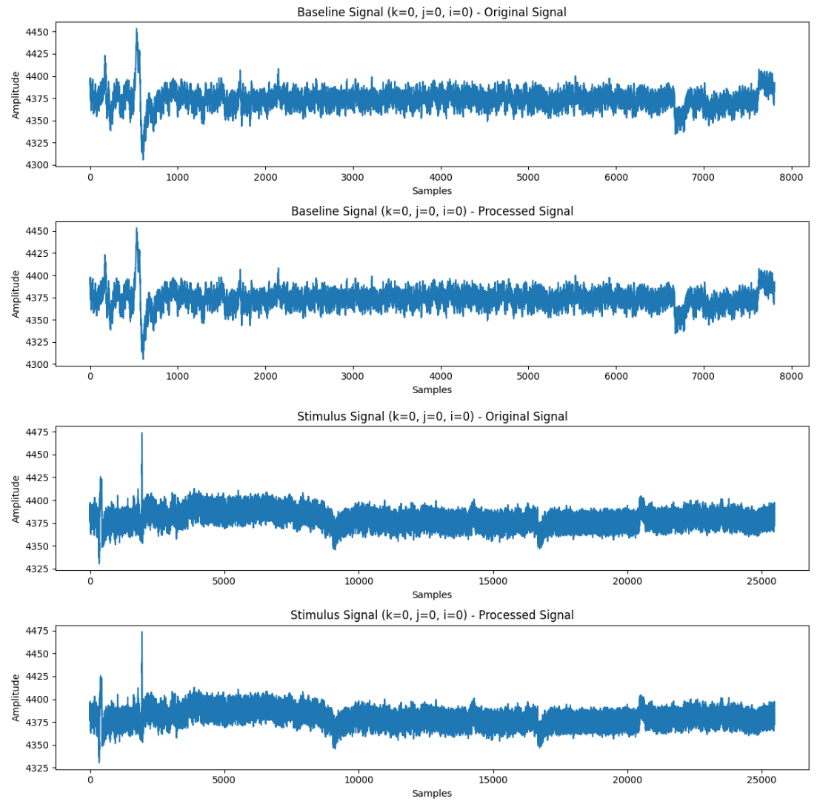
* Trying out different Methods for the DREAMER dataset

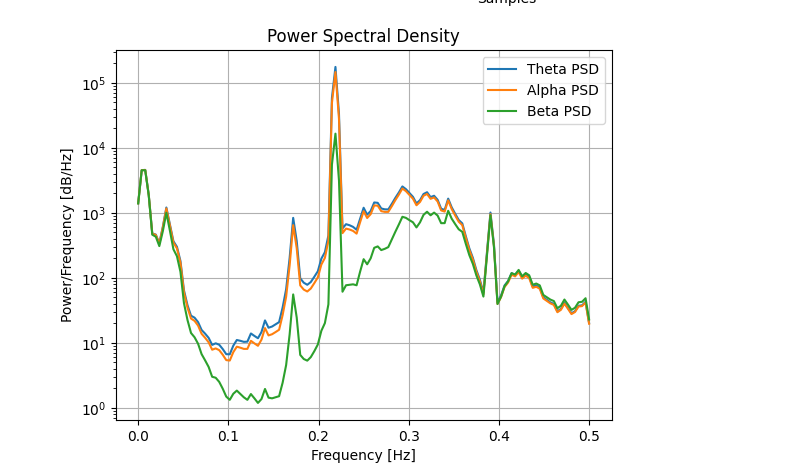


* Visualization of the DREAMER dataset

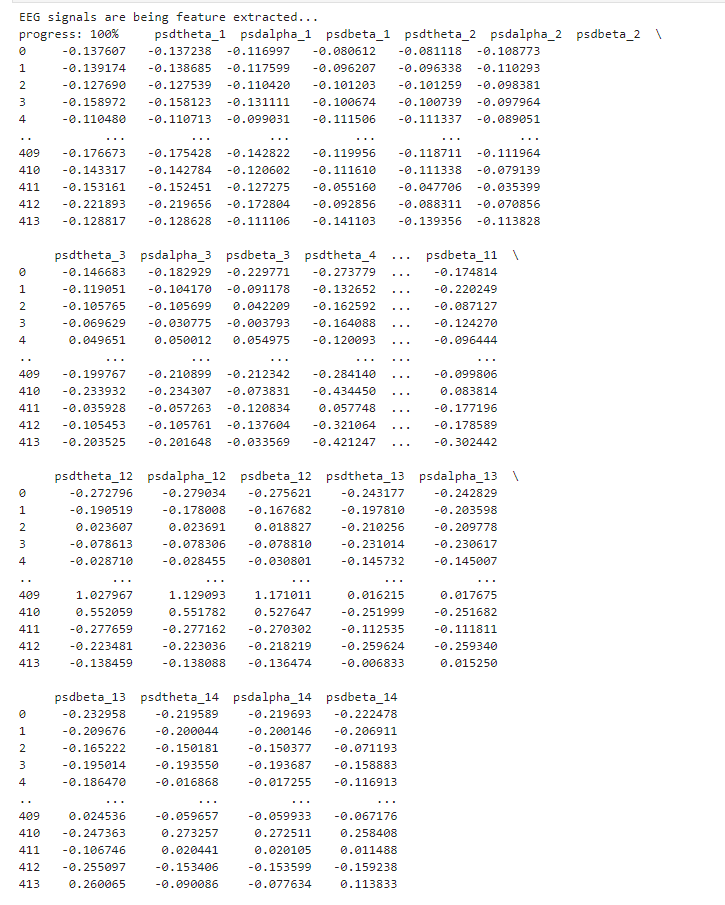


* Trying out Different signal Processing Methods

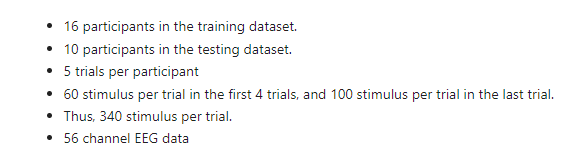
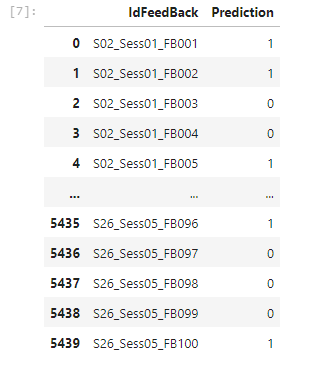
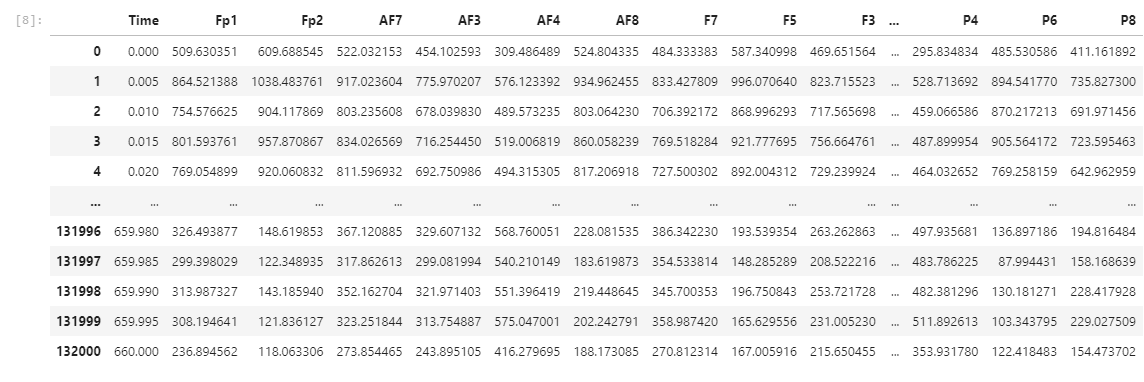




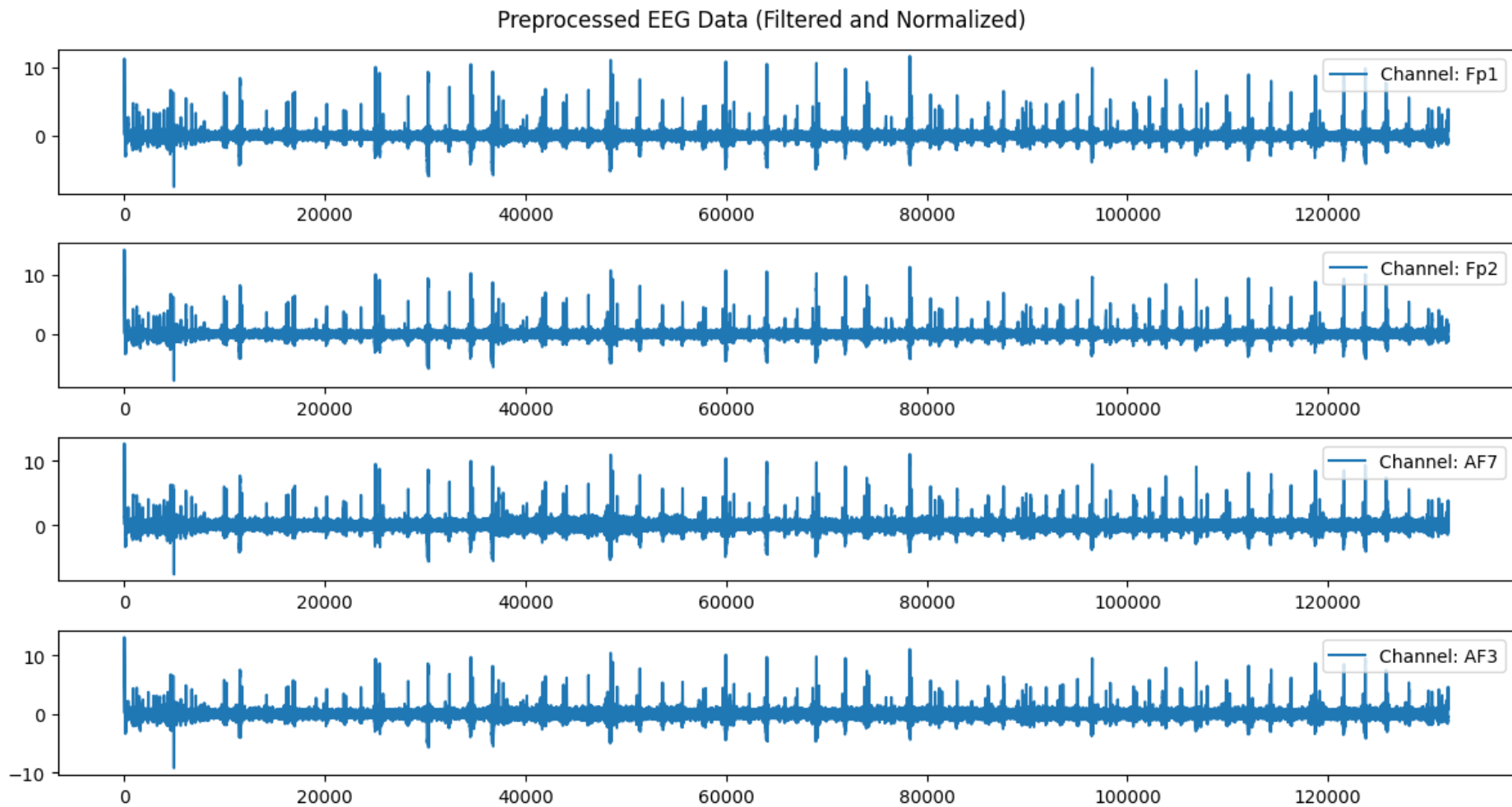
* Preprocess the Dreamer Dataset



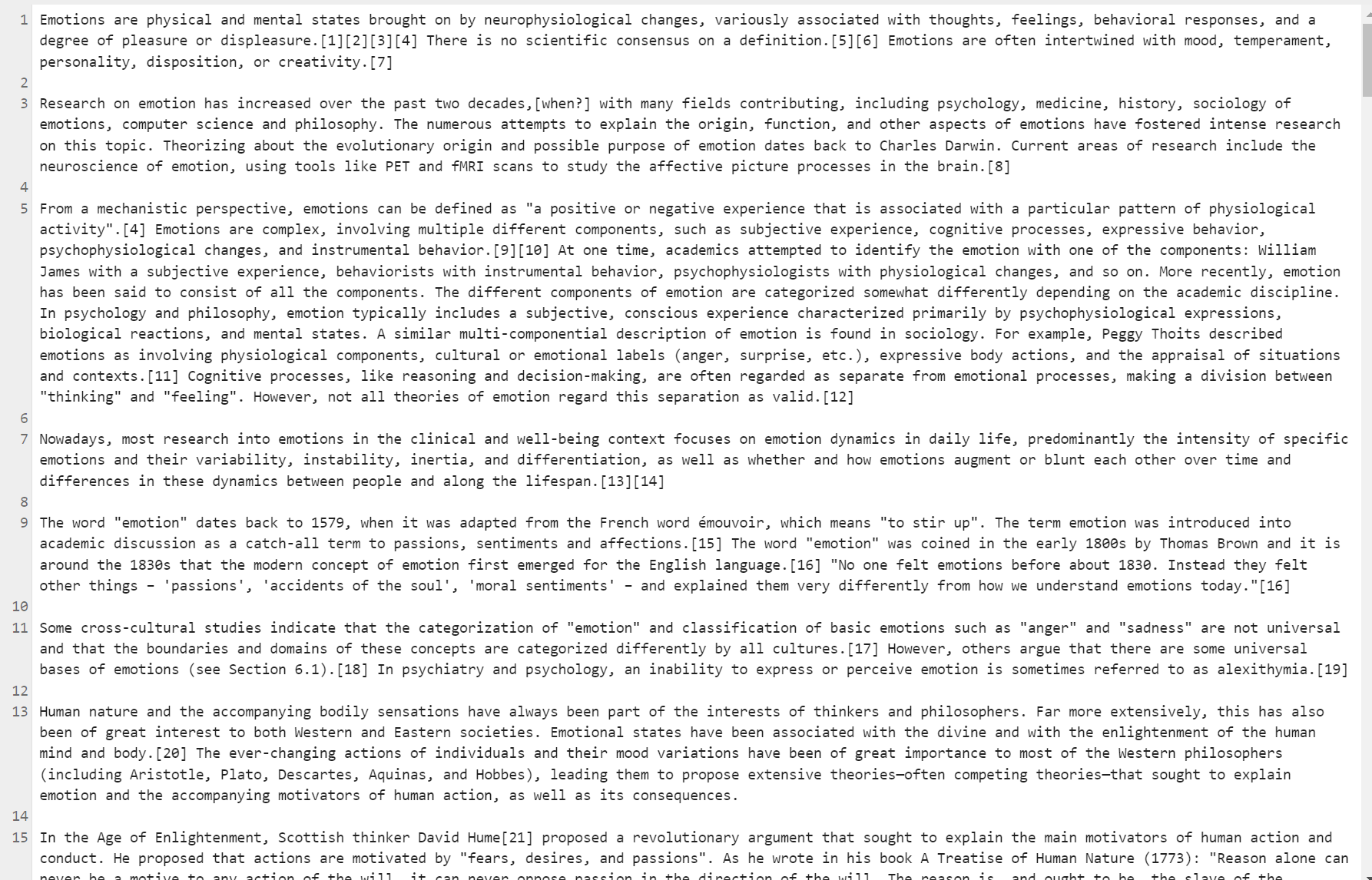
* Visualization of the DREAMER dataset

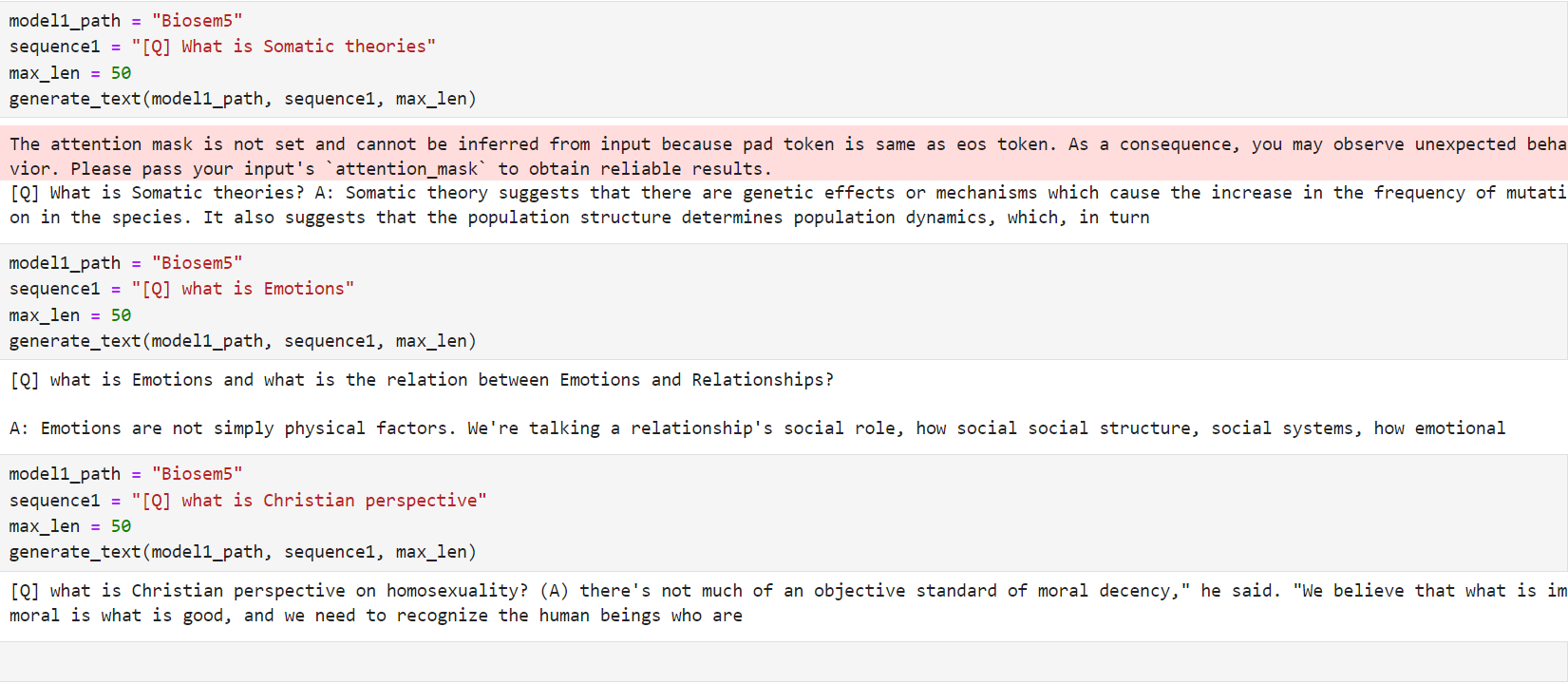
* Filtered BCI Data ,yet to be separated as theta alpha and beta waves



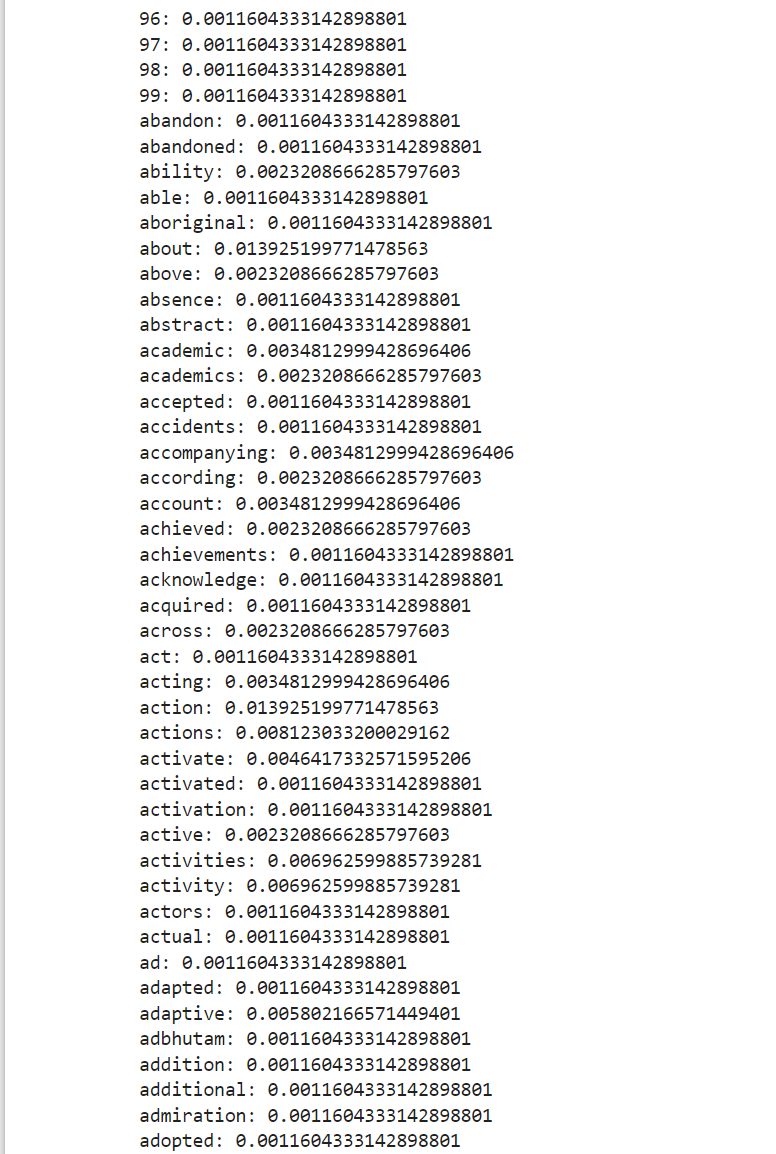
* Web scraped data



* Fine tuned LLM on the web Scraped Data



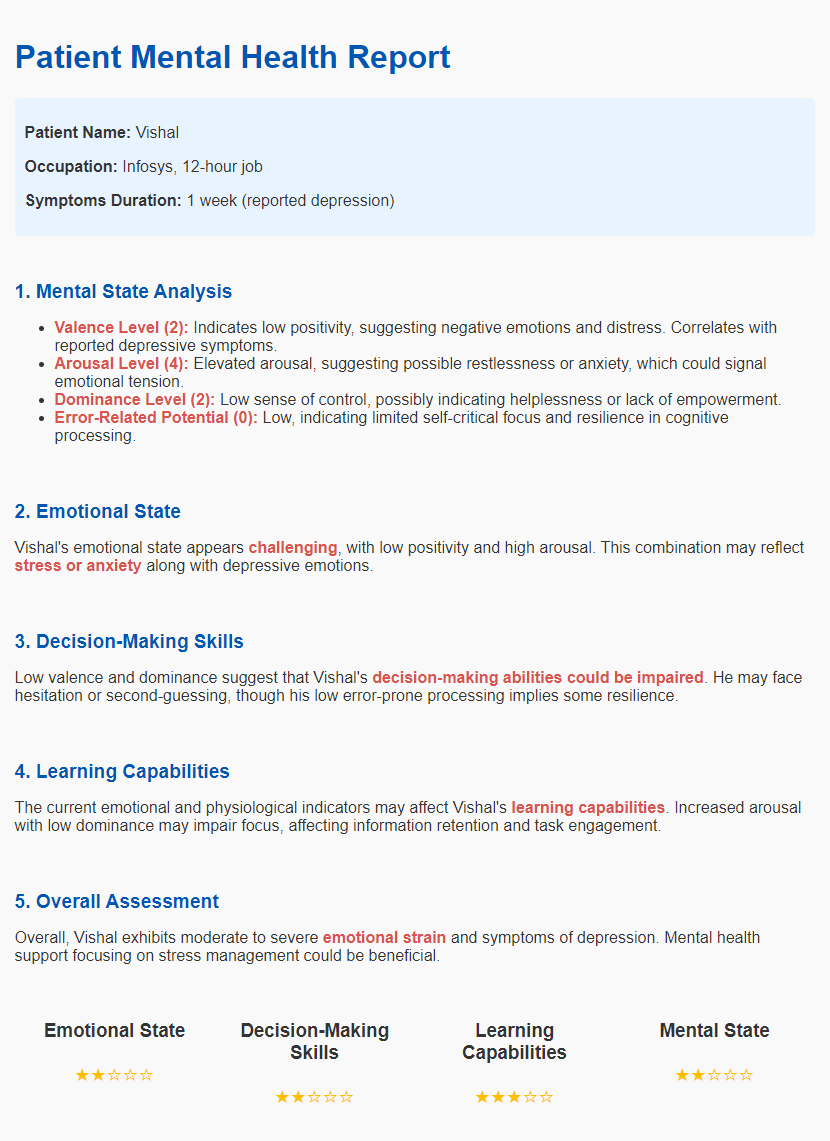
* Raw data is vector embedded to be fed into the LLM



**Expected Benefits**

* **Student Learning Enhancement**: Assessing mental readiness to tailor education based on a student’s cognitive load and learning ability.
* **Workplace Productivity Optimization**: Providing feedback to adjust workloads dynamically, ensuring efficiency and reducing stress.
* **Healthcare and Psychological Support**: Assisting doctors and psychologists in understanding patients' mental states for more accurate diagnoses and treatment plans.
* **Versatile Applications**: Useful in various fields, including sports, therapy, and performance coaching, to optimize well-being and decision-making.

**Synthetic Output**:



**Project Timeline**

| **Timeline** | **Task Description** |
| --- | --- |
| **Until Review 0** | - Create a pipeline for the project.  - Identify and acquire the BCI and DREAMER datasets.  - Research and select appropriate preprocessing techniques for EEG data. |
| **Until Review 1** | - Visualize the datasets to understand data distributions and characteristics.  - Implement preprocessing techniques for both datasets, including filtering and feature extraction.  - Perform web scraping to gather additional data for fine-tuning the large language model (LLM).  - Fine-tune the LLM on the prepared dataset and conduct initial tests for performance. |
| **Pending Works** | - Fully fine-tune the LLM with additional datasets and perform validation.  - Create and train specialized models for BCI data and DREAMER data using the CNN and transformer architectures.  - Complete the workflow, ensuring all components integrate seamlessly and perform as expected.  - Prepare the final report and presentation based on the results. |

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