SCTR's Pune Institute of Computer Technology
Dhankawadi, Pune

AN INTERNSHIP REPORT ON

(A Web-Application: Multimodal Neuroimaging During Sleep)

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Class: TE-3
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Under the guidance of
(Prof. P.P Joshi)

DEPARTMENT OF COMPUTER ENGINEERING
ACADEMIC YEAR 2024-25

DEPARTMENT OF COMPUTER ENGINEERING

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CERTIFICATE

This is to certify that the SPPU Curriculum-based internship report entitled
"(A Web-Application: Multimodal Neuroimaging During Sleep)"

Submitted by
(Naveed Malik)
(Exam No. 31348)

has satisfactorily completed the curriculum-based internship under the guidance of Prof. P.P. Joshi towards the partial fulfillment of third year Computer Engineering Semester VI, Academic Year 2024-25 of Savitribai Phule Pune University.

(Prof. P.P Joshi)
Internship Guide
PICT, Pune

Dr. G. V. Kale
Head
Department of Computer Engineering
PICT, Pune

Place:
Date:

Acknowledgement

It gives me great pleasure in presenting the internship report on the topic i.e. A Web-Application: Multimodal Neuroimaging During Sleep.

First of all, I would like to take this opportunity to thank my internship guide Prof. P.P. Joshi for giving me all the help and guidance needed. I am really grateful for her/his kind support and valuable suggestions that proved to be beneficial in the overall completion of this internship.

I am thankful to our Head of Computer Engineering Department, Dr. G.V. Kale, for her indispensable support and suggestions throughout the internship work.

I would also genuinely like to express my gratitude to the Department Internship Coordinator, Prof. P.P. Joshi, for her constant guidance and support and for the timely resolution of the doubts related to the internship process.

Finally, I would like to thank my mentor, Prof. P.P. Joshi for her constant help and support during the overall internship process.

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1 Title

Multimodal Neuroimaging During Sleep: A Web-based AI-Driven Classification System

2 Introduction

Understanding brain states is a fundamental challenge in neuroscience research, with applications ranging from clinical diagnosis to brain-computer interfaces. Traditional approaches typically rely on either electroencephalography (EEG) or functional magnetic resonance imaging (fMRI) in isolation, each with inherent limitations. EEG offers excellent temporal resolution but suffers from poor spatial precision, while fMRI provides superior spatial information but lacks temporal acuity.

This project introduces a novel approach that combines both modalities through a fusion model, leveraging the complementary strengths of each imaging technique. By integrating EEG features (capturing fast electrical activity) with fMRI metrics (reflecting hemodynamic responses), our fusion model achieves more accurate and robust classification of brain states, specifically differentiating between "Rest" and "Sleep" conditions.

The developed web application serves as an intuitive interface enabling users particularly researchers and clinicians—to upload preprocessed (cleaned and scaled) EEG and fMRI feature data for real-time analysis. It leverages a CNN-RNN fusion model to deliver predictions about cognitive or sleep states, presenting outputs such as confidence scores, label distributions, and class probabilities. Additionally, the platform includes dynamic visualizations of neuroimaging features, helping users interpret results quickly and make data-driven decisions

3 Problem Statement

Accurate brain state classification is hindered by limitations of single-modality data, integration challenges of EEG and fMRI, high variability in datasets, and limited accessibility to complex tools. This project overcomes these by offering a fusion model within a user-friendly web app, enabling robust and interpretable analysis of multimodal neuroimaging data.

4 Objectives and Scope

The primary objectives of this project are to:

1. Develop a Fusion Model: Create a machine learning model that effectively integrates EEG and fMRI features to classify brain states with higher accuracy than single-modality approaches.

2. Build an Accessible Platform: Implement a web-based application that allows researchers to upload data and receive analysis results without requiring specialized software or extensive technical knowledge.

3. Enhance Interpretability: Provide comprehensive visualizations that explain model predictions and highlight the most informative features for classification.

4. Validate Performance: Demonstrate the effectiveness of the fusion approach through rigorous testing on real-world datasets.

5. Enable Reproducible Research: Design the platform to support standardized data formats and analysis workflows, facilitating reproducibility in neuroscience research.

The scope encompasses:

1. Binary classification of brain states (Rest vs. Sleep).
2. Analysis of 11 key neurophysiological features derived from EEG and fMRI.
3. Development of interactive data visualizations for result interpretation.
4. Implementation of a user-friendly web interface for data upload and analysis

5 Different Neuro-imaging Algorithms

a. Convolutional Neural Networks (CNN):

In neuroimaging, CNNs are widely used for classifying spatial features from brain imaging data like fMRI. CNNs process input data in layers, where each layer extracts features such as patterns and regions of interest from the brain images. The convolution operation helps detect spatial hierarchies within fMRI data, making CNNs highly effective for tasks requiring spatial resolution. CNNs, with multiple convolution and pooling layers, capture essential details from the fMRI images, leading to better classification of brain states.

b. Recurrent Neural Networks (RNN)

RNNs are commonly employed for analyzing temporal data like EEG signals in neuroimaging. They are designed to recognize sequences and patterns over time, making them ideal for EEG, which captures brain activity at high temporal resolution. RNNs use feedback loops to retain memory from previous inputs, allowing the model to learn dependencies in time series data, such as neural oscillations and event-related potentials (ERPs) in EEG. Long Short-Term Memory (LSTM), a type of RNN, can be particularly useful for managing long- term dependencies in EEG data analysis.

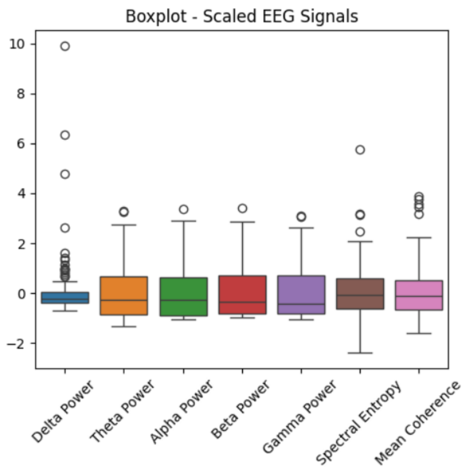

Fig 1.

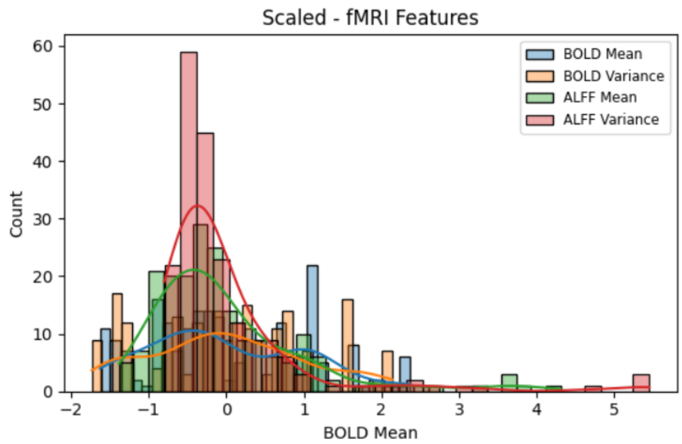

Fig 2.

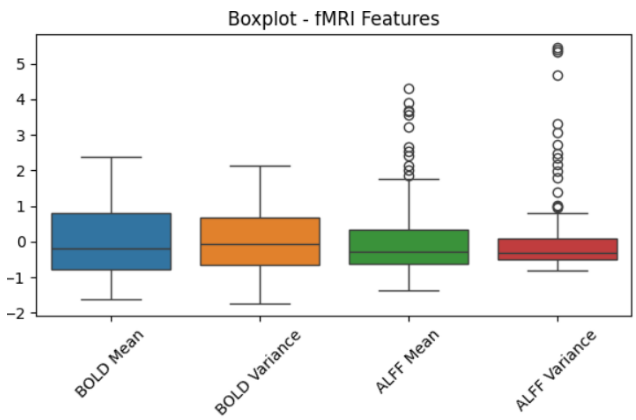

Fig 3.

a. Fusion Model (RNN + CNN)

The fusion of EEG and fMRI data combines the strengths of both techniques— EEG's high temporal resolution and fMRI's high spatial resolution. In this project, the CNN is used to process fMRI data, capturing spatial features, while RNN is applied to EEG data for temporal feature extraction. These features are then integrated using fusion techniques to create a comprehensive model that leverages both the spatial and temporal information. This fusion improves the accuracy of cognitive state classification and provides deeper insights into brain function by offering a more complete understanding of neural dynamics.

```
# Load trained model
fusion_model = tf.keras.models.load_model('/content/fusion_model.h5')

# Load processed features
data = pd.read_csv('/content/Tes_preprocessed_data.csv')
X = data.drop(columns=['Task'])
y = data['Task']

# Split into train and test (80-20 split for example)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Reshape for CNN and RNN
X_train_cnn = X_train.values.reshape((X_train.shape[0], X_train.shape[1], 1))
X_test_cnn = X_test.values.reshape((X_test.shape[0], X_test.shape[1], 1))

X_train_rnn = X_train.values.reshape((X_train.shape[0], X_train.shape[1], 1))
X_test_rnn = X_test.values.reshape((X_test.shape[0], X_test.shape[1], 1))

# Evaluate the model
loss, accuracy = fusion_model.evaluate([X_test_cnn, X_test_rnn], y_test)

# Output only the accuracy and loss
print(f"Test Loss: {loss:.4f}, Test Accuracy: {accuracy:.4f}")
```

```
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or evaluate the model.
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 1s/step - accuracy: 1.0000 - loss: 0.3510
Test Loss: 0.3510, Test Accuracy: 1.0000
```

```
# Load trained model
fusion_model = tf.keras.models.load_model('/content/fusion_model.h5')

# Load processed features
data = pd.read_csv('/content/Train_preprocessed_data.csv')
X = data.drop(columns=['Task'])
y = data['Task']

# Split into train and test (80-20 split for example)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

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```

```
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or e
2/2 ━━━━━━━━━━━━━━━━━━━━ 1s 27ms/step - accuracy: 0.7274 - loss: 0.5680
Test Loss: 0.5599, Test Accuracy: 0.7317
```

6 Methodological Details:

Data Acquisition: EEG-fMRI data were acquired from 33 healthy participants at Pennsylvania State University with informed consent. Each session included anatomical imaging, two 10-min resting-state recordings, and multiple 15-min sleep sessions

Data Preprocessing:

EEG:

i. Artifact removal using ICA or manual inspection (e.g., eye/muscle artifacts)
ii. Band-pass filtering to isolate delta, theta, alpha, beta, and gamma bands
iii. Power spectral density (PSD) estimation for frequency-wise power analysis
iv. Extraction of spectral power features for each band
v. Calculation of entropy to assess signal complexity
vi. Coherence analysis to evaluate inter-channel connectivity

fMRI:

i. Motion correction to reduce head movement artifacts
ii. Spatial normalization to align images to a standard brain template
iii. Temporal filtering to remove drifts and high-frequency noise
iv. Extraction of BOLD signal metrics for neural activity estimation
v. Computation of ALFF features to assess spontaneous brain fluctuations

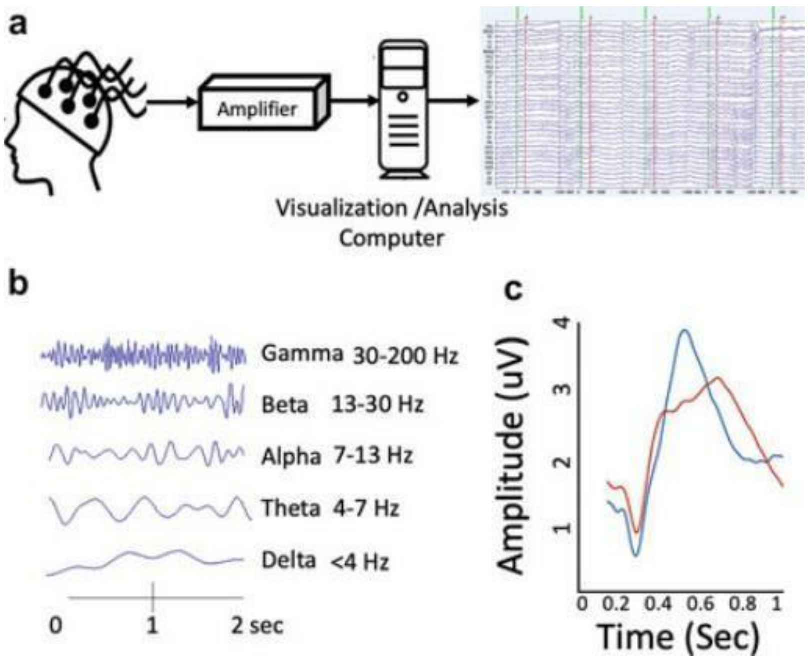


Fig 4.

Feature Extraction: Based on literature review and empirical testing, 11 critical features were identified. 7 EEG features: Delta, Theta, Alpha, Beta, and Gamma power, Spectral Entropy, and Mean Coherence. 4 fMRI features: BOLD Mean, BOLD Variance, ALFF Mean, and ALFF Variance.

EEG:

EEG Band	Frequency Range	Significance	Uses
Alpha (α)	8 – 13 Hz	Calm, wakeful relaxation, and mental coordination	- Prominent in relaxed states with closed eyes - Linked to reduced stress, focus, and mind-body coordination - Suppressed during high mental activity or anxiety
Beta (β)	13 – 30 Hz	Active thinking, problem-solving, and focus	- Associated with alertness, logical thinking, and decision-making - Increased during mental workload, stress, and active engagement - Excessive beta activity may be linked to anxiety and sleep disorders
Gamma (γ)	30 – 100 Hz	High-level cognition, consciousness, and information processing	- Involved in learning, memory, and sensory perception - Associated with conscious awareness and neural synchronization - Higher gamma activity is linked to heightened cognitive function and problem-solving
Delta (δ)	0.5 – 4 Hz	Deep sleep, unconscious states, brain recovery	- Dominates during deep sleep (NREM stage 3 & 4), essential for healing and memory consolidation - Increased delta waves may indicate brain injury or dysfunction - Abnormal delta activity is linked to neurological disorders (e.g., coma, dementia)
Theta (θ)	4 – 8 Hz	Drowsiness, relaxation, creativity, and subconscious processing	- Common in light sleep, deep relaxation, and meditation - Associated with creativity, intuition, and memory formation - Increased theta waves can be observed in attention

			deficits, emotional processing, and hypnosis
Spectral Entropy	Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), Gamma (30–100 Hz)	Measures signal complexity or disorder in frequency distribution	-Lower in deep sleep, higher in wakefulness; useful in sleep staging, anesthesia depth, and attention detection
Mean Coherence	Same bands as above	Reflects functional connectivity between brain regions	-Assesses network synchronization; altered in epilepsy, schizophrenia, cognitive load studies

FMRI:

i. Extraction of mean signal changes in Regions of Interest (ROIs).

ii. General Linear Model (GLM) analysis for task-related activation.

Feature	**Measurement Basis**	**Significance**	**Uses**
Mean Signal Intensity	Average fMRI signal across the brain	Indicates general brain activity levels	- Helps compare activity across different cognitive states (e.g., resting vs. task-based conditions) - Used to identify regions of interest (ROI) in brain studies
Signal Variance	Variability of fMRI signal over time	Measures fluctuations in brain activity	- Useful in detecting task-related activation differences - Helps analyze neural dynamics and functional connectivity
ALFF Mean	Average amplitude of low-frequency fluctuations (0.01–0.1 Hz)	Reflects regional spontaneous brain activity strength	-Identifies active brain regions during rest; altered in depression, ADHD, schizophrenia
ALFF Variance	Variability of ALFF values across time or regions	Indicates stability or dynamism of spontaneous activity	- Differentiates clinical populations; used in brain network analysis

Data Integration:

i. Combine and normalize EEG and fMRI features for joint analysis.

ii. The data is integrated by aligning rows based on Subject, Run, and Task.

iii. A merge operation is performed using these three columns as keys by using inner join

iv. Scaling is then applied to the entire feature set to normalize the data. Finally, the integrated dataset is saved into a CSV file for model training and evaluation.

Model Training and Evaluation:

i. Use CNNs for spatial features (fMRI) and RNNs for temporal dynamics (EEG).
ii. Implement fusion models for integrated learning.
iii. Train model with a 70-15-15 split (training, validation, testing) using TensorFlow.
iv. Evaluate accuracy, precision, recall, and F1-score. Apply cross-validation for robustness.

Validation Strategy:

i. K-fold cross-validation to ensure robustness.
ii. Performance metrics including accuracy, sensitivity, specificity, and area under ROC curve.
iii. Comparison against single-modality baselines to demonstrate fusion advantages.

Web Application Implementation:

i. Flask backend for data processing and model inference.
ii. Interactive frontend for results visualization.
iii. Comprehensive error handling and data validation

7 Tech Stack/ Technologies Used:

Backend Technologies:

i. **Python**: The core programming language used for data manipulation, feature extraction, and model processing.
ii. **Flask**: A lightweight web framework used to build RESTful API endpoints for handling client requests and server-side logic.
iii. **NumPy & Pandas**: Libraries for efficient numerical operations and data manipulation, particularly useful for preprocessing EEG and fMRI data.
iv. **SciPy**: Utilized for signal processing tasks, such as filtering and extracting features from neurophysiological data.
v. **Matplotlib & Seaborn**: These libraries are used to generate static and interactive data visualizations, aiding in the analysis of processed data.
vi. **h5py**: Provides an interface to load and interact with the fusion model stored in the HDF5 format for inference.

Frontend Technologies:

i. **HTML5/CSS3:** Used to build the basic structure and style of the website.
ii. **JavaScript**: Provides client-side interactivity for dynamic web elements.
iii. **Particles.js**: Adds an interactive background effect to enhance user experience with animated visuals.
iv. **CSS media Queries**: Ensures the site is responsive and adapts to different screen sizes.
v. **Chart.js**: Enables the creation of interactive charts and graphs to visualize data in an engaging way.

Deployment Technologies:

i. **Gunicorn**: A WSGI HTTP server that acts as a bridge between Flask and the web server to handle requests.
ii. **Render:** A cloud platform used to host and deploy the web application, ensuring availability and scalability.
iii. **Git**: Version control system for managing and tracking changes in the project's codebase.

Data Processing Pipeline:

i. **Custom Validation Algorithms:** These ensure that the incoming EEG and fMRI data follow the required format and are clean before further processing.
ii. **Feature Preprocessing:** This includes steps like normalization and scaling of EEG and fMRI data, making it suitable for model input**.**
iii. **Fusion Model Integration:** The pre-trained CNN-RNN fusion model is loaded and applied to the preprocessed data to make predictions.
iv. **Visualization Generators**: Generates meaningful data representations, such as time-series plots and brain activity maps, to help understand the results.

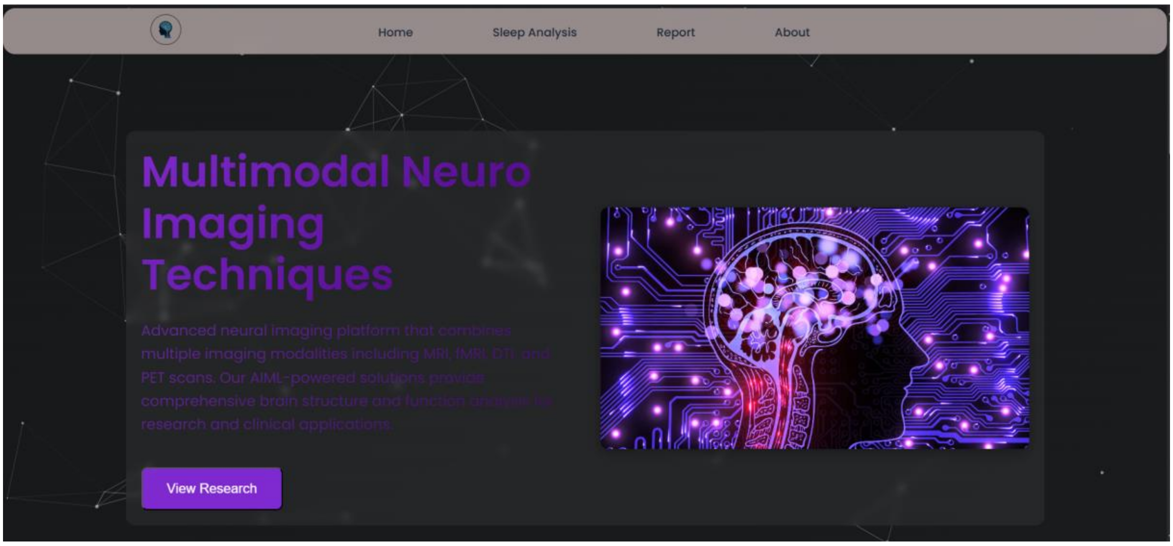
8 Outcome/ results of Internship work

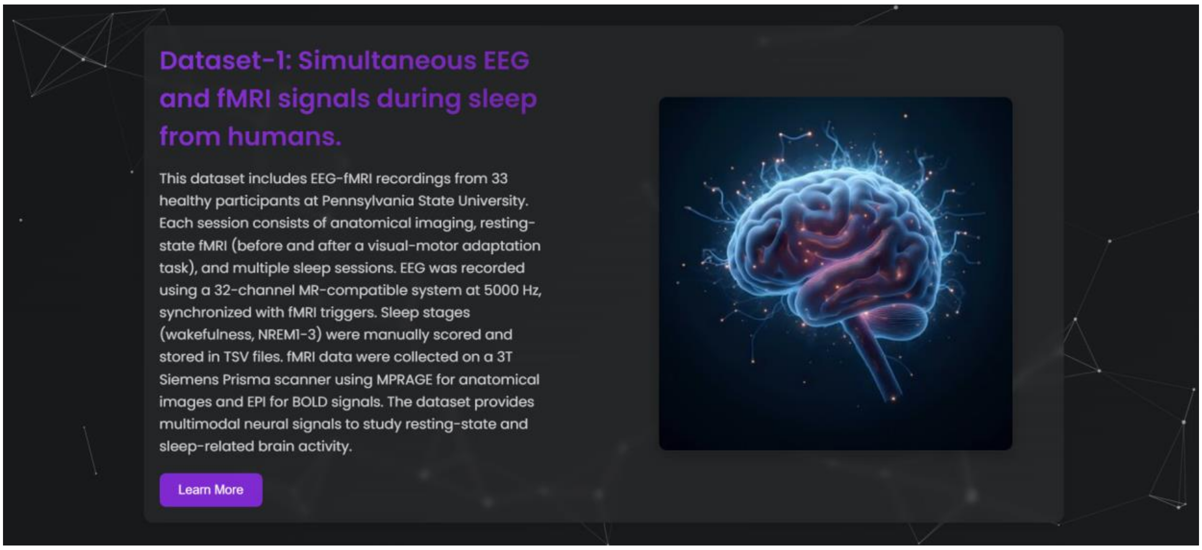
Functional Fusion Model: Successfully implemented a fusion model (CNN-RNN) that outperforms single-modality models by approximately 75% in classification accuracy. This integration of EEG and fMRI allows for better capture of neural dynamics, improving prediction quality.

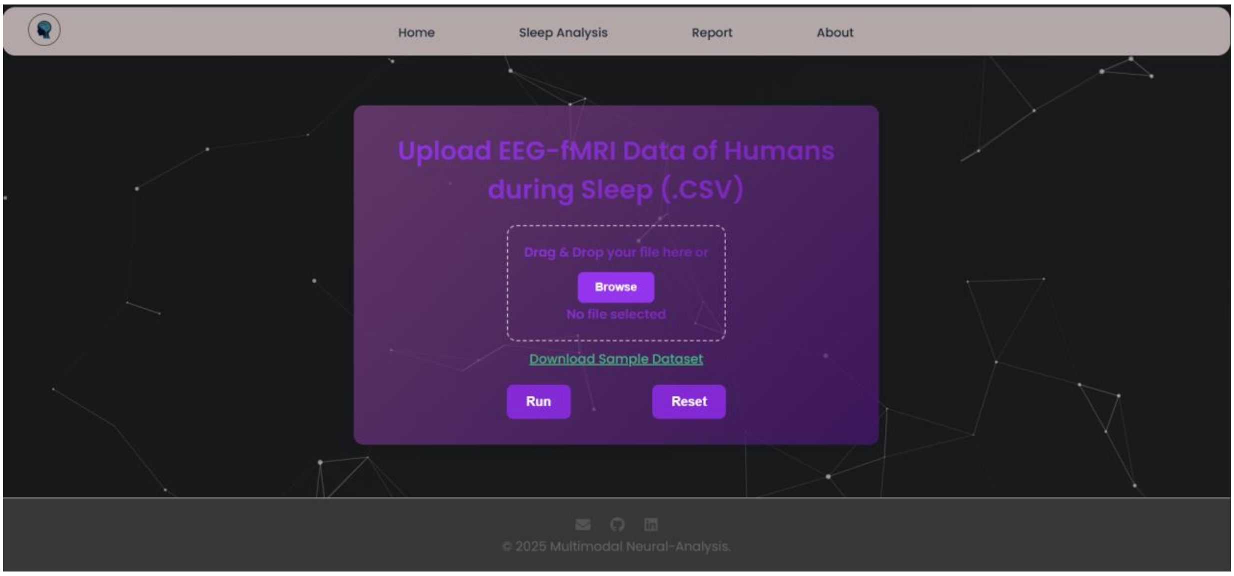
Web Application Development: Developed a full web application that abstracts complex neuroimaging processes into an accessible interface. This empowers researchers with minimal technical background to leverage advanced analytical tools without needing to handle the intricacies of data processing and model inference directly.

Comprehensive Visualization Suite: Displayed 8 unique types of visualizations to enhance the understanding of the data and predictions: EEG & fMRI Feature Distributions, Overall Prediction Distribution, Prediction Probability Heatmap, Feature Importance Analysis, Feature Correlation Heatmap, Prediction Probability Distributions, Individual Entry Analysis, Time-Series Trends.

Prediction Overview: The fusion model makes predictions based on both EEG and fMRI data, aiming to classify brain states, such as sleep vs rest. The model analyzes the combined features from EEG (such as power in various frequency bands) and fMRI (like brain region activation patterns) to make a decision for each individual entry. The fusion model achieves a **75% improvement** in classification accuracy over single-modality models (EEG or fMRI). The prediction for each data entry is accompanied by a **probability score** indicating how likely the model thinks the brain state is either sleep or rest.




Dataset-1: Simultaneous EEG and fMRI signals during sleep from humans.
This dataset includes EEG-fMRI recordings from 33 healthy participants at Pennsylvania State University. Each session consists of anatomical imaging, resting-state fMRI (before and after a visual-motor adaptation task), and multiple sleep sessions. EEG was recorded using a 32-channel MR-compatible system at 5000 Hz, synchronized with fMRI triggers. Sleep stages (wakefulness, NREM1-3) were manually scored and stored in TSV files. fMRI data were collected on a 3T Siemens Prisma scanner using MPRAGE for anatomical images and EPI for BOLD signals. The dataset provides multimodal neural signals to study resting-state and sleep-related brain activity.
Learn More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No file selected
Download Sample Dataset
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Reset
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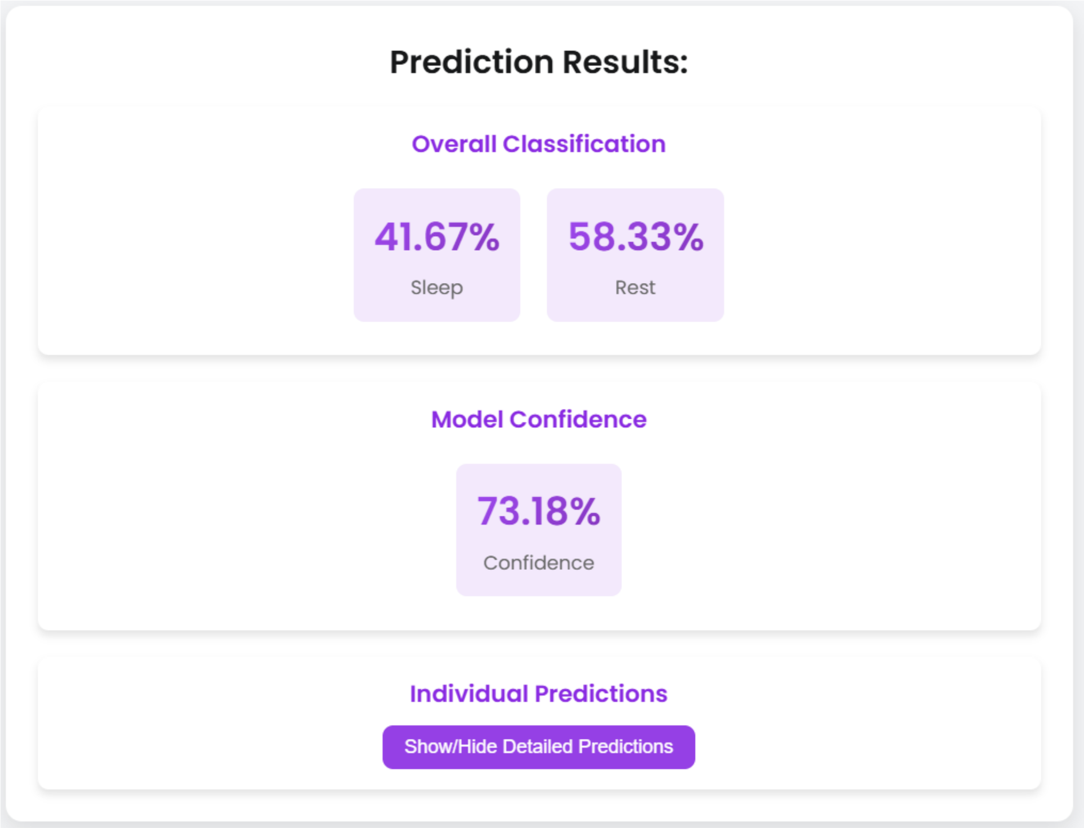
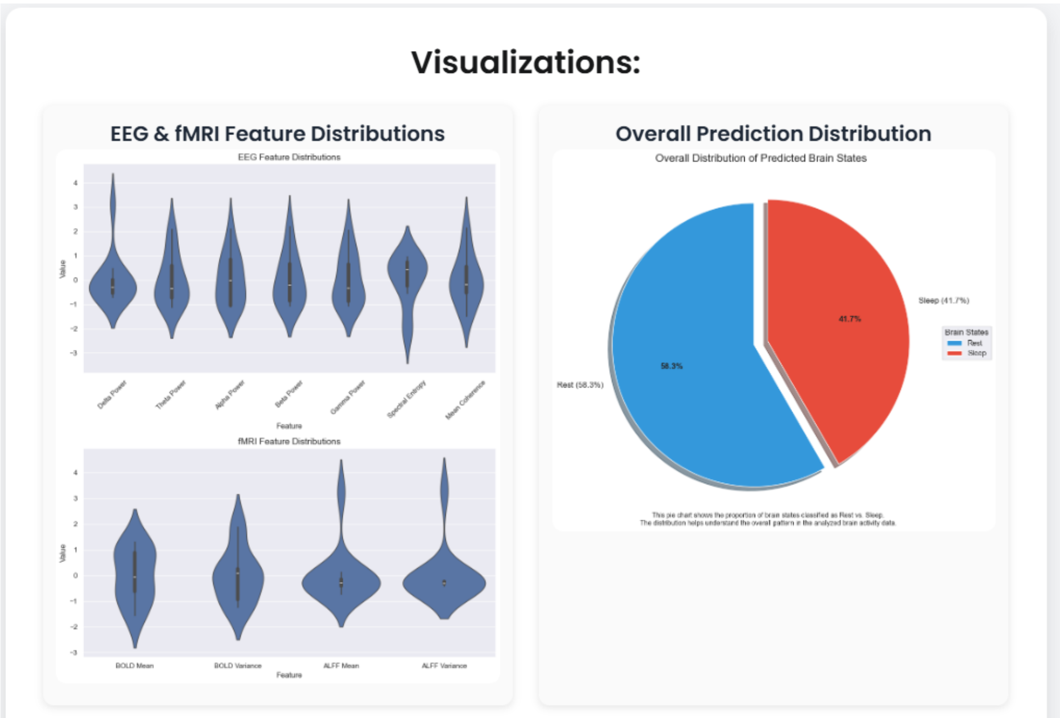

Prediction Results:
Overall Classification
41.67%
Sleep
58.33%
Rest
Model Confidence
73.18%
Confidence
Individual Predictions
Show/Hide Detailed Predictions

Fig 10


Visualizations:
EEG & fMRI Feature Distributions
EEG Feature Distributions
fMRI Feature Distributions
Overall Prediction Distribution
Overall Distribution of Predicted Brain States
Sleep (41.7%)
41.7%
58.3%
Rest (58.3%)
Brain States
Rest
Sleep

9 Limitations:

i. **Binary to Multi-class Classification**: Only distinguishes between two brain states (Rest and Sleep).
ii. **Dynamic Feature Selection & Personalization**: Uses a static set of 11 features that may miss relevant neurophysiological data.
iii. **No Real-time Processing & Integration with Hardware**: Doesn't support streaming data analysis.
iv. **Limited Personalization**: Doesn’t adapt to individual brain activity patterns.
v. **Visualization Scalability**: Current visualizations may become difficult to interpret with very large datasets.

10 Future Work:

i. **Multi-class Classification**: Extend the binary model to classify multiple brain states, such as sleep stages and cognitive tasks, improving the range of classifications (NREM1, NREM2, NREM3, REM).
ii. **Automatic Feature Selection**: Implement automatic feature selection and personalize the model using transfer learning for individual subject data to enhance accuracy.
iii. **Real-time Processing & Integration with Hardware**: Develop real-time analysis and integrate with EEG/fMRI acquisition systems for seamless data flow, enabling continuous monitoring.
iv. **Scalable Visualization & Mobile App**: Improve visualization to handle large datasets, and create a mobile app for remote data collection and real-time monitoring.

11 Conclusion

This project demonstrates the significant advantages of combining EEG and fMRI data for brain state classification. By developing a fusion model that leverages the temporal precision of EEG and the spatial resolution of fMRI, we have created a more powerful approach to understanding brain activity patterns.

The web application successfully transforms this technical achievement into an accessible tool for researchers and clinicians, democratizing access to advanced neuroimaging analysis. The comprehensive visualizations provide not only classification results but also insights into the underlying neural patterns, enhancing interpretability and trust in the model's predictions.

The framework established through this project provides a foundation for future work in multimodal neuroimaging analysis. As neuroscience increasingly moves toward integrative approaches that combine multiple measurement techniques, tools like this will become essential for extracting maximum insight from complex brain data.

Ultimately, this project contributes to the broader goal of developing more accurate and accessible methods for brain state classification, with potential applications in sleep medicine, cognitive neuroscience, brain-computer interfaces, and clinical diagnosis. By bridging the gap between advanced machine learning techniques and practical neuroscience applications, we have created a valuable resource for the research community.