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

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*Abstract*—**This project presents a comprehensive system that uses EEG signals for real-time health analysis and personalized recommendations. The collected signals are preprocessed with biomedical signal preprocessing and forwarded into deep learning models, trained on entirely different datasets to target various physiological and psychological states, such as different sleep stages, mental states, cognitive load, and emotions. The system employs a large language model (LLM) for the processing of outputs, which comprise a highly detailed health report incorporating cumulative insights. It offers personalized activity and dietary recommendations and medical advice while correlating multiple signals to identify potential health risks and advising appropriate actions such as rest, study, or consultation. This approach provides a comprehensive view of well-being to patients and helps in making informed decisions for a healthier lifestyle.**

## I. 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..

## II. Research Gap

There is currently no model or project that generates a comprehensive report on a person's mental state by integrating both GSR and EEG data. While there are papers that combine GSR and 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.

## III. Data Description

### A. BCI Dataset

The BCI dataset consists of the following key components:

- **EEG Sensors:** The 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.

### B. DREAMER Dataset

The DREAMER dataset consists of the following key components:

- **Participants:** The dataset includes EEG and ECG recordings from 23 participants who were exposed to 18 audio-visual 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.

*Note:* Only EEG signals are used from both datasets in this study.

## IV. Literature Review

### A. 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.

### B. 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.

### C. 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.

### D. 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.

### E. 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.

### F. 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.

## V. Deep Learning Architecture for BCI and AdaBoost for DREAMER

### A. CNN-LSTM-Attention Architecture

*1) Convolutional Neural Networks (CNN):*

- Extracts spatial features from EEG channels
- Learns hierarchical representations

**Reference:** S. Schirrmeister, F. H. Salentin, and A. S. Hyvärinen, "Deep learning with convolutional neural networks for EEG decoding and visualization," *IEEE Transactions on Biomedical Engineering*, vol. 65, no. 4, pp. 788–795, 2018.

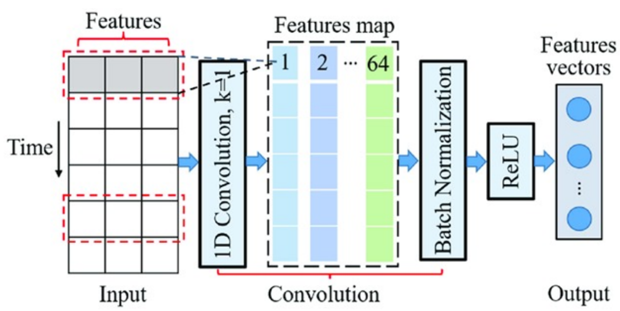



Fig. 1. Convolution for feature extraction

*2) Long Short-Term Memory (LSTM):*

- Captures temporal dependencies in EEG signals
- Maintains long-term memory

**Reference:** K. H. R. A. M. M. Elakkiya, V. K. M. V. Murali, and N. N. V. S. P. R. P. Reddy, "Converting your thoughts to texts: Enabling brain typing via deep feature learning of EEG signals," *IEEE Access*, vol. 8, pp. 180755–180765, 2020.

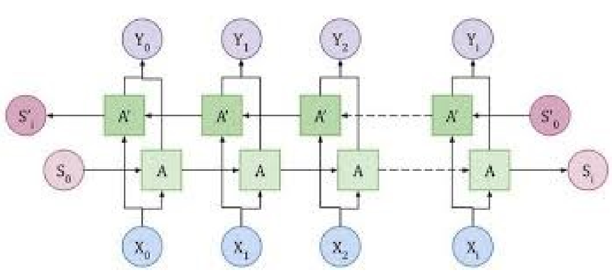


Fig. 2. BiLSTM

*3) Attention Mechanism:*

- Weights important temporal features
- Improves model interpretability

**Reference:** P. Li, Y. Wang, X. Zhang, and J. Wang, "A survey on deep learning-based non-invasive brain signals: Recent advances and new frontiers," *Neurocomputing*, vol. 370, pp. 115–132, 2019.

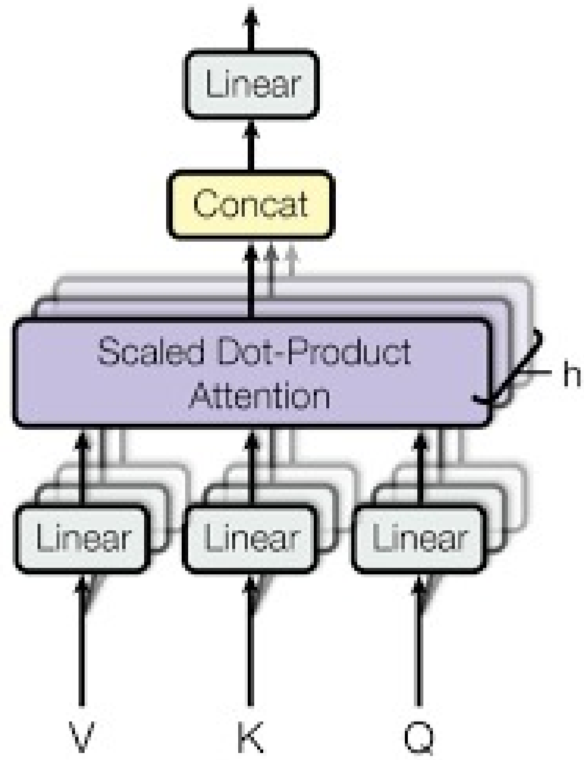



Fig. 3. Attention Head

### B. Advanced Training Methodologies

*1) Weight Initialization:* **Xavier Initialization:**

- Maintains variance across layers
- Prevents vanishing/exploding gradients
- Particularly effective for tanh activation

**Reference:** X. Glorot and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," *Proceedings of the 13th International Conference on Artificial Intelligence and Statistics*, pp. 249–256, 2010.

$$W \sim \mathcal{U}\left(-\sqrt{\frac{6}{n_{\text{in}} + n_{\text{out}}}}, \sqrt{\frac{6}{n_{\text{in}} + n_{\text{out}}}}\right)$$

Fig. 4. Xavier Initialization

**Kaiming Initialization:**

- Adapted for ReLU activations
- Improves convergence in deep networks

**Reference:** K. He, X. Zhang, and J. Sun, "Delving deep into rectifiers: Surpassing human-level performance on ImageNet classification," *Proceedings of the IEEE International Conference on Computer Vision*, pp. 1026–1034, 2015.

*2) Mixed Precision Training:*

- Combines FP16 and FP32 computations
- Reduces memory usage

$$W \sim \mathcal{U}\left(-\sqrt{\frac{6}{n_{\text{in}}}}, \sqrt{\frac{6}{n_{\text{in}}}}\right)$$

Fig. 5. Kaiming Initialization

- Accelerates training

**Reference:** D. Micikevicius et al., "Mixed precision training," *Proceedings of the 30th Conference on Neural Information Processing Systems*, 2017.

### C. Optimization Techniques

#### 1) AdamW Optimizer:

- Combines Adam with decoupled weight decay
- Better generalization than standard Adam

**Reference:** I. Loshchilov and F. Hutter, "Decoupled weight decay regularization," *Proceedings of the 31st International Conference on Neural Information Processing Systems*, 2017.

$$m_t = \beta_1 * m_{t-1} + (1 - \beta_1) * g_t$$
$$v_t = \beta_2 * v_{t-1} + (1 - \beta_2) * g_t^2$$
$$\hat{m}_t = m_t / (1 - \beta_1^t)$$
$$\hat{v}_t = v_t / (1 - \beta_2^t)$$
$$\theta = \theta - (\alpha * \hat{m}_t / \sqrt{(\hat{v}_t + \varepsilon)})$$

Fig. 6. AdamW Optimizer

#### 2) BCE with Logits Loss:

- Combines sigmoid with BCE
- Numerically more stable

**Reference:** G. S. D. S. Tsang, Y. P. S. Z. M. Ramasubramanian, "A Comprehensive Review on Loss Functions in Deep Learning," *IEEE Access*, vol. 6, pp. 9389–9397, 2018.

$$L = \frac{1}{N}\sum_{i=1}^{N}\left[\log_e\left(1 + e^{-z}\right) + z(1 - y_i)\right]$$

Fig. 7. BCE with Logits Loss

#### 3) Cosine Annealing Learning Rate Scheduling:

- Cyclical learning rate adjustment
- Helps escape local minima

**Reference:** L. Loshchilov and F. Hutter, "SGDR: Stochastic gradient descent with warm restarts," *Proceedings of the 5th International Conference on Learning Representations*, 2017.

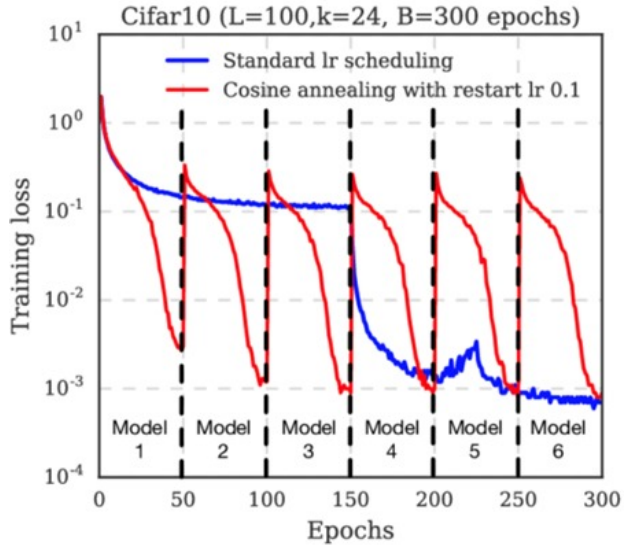



Fig. 8. Cosine Annealing Learning Rate Scheduling

#### 4) GradScaler for Mixed Precision:

- Prevents underflow in FP16
- Maintains training stability
- Dynamic loss scaling

**Reference:** D. Micikevicius et al., "Mixed precision training," *Proceedings of the 30th Conference on Neural Information Processing Systems*, 2017.

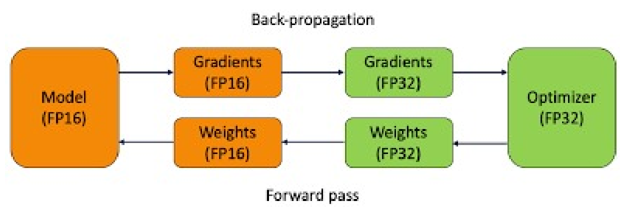



Fig. 9. GradScaler for Mixed Precision Training

### D. Implementation Benefits and Considerations

#### 1) Feature Selection Benefits:

- Time-domain features: Capture temporal dynamics
- Frequency-domain features: Reveal spectral characteristics
- Entropy measures: Quantify signal complexity
- Combined approach: Robust feature representation

#### 2) Training Methodology Advantages:

- Mixed precision: 2-3x memory reduction
- AdamW: Better convergence properties
- Cosine annealing: Improved exploration of loss landscape
- GradScaler: Training stability at reduced precision

## VI. 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.

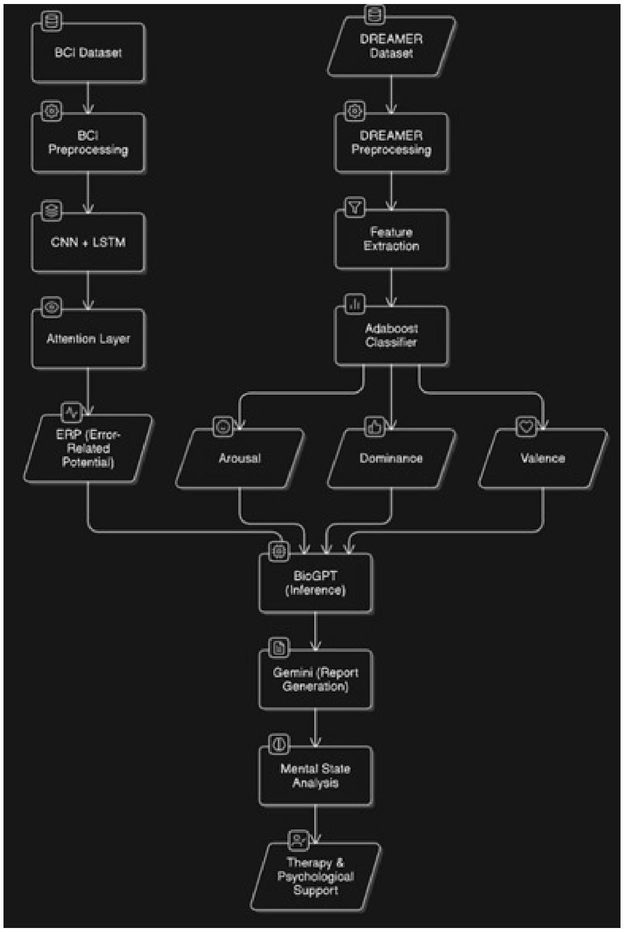



Fig. 10. PipeLine

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

$$b = \text{firwin}(N, W_n, \text{window} =' hamming')$$

where $N$ is the filter order and $W_n$ 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]

*2) Feature Extraction:* **Shannon Entropy:** Shannon entropy measures the unpredictability or randomness of the signal:

$$H(X) = -\sum_{i=1}^{n} p(x_i) \log_2 p(x_i)$$

where $p(x_i)$ is the probability of occurrence of the event $x_i$. Higher entropy indicates more complex brain activity, while lower entropy may indicate more predictable or repetitive patterns.

**Renyi Entropy:** A generalization of Shannon entropy that measures the diversity of the signal distribution based on the parameter alpha:

$$H_\alpha(X) = \frac{1}{1-\alpha} \log \left( \sum_{i=1}^{n} p(x_i)^\alpha \right)$$

where $\alpha$ is the parameter controlling the degree of generalization.

**Power Spectral Density (PSD):** The PSD is computed for each filtered signal. It is defined as:

$$\text{PSD}(f) = |X(f)|^2$$

where $X(f)$ is the Fourier Transform of the windowed signal. PSD measures the power distribution of the signal across different frequency components, providing insights into the dominant brainwave activity.

**Statistical Features:** The following statistical features are computed from the filtered EEG signals:

- Mean: Average value of the filtered signal.
- Variance: Measure of signal variability.
- Standard Deviation: Measure of signal dispersion.
- Root Mean Square (RMS): Represents the signal's power.
- Maximum Amplitude: Highest absolute value in the filtered signal.
- Minimum Amplitude: Lowest absolute value in the filtered signal.
- Kurtosis: Measure of the tailedness of the signal distribution.
- Skewness: Measure of asymmetry in the signal distribution.

**Power Ratios (Theta, Alpha, Beta, Band Power Ratio):** The formula for calculating the Band Power Ratio is as follows:

$$\text{Power Ratio} = \frac{\text{Power in Band}}{\text{Total Power in Signal}}$$

where the power in each frequency band (theta, alpha, beta) is computed and normalized.

### B. Channel Management

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

### *C. Deep Learning Models*

After preprocessing, the extracted features are utilized by specialized models tailored for specific tasks from the BCI Dataset and DREAMER Dataset.

*1) BCI Dataset: Error-Related Potential (ERP) Prediction:* The BCI dataset focuses on predicting Error-Related Potentials (ERP), which are essential for monitoring cognitive functions and error detection. This task uses a deep learning model comprising the following components:

**CNN for Feature Extraction:** A Convolutional Neural Network (CNN) extracts spatial features from the preprocessed EEG signals. We use only the 1D convolution block for feature extraction.

**LSTM for Temporal Dependencies:** The CNN-extracted features are fed into a Long Short-Term Memory (LSTM) network to capture temporal patterns and sequential information in the EEG signals.

**Self-Attention Mechanism:** The output from the LSTM is passed through a Self-Attention Transformer. This mechanism helps capture long-term dependencies and enhances the model's ability to focus on critical temporal correlations within the EEG signals.

*2) DREAMER Dataset: Emotional State Prediction:* For the DREAMER dataset, the goal is to predict Arousal, Valence, and Dominance, which represent the user's emotional state. This task employs a non-deep learning approach using the following method:

**Adaboost Classifier:** A Boosting Algorithm, specifically Adaboost, is applied to classify the emotional states. Adaboost combines the outputs of multiple weak classifiers, optimizing for better accuracy and generalization across the emotional parameters.

### *D. 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 the BCI and DREAMER models are processed using BioGPT, fine-tuned on emotion analysis and psychology datasets. BioGPT performs Named Entity Recognition (NER) to identify significant psychological and emotional markers in the data. Additionally, it extracts key insights by analyzing the contextual relationships between these markers, providing a comprehensive summary of the user's cognitive and emotional states.

**LLaMA 3.1 for Report Generation:** The insights from BioGPT are 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.

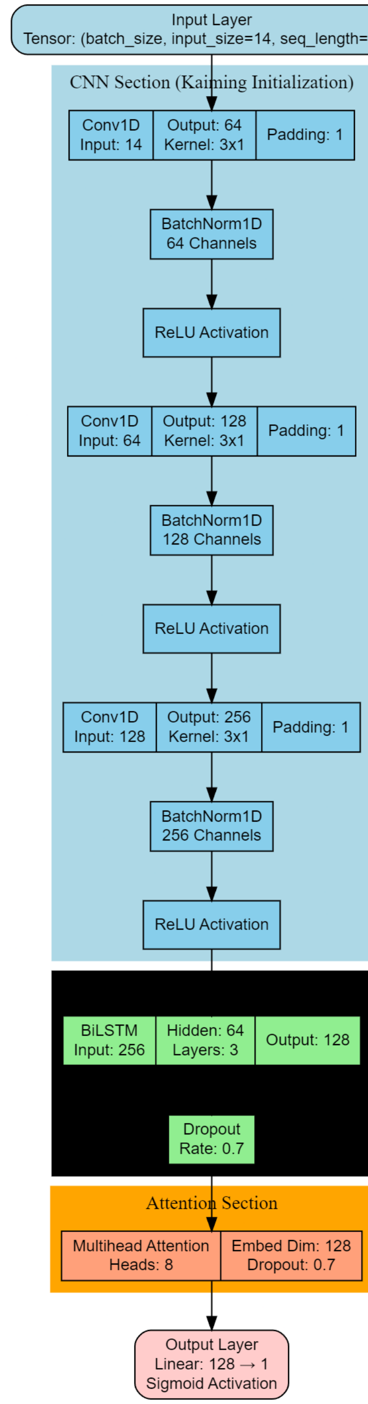



Fig. 11. Model Architecture

## VII. Results

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.

For the DREAMER dataset, the Adaboost classifier achieved an impressive accuracy of 97.5% on the Theta data, which is the highest performance observed across all frequency bands. This result highlights the efficiency of the Adaboost model in classifying emotional states based on EEG signals.

For the BCI dataset, even though only 14 EEG channels were used, and the model was trained for a limited number of epochs with minimal hyperparameter tuning, the model still managed to achieve an Area Under the Curve (AUC) score of 0.68, demonstrating its capability to predict Error-Related Potentials (ERP) despite these constraints.

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

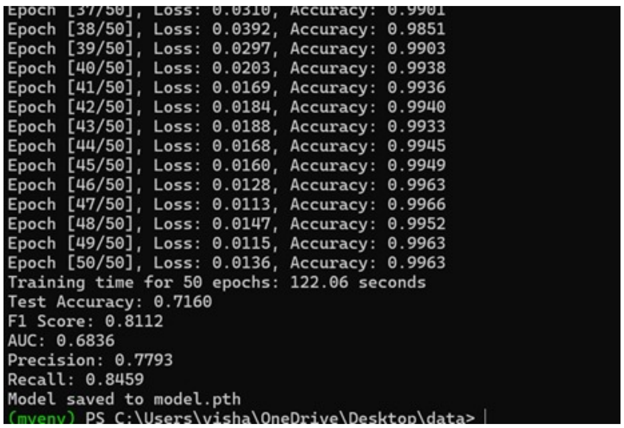
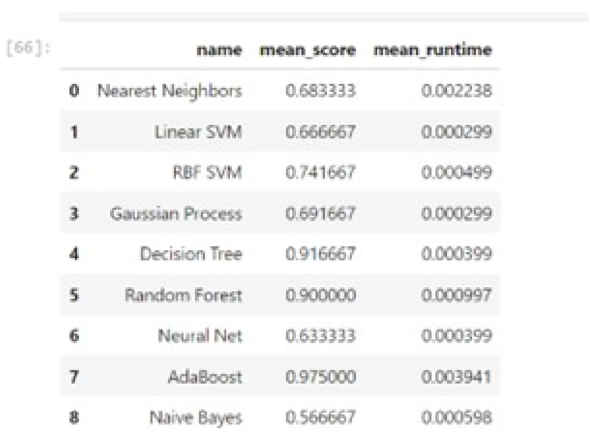



Fig. 12. BCI Results



[66]:

| | name | mean_score | mean_runtime |
|---|---|---|---|
| 0 | Nearest Neighbors | 0.683333 | 0.002238 |
| 1 | Linear SVM | 0.666667 | 0.000299 |
| 2 | RBF SVM | 0.741667 | 0.000499 |
| 3 | Gaussian Process | 0.691667 | 0.000299 |
| 4 | Decision Tree | 0.916667 | 0.000399 |
| 5 | Random Forest | 0.900000 | 0.000997 |
| 6 | Neural Net | 0.633333 | 0.000399 |
| 7 | AdaBoost | 0.975000 | 0.003941 |
| 8 | Naive Bayes | 0.566667 | 0.000598 |

Fig. 13. Dreamer Results

## VIII. 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.

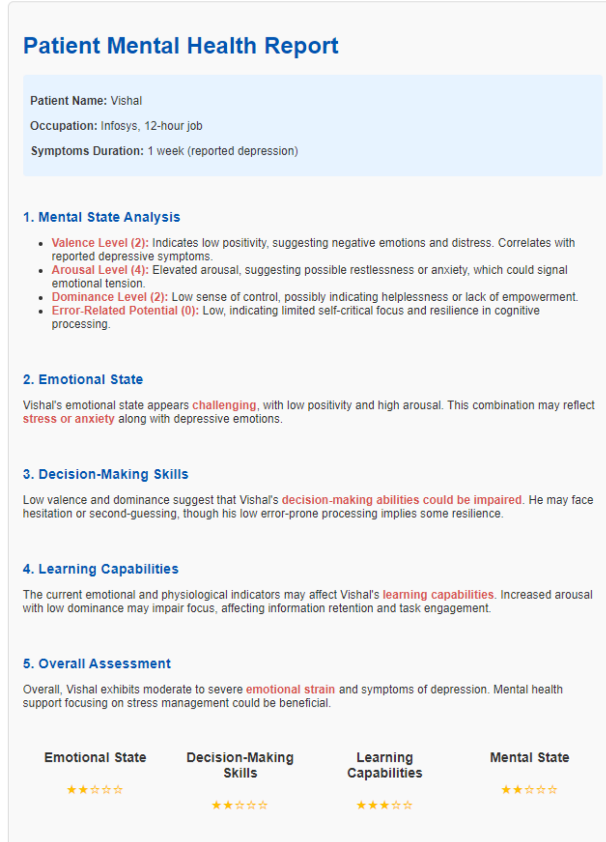



Fig. 14. Generated Report

- **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.

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