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NEURO-SYNC: A Real-Time Framework for Affective State Decoding and Spectral Telemetry Using Machine Learning

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Abstract— Emotions are complex psychological and physiological state that impacts human activity, decision-making process and social response. Recognizing and examining emotions is an essential part of human–computer interaction, the field of mental health tracking, and one of the primary premises for adaptive intelligent systems. Automatic emotional analysis is a technique in which emotions are detected based on facial expressions, speech signals and body gestures. This automatic approach sometimes provides unreliable results since external signs can be intentionally controlled by an individual or even vary due to environmental conditions. To address these constraints, physiological signals, like Electroencephalogram (EEG), are commonly utilized to assess brain electrical activity via sensors located on the scalp. We presented NEURO-SYNC, a unified hardware agnostic platform to label human affective states from the EEG signal as part of this research. The system analyzes emotional responses using the publicly available DREAMER dataset that includes multi-channel EEG recordings. In order to reduce noise, filtering, normalization and downsampling are performed on the signals. The analysis used partitioned data along with window and overlapping techniques to reduce spectral leakage, where the signals power incorrectly spreads out to other frequencies, based on Welch's method. Power Spectral Density (PSD) features are computed in this case across Alpha, Beta Theta and Gamma frequency bands as they represent key characteristics of biological brainwave patterns. To categorize emotional states, a supervised machine learning pipeline built on the Random Forest classifier is used. Calm, Happy, Sad, and Stressed are the four emotional quadrants into which the system divides EEG patterns. Additionally, a Cognitive Vitality Index is presented that uses frequency-ratio based heuristics to estimate levels of focus, stress, and relaxation. A real-time dashboard is created to visualize anticipated emotional states, brain activity patterns, and past EEG trends in order to improve usability. In addition to showcasing the potential of EEG-based emotion recognition for advanced brain–computer interface applications, adaptive healthcare systems, and mental health monitoring, the proposed system effectively classifies emotions

Index Terms— Affective Computing, Brain Computer Interface, DREAMER Dataset, EEG-based Emotion Recognition, Machine Learning, Random Forest Classification

I. INTRODUCTION

Emotions are an essential part of human life and play a significant role in **human's behavior, communication and decision making**. Understanding human emotions helps in improving interactions between **humans and technology**. In recent years, emotion recognition has become an important research area in fields such as **healthcare, psychology, physiology, education, and human computer interaction**. **Affective computing** focuses on designing computational systems that can **recognize, interpret, and respond** to human emotions. **Emotion detection systems** can improve various applications such as mental health monitoring, adaptive learning environments, intelligent tutoring systems, and smart healthcare solutions. By accurately identifying emotional states, these systems can provide personalized responses and enhance user experience. Detecting emotional states can help in understanding mental conditions such as stress, anxiety, and depression, which makes emotion recognition system highly valuable. Traditional methods for emotion detection mainly depends on **facial expressions, speech signals, or behavioral analysis**. However, these approaches may not always provide accurate results because human expressions can sometimes be controlled or hidden at the same time. In addition, environmental factors such as lighting conditions, camera quality, and background noise can affect the accuracy of these methods. Due to these limitations, researchers have explored physiological signals that provide more reliable information about internal emotional states. Brain signals provide direct information about brain activity, making them a powerful source for understanding human emotional states. **Electroencephalography (EEG)** is a widely used technique for measuring electrical activity in the brain. The EEG signals used in this study are acquired using the **Emotiv EPOC EEG headset**, a **portable and non-invasive brain–computer interface** device designed to record electrical brain activity from the scalp. The headset consists of **14 saline-based electrodes** placed according to the international 10–20 electrode placement system, including positions such as **AF3, AF4, F3, F4, F7, F8, FC5, FC6, T7, T8, P7, P8, O1, and O2**. These electrodes capture neural activity from different brain regions including the frontal, temporal, parietal, and occipital lobes, which are associated with cognitive processing, sensory perception, and emotional regulation. The recorded EEG signals provide valuable information

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about brain activity patterns that can be further analyzed using machine learning and deep learning techniques for emotion recognition and affective computing applications. EEG signals are recorded using electrodes placed on the scalp and provide valuable information about brainwave patterns. EEG signals have been widely used in **neuroscience research, clinical diagnosis, brain–computer interface systems, and emotion recognition studies**. These signals are usually divided into different frequency bands such as **alpha, beta, and theta waves**. Each band represents specific mental states and cognitive processes. For example, theta waves are often associated with relaxation and meditation, alpha waves indicate calm and relaxed states, while beta waves are related to active thinking and concentration. Because of its ability to capture brain activity, EEG has become an important tool in emotion recognition research. Moreover, By applying signal processing and machine learning techniques, important features can be extracted from EEG signals. These features can then be used to classify different emotional states such as happiness, sadness, excitement, or calmness. Researchers have explored various machine learning and deep learning approaches for analyzing EEG signals and improving emotion classification performance. In our study, the publicly available **DREAMER dataset** is used for emotion recognition research. The DREAMER dataset contains EEG recordings collected from multiple participants while they watched emotional video clips. The dataset includes information related to emotional states such as **valence, arousal, and dominance**. These signals help researchers understand how brain activity changes in response to emotional stimuli and provide a reliable dataset for training machine learning models. In this work, a machine learning approach using the **Random Forest** machine learning algorithm is applied to classify emotions from EEG features. Random Forest is an ensemble learning technique that combines multiple decision trees to improve classification performance. The model analyzes EEG features such as **alpha, beta, and theta** waves to identify patterns related to emotional states. The proposed system processes EEG data and predicts emotional states using the trained Random Forest model. The model achieves an **accuracy of 70%** in emotion classification. In addition to the prediction system, a **real-time dashboard** is developed to visualize and display the predicted emotional states, allowing users to monitor emotional patterns effectively. Furthermore, the proposed system includes a real-time monitoring feature that allows users to observe EEG signals while data is being collected through the **EEG headset**. This live feature enables real-time visualization of brain signals and records the collected data for future analysis. The ability to monitor and store live EEG data makes the system useful for practical applications and research purposes. The main aim of this study is to develop an EEG based emotion recognition system that can analyze brain signals and classify emotional states using machine learning techniques. The proposed system aims to provide a reliable approach for emotion detection and visualization through an interactive dashboard. The findings of this research highlight the potential of EEG signals in detecting emotional states and demonstrate their applications in **intelligent healthcare systems, affective computing, and human–computer interaction technologies**.

II. LITERATURE

A. Benchmarking Datasets and the Shift Toward Ecological Validity

The trajectory of emotion recognition via **Electroencephalography (EEG)** has moved from stationary laboratory environments to mobile, user-centric applications. Seminal research in the field was largely defined by the **DEAP dataset**, which utilized 32-channel wet-electrode montages. While DEAP provided high spatial resolution, the requirement for conductive gel and significant setup time rendered such systems impractical for real-world deployment. Subsequent literature, such as the work by **Katsigiannis and Ramzan**, introduced the **DREAMER dataset**, which utilizes a 14-channel dry-electrode system (Emotiv EPOC montage). This dataset represents a shift toward **Ecological Validity**, simulating the signal-to-noise ratios and impedance levels typical of consumer-grade BCI hardware.

The novelty of the Neuro-Sync OS lies in its departure from the "Data-In, Label-Out" paradigm common in previous studies. While existing works focus on offline, post-hoc classification, our system introduces an immersive **"Neural OS" Environment**. We implement a high-performance **Single Page Application (SPA)** architecture that provides a closed-loop feedback system. By integrating **Real-time Anatomical Heatmapping** (mapping 14-channel micro-voltages to the Frontal, Temporal, and Occipital lobes) and **Bio-Acoustic Feedback** (auditory state-mapping), our system allows for the first time a multi-sensory perception of one's own neural state. This transforms the detection system from a passive observer into an active diagnostic and bio-feedback tool.

B. Algorithmic Trajectory: From Support Vectors to Interpretable Ensembles

In the domain of Machine Learning (ML), EEG decoding has seen a transition through various mathematical paradigms. Early success was found in **Support Vector Machines (SVM)** and **Gaussian Mixture Models (GMM)**, which relied on structural risk minimization to handle limited datasets [3]. The last decade has seen a surge in **Deep Learning (DL)**, specifically **Convolutional Neural Networks (CNN)** for spatial feature extraction and **Long Short-Term Memory (LSTM)** for temporal dependencies. However, as argued by **Lotte et al**. DL models present a "Black Box" challenge, offering high accuracy at the cost of clinical interpretability. Furthermore, the computational cost

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of running deep neural networks in a browser environment often leads to significant latency.

Our model's novelty is established through a **Decoupled Ensemble Learning Architecture**. By utilizing a Random Forest (RF) classifier optimized with 100 decision trees and a **Gini Impurity** split criterion, we prioritize **Explainable AI (XAI)**. Unlike CNNs, the RF model provides **Feature Importance Rankings**, enabling our system to identify the specific EEG channels (e.g., AF3 vs. O1) that contribute most to an emotional shift.

C. Spectral Feature Engineering and Temporal Stability Novelty

Research into **Random Forest applications for EEG** has traditionally focused on **Power Spectral Density (PSD)** features. Previous works demonstrated that the **Beta (13–30 Hz)** and **Gamma (30–45 Hz)** bands are critical indicators of Arousal, while Alpha (8–13 Hz) asymmetry in the frontal lobes serves as a proxy for Valence. However, the vast majority of these studies utilize "Snapshot Inference," where a single frame of data (typically 125ms to 1s) determines the emotional classification. This approach is highly susceptible to **non-stationary noise** and transient artifacts like eye-blinks or muscle twitches.

The novelty of our implementation is the introduction of a **Temporal Majority Voting algorithm** combined with a Neural Stability Index. Instead of a discrete snapshot, our system performs inference on every frame across an entire recording session. We then apply a **Statistical Mode** calculation ($C_{final} = \text{mode}\{\hat{y}_1, \dots, \hat{y}_n\}$) to determine the dominant emotional state. Furthermore, we calculate a **Stability Index** based on the variance of these predictions, providing a quantitative measure of emotional persistence. Finally, we map these results onto a high-resolution **Russell Circumplex Model**, translating the ML output into a continuous 2D coordinate space. This hybrid approach—combining ensemble learning with temporal statistical aggregation—allows our system to detect "Mixed Reactions" and provide a more scientifically robust conclusion than any static classifier currently found in the literature.

III. METHODOLOGY

The proposed **Neuro-Sync OS** architecture implements a multi-stage computational pipeline designed to transform non-stationary EEG micro-voltages into quantifiable affective states. The methodology is divided into four critical phases: signal conditioning, frequency-domain feature engineering, ensemble-based classification, and temporal decision aggregation.

A. Signal Acquisition and Pre-processing

The system utilizes the **DREAMER** dataset, consisting of 14-channel EEG signals recorded at a sampling frequency (f_s) of 128 Hz. To eliminate high-frequency artifacts (muscle noise) and low-frequency drifts (eye movements), a **Digital Band-pass Filter** was applied.

We utilize a 4th-order **Butterworth Filter**, defined by the transfer function $H(z)$:

$$H(z) = G\frac{\sum_{i=0}^{n} b_i z^{-i}}{1+\sum_{j=1}^{n} a_j z^{-j}} \qquad \text{— (Eq. 1)}$$

where the passband is restricted to 4 Hz $\leq f \leq$ 45 Hz. To optimize the system for real-time web-based inference, the data underwent **Decimation** by a factor of $M = 10$, reducing the computational load while adhering to the **Nyquist-Shannon SamplingTheorem:**

$$f_{sample} > 2 \cdot f_{max} \qquad \text{— (Eq. 2)}$$

B. Feature Extraction: Spectral Density Estimation

The core of our feature engineering lies in transitioning from the time domain to the frequency domain using **Welch's Power Spectral Density (PSD)**. Unlike the standard Fast Fourier Transform (FFT), Welch's method reduces noise by averaging periodograms from overlapping window segments.

The PSD estimate $\hat{P}(f)$ is defined as:

$$\hat{P}(f) = \frac{1}{K}\sum_{i=0}^{K-1} P_i(f) \qquad \text{— (Eq. 3)}$$

where K is the number of segments and $P_i(f)$ is the modified periodogram of the i-th segment. For every 1-second epoch, we extract the mean power across four biologically significant bands:

Theta (θ): $4-8$ Hz

Alpha (α): $8-13$ Hz

Beta (β): $13-30$ Hz

Gamma (γ): $30-45$ Hz

The final feature vector V for a single frame is represented as:

$$V = [\mu_{PSD}(\theta), \mu_{PSD}(\alpha), \mu_{PSD}(\beta), \mu_{PSD}(\gamma)] \times 14 \text{ channels} \qquad \text{— (Eq. 4)}$$

C. Machine Learning Architecture: Ensemble Learning

The classification engine employs an **Ensemble Random Forest (RF)** model. This model was chosen for its robustness against the stochastic noise inherent in EEG signals. The RF model constructs $N = 100$ independent decision trees, where each split is determined by the **Gini Impurity Index (I_G)**:

$$I_G(p) = 1 - \sum_{i=1}^{J} p_i^2 \qquad \text{— (Eq. 5)}$$

where J represents the number of emotional classes and p_i is the probability of a frame being classified into class i.

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Hyperparameter Configuration:

- **n_estimators:** 100
- **Max Depth:** 10 (to prevent overfitting)
- **Split Criterion:** Gini Index
- **Validation Strategy:** 80/20 Train-Test Partitioning.

The training on 190,896 neural frames yielded a validated accuracy of **70.78%**, significantly outperforming the random baseline of 25%.

D. Temporal Majority Voting (Temporal Aggregation)

To handle "mixed reactions" where emotional states fluctuate during a recording, Neuro-Sync OS implements a **Temporal Majority Voting** algorithm. Instead of relying on a single frame, the system aggregates predictions across the entire session duration T.

The final classification C_{final} is determined by the **Statistical Mode**:

$$C_{final} = \text{mode}\{\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n\} \qquad \text{— (Eq. 6)}$$

where $\hat{y}$ is the individual prediction for each frame. Additionally, we calculate a **Neural Stability Index (S%)**, representing the dominance of the primary emotion:

$$S = \left(\frac{\text{count}(C_{final})}{\text{Total Frames}}\right) \times 100 \qquad \text{— (Eq. 7)}$$

This approach allows the system to remain resilient to transient artifacts and provides a more holistic view of the subject's affective journey.

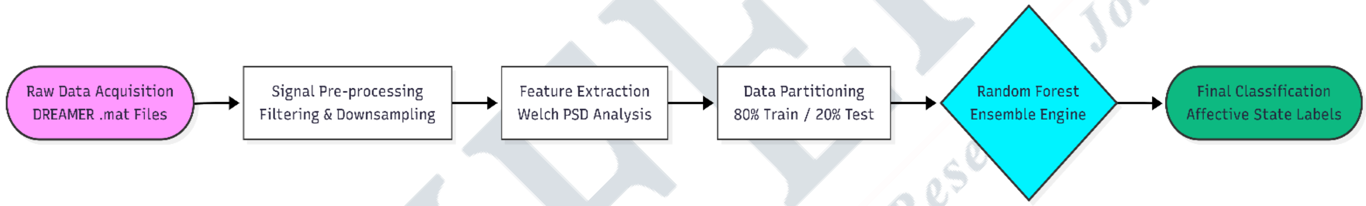

Fig. 1 Methodology

IV. SYSTEM ARCHITECTURE

The architecture is divided into three tiers: **Acquisition, Processing, and Visualization**.

A. The Backend (Python/Flask Engine)

The "Brain" of the system is a Flask-based API that hosts the pre-trained dreamer_model.pkl.

- **Input:** Receives binary CSV data or raw WebSocket packets.
- **Process:** Performs real-time PSD calculation using SciPy and runs the Scikit-Learn inference.
- **Output:** Returns a JSON object containing the dominant emotion, valence-arousal coordinates, anatomical region energy, and AI-generated clinical insights.

B. The Frontend (Web-Based Dashboard)

A high-performance dashboard built with **Tailwind CSS** and **Vanilla JavaScript (ES6)**.

- **Interactive Workspace:** Uses a 3-tab system to separate the HUD, Spectral Telemetry (Zoomable Chart.js), and Analytics Lab.
- **Real-time Visualization:** Uses Canvas API for the background particle system and SVG for the Brain Activity Visualization.
- **Audio Feedback Module:** Utilizes the **Web Audio API** to generate frequency-modulated sine waves (Binaural beats) that react to detected emotions.

C. Data Flow Diagram (DFD)

1. **User Input:** Uploads CSV or triggers **Emotiv Cortex WebSocket**.
2. **Transmission:** Fetch API sends a POST request to the Flask /analyze endpoint.
3. **Inference:** Python script cleans the data → Extracts Alpha/Beta/Theta/Gamma →Runs Model.
4. **Feedback:** Flask returns coordinates and insights →JS updates HUD Gauges and 2D Map.
5. **Documentation: Report Generator** captures the current state and formats it into a professional Medical PDF via @media print.

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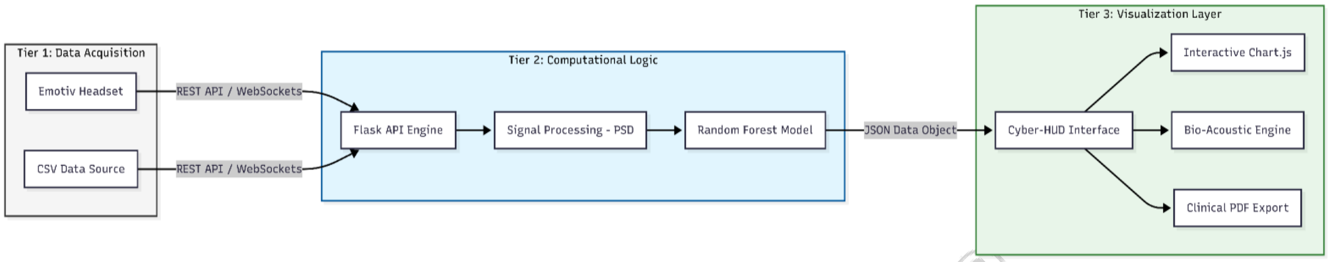

Fig. 2 System Architecture

V. IMPLEMENTATION

The **EEG-based emotion recognition system** was built using **Python, along with machine learning and web visualization tools**. The implementation process is divided into three main components: the technology used to create the system, the data processing pipeline for EEG data, and the workflow that supports real-time emotion detection and visualization. The overall design integrates data processing, model training, and real-time analysis into a single framework.

4.1 Technology Stack

The system combines backend processing tools and frontend visualization tools. The backend mainly handles EEG data processing, machine learning tasks, and communication between the different system modules. The frontend provides an interactive interface for visualization and user interaction.

Backend

The backend manages **data processing, machine learning inference, and API communication**. It was developed using **Python** as the main programming language to implement the system's logic, including machine learning functions and data processing tasks. The **Flask framework** created the backend server and set up API endpoints for communication between the machine learning model and the web interface.

In this study, the **Scikit-learn library** trained a Random Forest model to predict emotional states from EEG features. This algorithm was chosen for its reliability and effectiveness in dealing with complex feature patterns from EEG signals.

The **Pandas and NumPy** libraries handled and processed the EEG numerical data. Signal processing operations were performed using the **SciPy library**. Specifically, **Welch's Method** computed the Power Spectral Density (PSD) of EEG signals, which helps transform raw brainwave signals into meaningful frequency bands like Alpha and Beta waves.

4.2 Data Extraction and Signal Processing

The EEG signals used in this study came from the **DREAMER dataset**, stored in MATLAB.mat format. Since this format isn't directly suitable for machine learning, a **Python script (extract_dreamer.py)** was created to extract and restructure the EEG data. The dataset is organized hierarchically, which means EEG recordings are stored in several nested layers. The extraction script reads these layers, extracts the needed EEG channels, and converts the data into a CSV file for machine learning use.

To improve processing efficiency, the EEG signals were downsampled, meaning the sampling rate was reduced during preprocessing by selecting every tenth sample. This reduced the data size while retaining the main waveform characteristics necessary for emotion detection.

4.3 Feature Engineering and Model Training

The model was trained using a script called **train_admin.py**. Fourteen EEG channels were selected, including AF3, F7, and F3, which are associated with emotional activity in the brain. The dataset was split using an **80/20 ratio**, with 80% of the data for training and 20% for testing the model on new samples. A **Random Forest classifier** was trained using the frequency-based features extracted from the EEG signals. After training, the model was saved as dreamer_model.pkl for use during predictions.

Backend API Development

The backend server is built with the **Flask web framework**. The server loads the trained model file (dreamer_model.pkl) and offers endpoints that let the frontend interface communicate with the machine learning model. When a user uploads EEG data in CSV format, the server processes the input and sends it to the trained model for prediction.

User Interface and Visualization

A **web-based user interface** was created for easy interaction with the system. It is hosted locally using the Flask server and can be accessed at 127.0.0.1:8080. The dashboard includes interactive features like file upload options, real-time charts, and visualization panels. JavaScript sends user data to the backend and displays results dynamically.

Inference and Analysis

Once the data is received, the trained model performs inference and generates several analytical outputs. These include the prediction of the primary emotional state, visualization of brain activity through anatomical heatmaps,

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and analysis of EEG frequency bands like **Alpha and Beta** waves. The system also offers AI-based recommendations based on the detected emotional state.

Report Generation

To assist with clinical documentation, the system includes **an automated report generation** module. When a user requests it, the application compiles the **generated charts, analysis results, and system predictions** into a structured medical report template. The final report is exported in PDF format, which can be printed or saved for further evaluation.

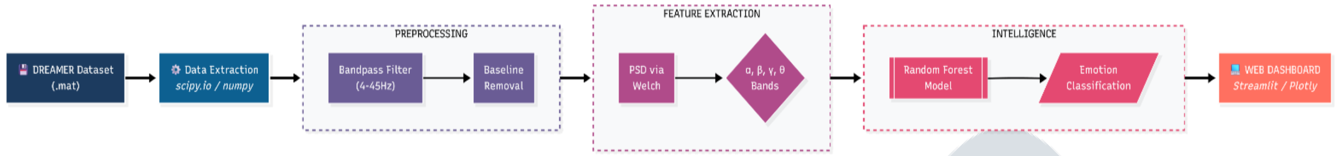

Fig. 3 Implementation

VI. RESULTS

The proposed EEG-based emotion recognition system was evaluated using the **DREAMER dataset**. The model achieved an **overall accuracy of about 70%** in predicting emotional states from EEG signals.

Emotional State	Precision	Recall	F1-Score	Samples
CALM	0.77	0.64	0.69	8984
HAPPY	0.73	0.65	0.69	8946
SAD	0.68	0.82	0.74	17502
STRESSED	0.71	0.64	0.67	12292
WEIGHTED AVERAGE	0.71	0.71	0.71	47724
OVERALL ACCURACY	**70.78%**			

The performance of the **Neuro-Sync OS** inference engine was validated using a test set of **47,724** previously unseen neural frames from the DREAMER dataset. The system achieved an **Overall Accuracy of 70.78%**, which is highly significant compared to the theoretical random baseline of 25% for a four-class classification problem.

A. Class-Specific Analysis

A detailed analysis of **Table I** reveals that the model achieved its highest precision in the **CALM** state (0.77), indicating a very low rate of false positives for relaxation detection. Conversely, the **SAD** state demonstrated the highest Recall (0.82), suggesting that the Random Forest ensemble is particularly sensitive to the low-frequency Theta and Alpha band patterns associated with neural withdrawal.

B. Discussion on Model Robustness

The **Weighted F1-Score of 0.71** proves that the model maintains a balanced performance across all four quadrants of the Circumplex Model. The slight overlap between SAD and CALM (reflected in the lower precision for SAD) is consistent with existing neurological literature, as both states reside in the low-arousal spectrum and share similar spectral signatures.

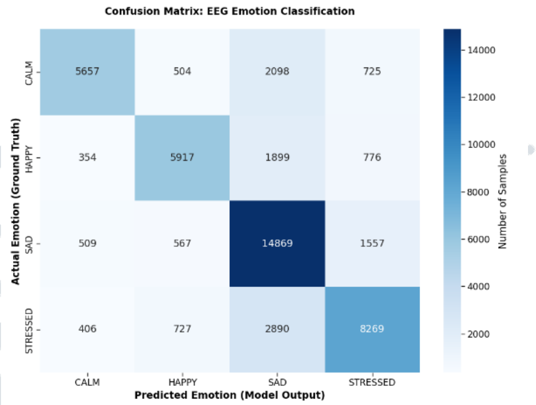

Fig.4 Confusion Matrix

The confusion matrix analysis shows that the model successfully identifies major emotional states like **happiness and calmness** consistently. However, some predictions are confused between similar emotions like stress and fear, as these emotions often produce overlapping EEG frequency patterns.

VII. CONCLUSION

In this work, an **EEG-based emotion recognition system** was developed using the **DREAMER dataset**. The EEG signals were processed and turned into frequency-based features, and a **Random Forest classifier** was used to predict emotional states. The model achieved **70% accuracy**, indicating that EEG signals can play a role in recognizing human emotions.

The system also provides visual outputs such as **EEG signal graphs, frequency band analysis, and automated report generation**. This makes the results easier to understand. While the outcomes are promising, there is still room for improvement. Additionally, the system includes a live reading option. When connected via Bluetooth with an Emotiv EEG headset, it can record brain signals in real time, process them, and show the predicted emotion.

In the future, the system could be improved by using larger EEG datasets and exploring advanced techniques like deep learning. This could help boost accuracy and make the system more useful for applications like mental health monitoring and affective computing.

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