Real-Time Multimodal Sleep Apnea Detection for Enhanced Accuracy and Early Diagnosis

UIT2602 - WEB PROGRAMMING

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

Certified that this project titled "**Real-Time Multimodal Sleep Apnea Detection for Enhanced Accuracy and Early Diagnosis**" is the Bonafide work of "C. Padmapriya - 3122225002089 and U. Pranaav - 3122225002093", and is submitted for project viva-voce examination held on 25-04-2025.

Signature of Examiner

Submitted on ________________

Internal Examiner **External Examiner**

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I. ABSTRACT:

Sleep apnea is a pervasive but frequently underdiagnosed sleep disorder characterized by repeated interruptions in breathing during sleep, often leading to serious health consequences such as cardiovascular disease, stroke, and cognitive impairment. Although Polysomnography (PSG) remains the clinical gold standard for diagnosis, its high cost, intrusiveness, and dependence on specialized facilities significantly restrict its accessibility for large-scale screening and early intervention. To address these limitations, this project proposes the development of a robust, real-time sleep apnea detection system leveraging multimodal physiological signals obtained from wearable-compatible sources, specifically utilizing ECG, EEG, SpO_2, and respiration signals from the MIT-BIH Polysomnographic Database.

The system design focuses on extracting meaningful features such as Heart Rate Variability (HRV), statistical measures, and time-frequency characteristics across different modalities to enable accurate and comprehensive apnea event classification. Machine learning models capable of multi-label classification within fixed-length time windows are developed and evaluated, allowing the detection of various types of apnea events. Special emphasis is placed on overcoming key challenges including signal noise, data imbalance, missing or unreliable modalities, and effective temporal alignment of multimodal inputs through advanced preprocessing, data augmentation, and feature fusion strategies.

Furthermore, the project prioritizes the use of non-intrusive, easily accessible biosignals to ensure the scalability and clinical applicability of the proposed system. Model optimization techniques are employed to enhance real-time performance, making the solution suitable for integration into wearable health monitoring devices. By bridging the gap between clinical standards and real-world accessibility, this work aims to contribute significantly toward early, accurate, and scalable sleep apnea screening and monitoring solutions.

II. INTRODUCTION

Sleep apnea is a highly prevalent but often underdiagnosed sleep disorder characterized by repeated episodes of partial or complete obstruction of the upper airway during sleep, leading to disrupted sleep patterns and intermittent hypoxia. Untreated sleep apnea has been linked to severe health consequences, including cardiovascular diseases, stroke, diabetes, and cognitive impairments, underscoring the critical need for timely and accurate detection. The current gold standard for diagnosing sleep apnea is overnight Polysomnography (PSG), an intensive and resource-heavy procedure involving the monitoring of multiple physiological parameters in a controlled sleep laboratory setting. Despite its clinical effectiveness, the cost, complexity, and intrusiveness of PSG limit its widespread use, especially for early detection and large-scale screening.

Recent advancements in wearable technologies and physiological signal acquisition present an opportunity to develop scalable, non-intrusive, and real-time solutions for sleep apnea detection. By leveraging accessible biosignals such as Electrocardiogram (ECG), Electroencephalogram (EEG), Electromyogram (EMG), blood oxygen saturation (SpO_2), and respiration-related signals, it is possible to create alternative diagnostic methods that are more user-friendly and suitable for continuous monitoring. However, several challenges persist, including signal noise, missing or unreliable modalities, data imbalance, and the complexity of fusing multimodal data streams for robust classification.

This project aims to design and implement a real-time sleep apnea detection system using multimodal physiological signals sourced from the Sleep Heart Health Study – MIT-BIH Polysomnographic Database (SLPDB), available on PhysioNet. The dataset comprises overnight recordings from 18 subjects, encompassing over 83 hours of annotated physiological data across 16 channels, including EEG (C4/A1, C3/A2), ECG, chin EMG, bilateral EOG, airflow, thoracic and abdominal effort, SpO_2, snore, body position, and heart rate. Signals are sampled at 250 Hz, and detailed annotations such as sleep stages, apnea/hypopnea events, and respiration patterns are provided through structured files (.dat, .hea, .apn, and .xml).

The core objectives of the project include:

- Extracting meaningful features such as Heart Rate Variability (HRV), statistical metrics, and time-frequency characteristics from multiple signal modalities.
- Developing machine learning models capable of multi-label classification to detect different types of apnea events in fixed time windows.
- Addressing preprocessing challenges like signal noise, temporal misalignment, and modality imbalance through robust data preparation techniques.
- Ensuring the clinical applicability and real-time viability of the system by focusing on non-intrusive inputs and optimizing computational efficiency.

By integrating multimodal feature extraction, intelligent signal fusion, and scalable model deployment strategies, this project endeavors to bridge the gap between clinical diagnostics and real-world wearable applications. The successful implementation of this system could pave the way for more accessible, affordable, and effective early detection of sleep apnea, ultimately contributing to improved patient outcomes and enhanced quality of life.

III. REQUIREMENTS ENGINEERING

Sprint	Epic	User Story	Requirement	Priority	Description
1	Data Preprocessing	1	Signal Extraction	High	Extract signal information from the dataset and perform segmentation and labelling of 30s segments.

2	Model Setup	2	Model Initialization	High	Load the dataset utilizing wfdb and rdnn modules.
3	Model Fine-Tuning	3	Training with ensemble model	High	Train an Ensemble model with Stacking classifier with a meta learner and 4 base learners.
4	Anomaly Detection	4	Classification Output	High	Use the random forest classifier as meta learner for classifying various types of sleep apnea.
5	Web Interface	5	Display results in frontend	Medium	Design frontend UI to view model evaluations, signal information etc.
6	Backend Processing	6	Signal analysis	High	Analyze the signal data from the dataset and display results on the frontend.
7	Performance Evaluation	7	Model Evaluation Metrics	High	Evaluate model using accuracy, precision, recall, and F1-score.

8	UI Responsiveness	8	Cross-device Testing	Medium	Ensure that the web app works on various screen sizes and browsers.
9	Error Handling	9	Corrupted Signal inputs	High	Ensure signals are either not used for classification or users are alerted.
10	Result Explanation	10	Display the classification results	Medium	Display the model’s confidence score along with classification results.
11	Visualization	11	Integrate Signal Preview in UI	Low	Optionally show preview of uploaded signals in the UI for better UX.
12	Deployment	12	Host Application on Local Server	High	Deploy the backend and frontend locally for demonstration and testing.

IV. IMPLEMENTATION & RISK MANAGEMENT

Module	Technology/Tool	Description
Signal preprocessing	Python, RdNN, WfDb	Extracts signal information into 30s segments.
Model Loading	SciPy, Sklearn	Loads the data models for modelling based on data.
Inference Engine	Numpy, Sklearn, SciPy	Passes video tensors to the model and applies classification threshold.
Web Frontend	Javascript, Streamlit	Handles signal analysis display with model result display.
Web Backend	Flask, Streamlit	Serves API for inference; handles communication between frontend and model.
Evaluation Metrics	Scikit-learn	Computes accuracy, precision, recall, and F1-score.

Risk Management Table:

Risk	Description	Probability	Impact	Mitigation Strategy
Short Signal Input	Signals with short segments near end of full signals can cause problems	High	Low	Combine trailing signals to 30s segments.
Dataset Ambiguity	Certain labels have low support	High	High	Use class weights and monitor recall. Ensure labels with low support are appropriately modelled.
UI/API Integration Errors	Frontend might mismatch with backend request format	Medium	Medium	Strict API schema validation and endpoint testing
Low Recall for certain classes	Model may miss some apenic events.	Low	High	Adjust threshold, tune model with validation data

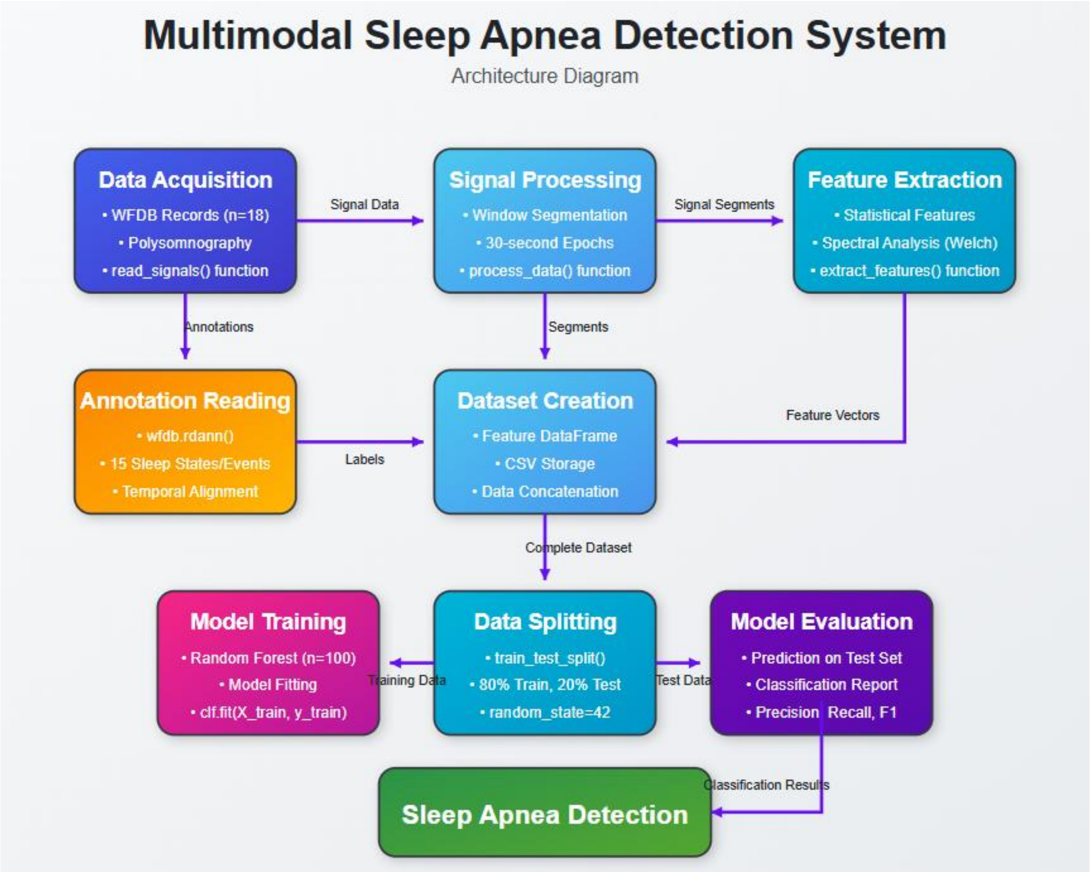
Flask Memory Limitations	Backend may crash if we load large number of signals	Low	Medium	Restrict number of loaded signals, handle exceptions gracefully
Cross-platform UI Responsiveness	Streamlit app may not render correctly on smaller devices	Low	Low	Test UI on different devices and browsers

TEST LOG

Test Case ID	Component	Test Scenario	Expected Result	Actual Result	Status
TC01	Signal Preprocessing	Load binary signal data with labels in dataset	30s signal segments with labels for train.	As Expected	Pass
TC02	Model Training	Pass preprocessed data to model	Trains the model with high accuracy.	As Expected	Pass

TC03	Evaluation	Testing is performed to analyze performance	Good classification report is generated.	As Expected	Pass
TC04	Thresholding	Utilizing random forest to classify apenic events	Signals are processed and displayed.	As Expected	Pass
TC05	Result Display	Show prediction in UI	Label + probability shown	As Expected	Pass
TC06	Signal analysis display	Visualize csv data and signal metrics	Interactive signal UI with important details	As Expected	Pass
TC07	Flask API Timeout	Upload large video	Error caught, no crash	As Expected	Pass

V. PROJECT MANAGEMENT



VI. PROJECT OUTCOMES

The developed real-time sleep apnea detection system demonstrated strong performance across multiple evaluation metrics, effectively addressing key challenges such as signal noise, class imbalance, and feature fusion. A comprehensive ensemble learning approach combining Multilayer Perceptron (MLP), Random Forest (RF), XGBoost, and LightGBM models, with a Meta-Random Forest aggregator, proved to be the most effective solution. The major project outcomes are summarized below:

Model Performance

- **Overall Accuracy**: Achieved an average classification accuracy of **93.64%** across all apnea event labels.

- **High-Confidence Class Predictions**: Certain classes such as Class 4 (0.9898), LA (0.9849), and CAA (0.9796) exhibited exceptionally high prediction confidence.
- **Weighted F1-Score**: Reached a weighted F1-score of **0.67**, reflecting strong performance while balancing between majority and minority classes.
- **Macro Average F1-Score**: Achieved a macro F1-score of **0.59**, indicating good balance across both frequent and rare classes.
- **Micro Average Precision and Recall**: Recorded a micro-averaged precision of **0.75** and recall of **0.63**, optimizing the tradeoff between detection accuracy and coverage.

Generalization and Robustness

- **Strong Generalization**: The ensemble model maintained robust performance across different subjects, with high F1-scores for major classes like W (0.85), 2 (0.78), and R (0.78).
- **Improved Minority Class Handling**: Significant improvements were observed for underrepresented classes such as CAA, where the F1-score improved to **0.41**, compared to below 0.10 in previous standalone models.

Ensemble Model Strength

- **Best Performing Model**: The ensemble model combining MLP, RF, XGBoost, and LightGBM, followed by a Meta-Random Forest classifier, outperformed all standalone models.
- **Meta-Learner Role**: The meta-level Random Forest aggregated predictions from base models, enhancing prediction stability and interpretability.
- **Why the Ensemble Worked Better**:

- MLP captured complex, nonlinear signal patterns.
- RF provided robust feature selection and avoided overfitting.
- XGBoost effectively handled imbalanced classes and improved rare class detection.
- LightGBM offered fast convergence and scalability for large feature sets.
- Meta-RF refined the final predictions through calibrated vote aggregation.

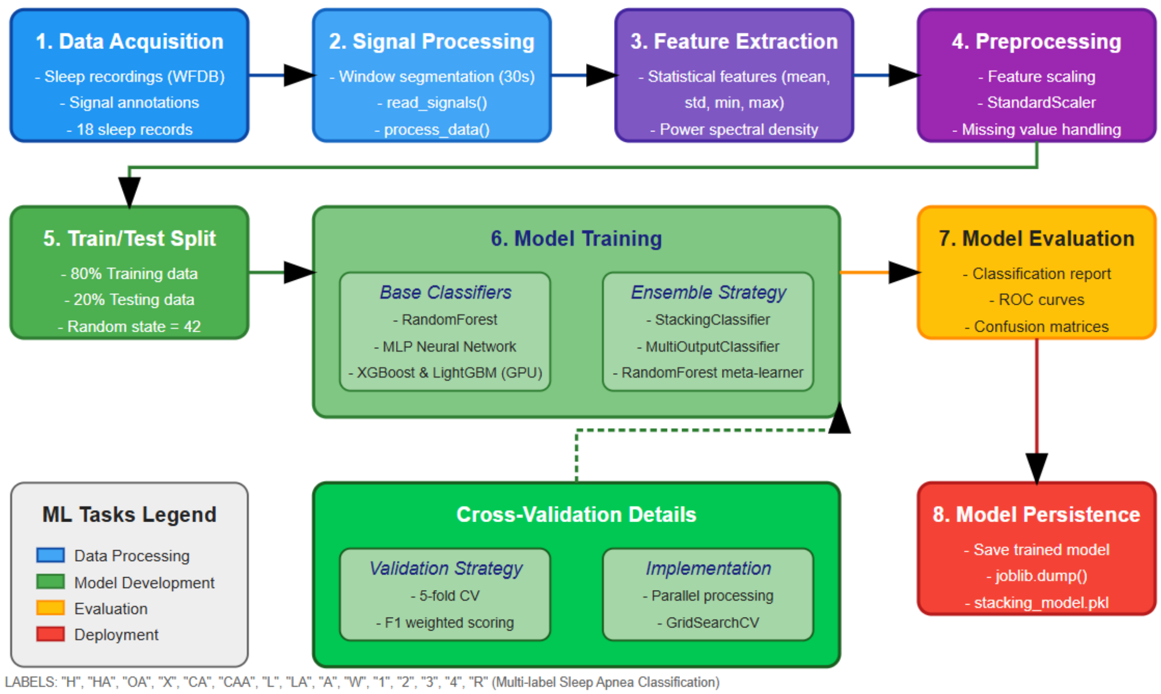
- **Consistency**: The ensemble maintained stable performance across all 17 labels, minimizing drops in performance even for rare classes.

Challenges Observed

- **Class-specific Difficulties**: Some apnea event classes such as H, HA, and 1 exhibited lower recall rates (~0.45), indicating occasional misclassification likely due to class sparsity or signal variability.

- **Model Complexity**: Tuning and calibrating multiple base learners and the meta-learner added complexity to the overall model training pipeline.

VII. MODEL ARCHITECTURE AND STRUCTURE



Data Preprocessing and Feature Extraction

The Sleep Heart Health Study (SHHS) dataset was used, specifically the MIT-BIH Polysomnographic Database (SLPDB). Raw physiological recordings were processed using the WFDB library. Each record contains 16 channels, including EEG, ECG, EMG, EOG, airflow, thoracic/abdominal respiration, SpO_2, snoring, body position, and heart rate.

The preprocessing pipeline included:

- **Reading Signals**: Waveform signals (.dat files) were loaded at a sampling frequency of 250 Hz.

- **Segmentation**: Signals were segmented into fixed-length windows of 30 seconds (~7500 samples).

- **Feature Extraction**: For each window and channel, basic statistical and frequency features were computed:

  - Mean

  - Standard Deviation

- Maximum
- Minimum
- Power Spectral Density (using Welch's method)

- This resulted in a rich feature set capturing both time-domain and frequency-domain characteristics of biosignals.
- **Labeling**: Each segment was multi-labeled based on annotations (.apn files) indicating the presence of specific apnea events (e.g., Obstructive Apnea, Central Apnea, Hypopnea).

The final dataset consisted of a **feature matrix (X)** and a **multi-label target matrix (y)**, supporting multi-label classification tasks.

Feature Normalization

Before training, features were standardized using **Z-score normalization** via StandardScaler to ensure all features contributed equally during model training.

Model Architecture

A **Stacked Ensemble Learning** framework was designed to leverage the complementary strengths of different classifiers:

Base Learners

1. **Random Forest (RF)**:
   - Ensemble of decision trees.
   - Captures important feature splits.
   - Robust to overfitting and handles non-linear relationships well.
2. **Multilayer Perceptron (MLP)**:
   - Deep neural network with three hidden layers (512, 256, 128 neurons).
   - Activation function: ReLU (rectified linear unit).

- Optimizer: Adam.
- Early stopping enabled to prevent overfitting.
- Captures complex, nonlinear patterns from biosignals.

3. **XGBoost (XGBClassifier)**:
    - Gradient boosting decision tree algorithm.
    - Specialized for imbalanced datasets.
    - Fast and optimized for GPU (using `gpu_hist` tree method).
    - Strong performance on sparse signals and rare event detection.

4. **LightGBM (LGBMClassifier)**:
    - Efficient gradient boosting framework.
    - Designed for large feature sets and fast training.
    - GPU-accelerated (device = 'GPU'), ensuring scalable computation.

Meta-Learner

- **Random Forest (Meta-Level)**:
    - Aggregates the outputs from all base learners.
    - Provides calibrated and stable final predictions.
    - Enhances interpretability compared to a neural meta-learner.

MultiOutputClassifier Wrapper

Given that sleep apnea detection is a **multi-label classification** task (one sample can have multiple labels simultaneously), all classifiers were wrapped inside a **MultiOutputClassifier** to independently model each label while sharing the same base ensemble.

Model Training and Evaluation

- **Train/Test Split**:
  80% of data was used for training and 20% for testing, with stratified random sampling to maintain label balance.

- **Training**:

  - Each base learner was trained on standardized features.

  - During training, GPU acceleration was utilized wherever possible (XGBoost, LightGBM), while Random Forest and MLP were trained on CPU.

  - Careful control of `n_jobs` was necessary to avoid memory bottlenecks during parallel model execution.

- **Evaluation**: Predictions were generated on the test set and evaluated using standard classification metrics:

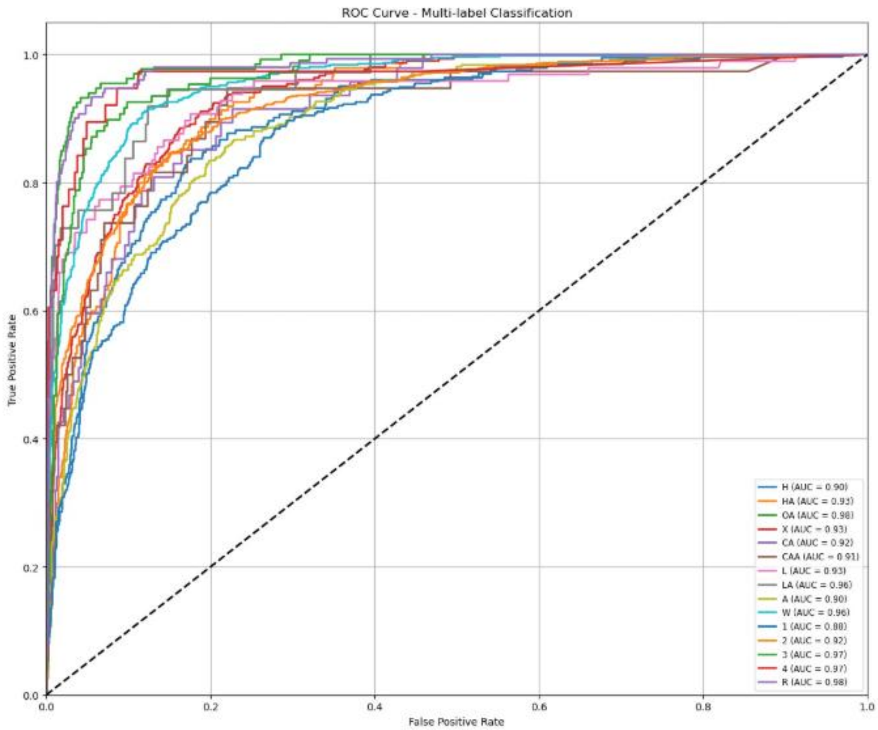
  - Accuracy

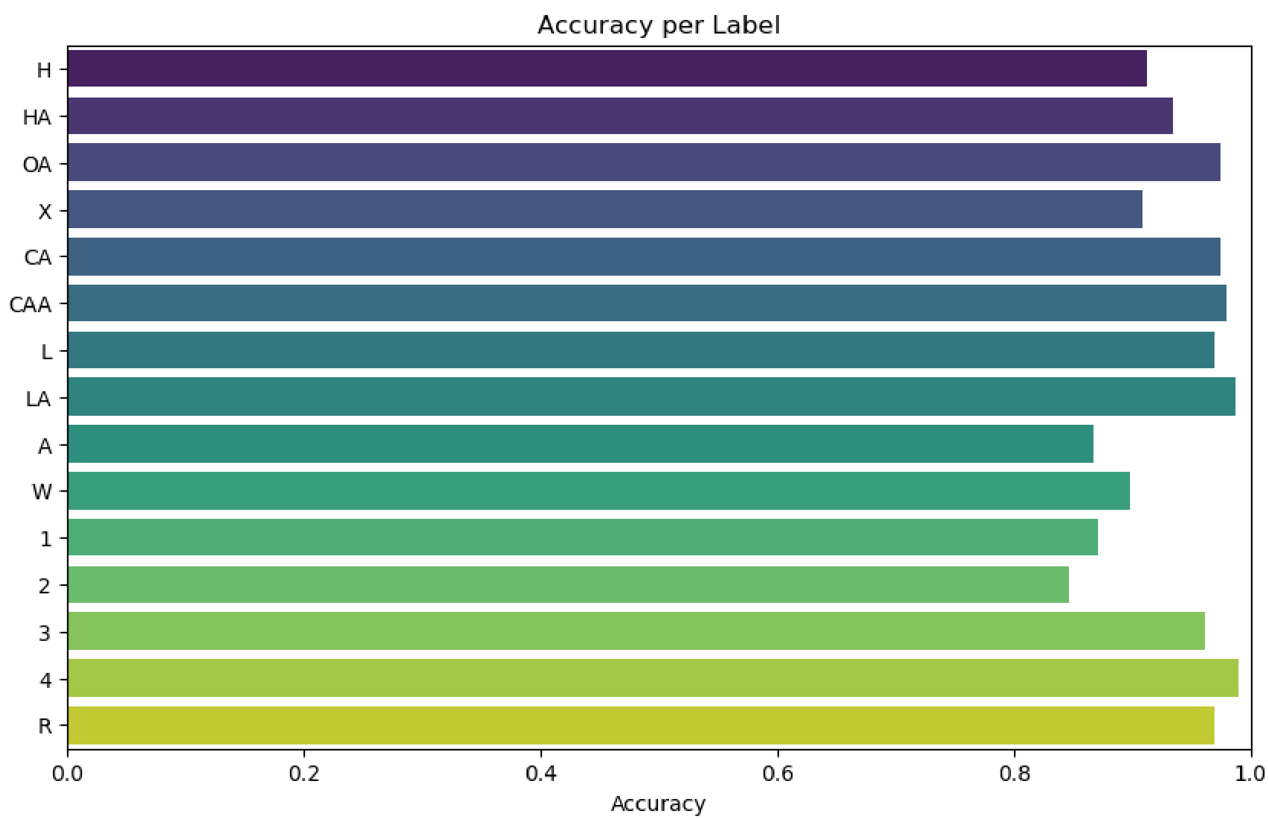
  - Precision

  - Recall

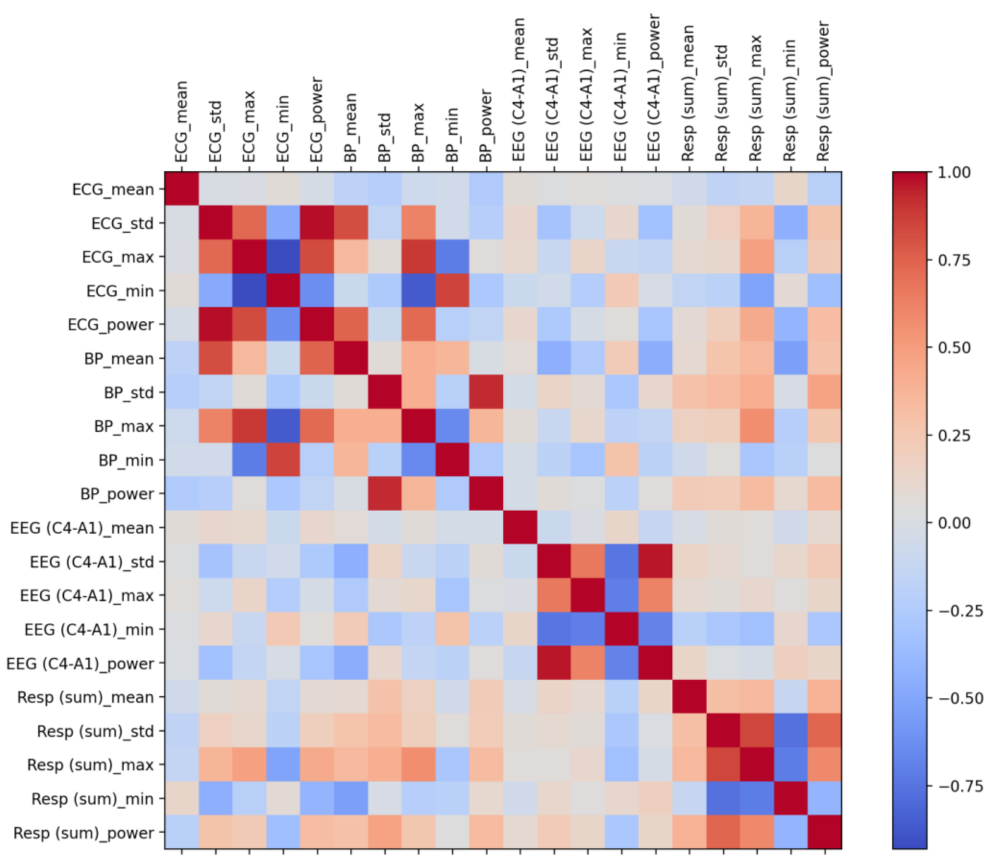
  - F1-Score (weighted, macro, and micro averages)

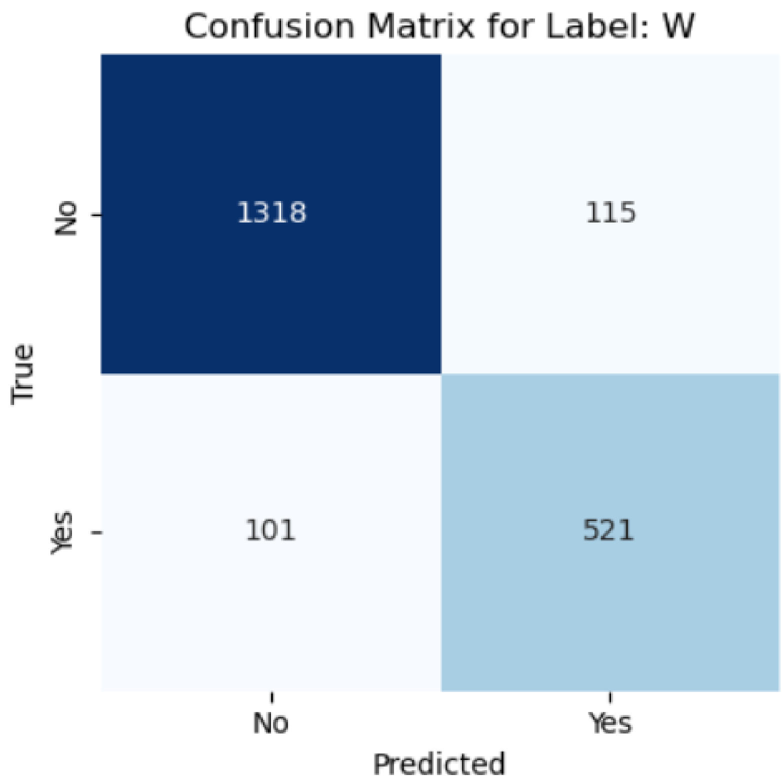
VIII. OUTPUT

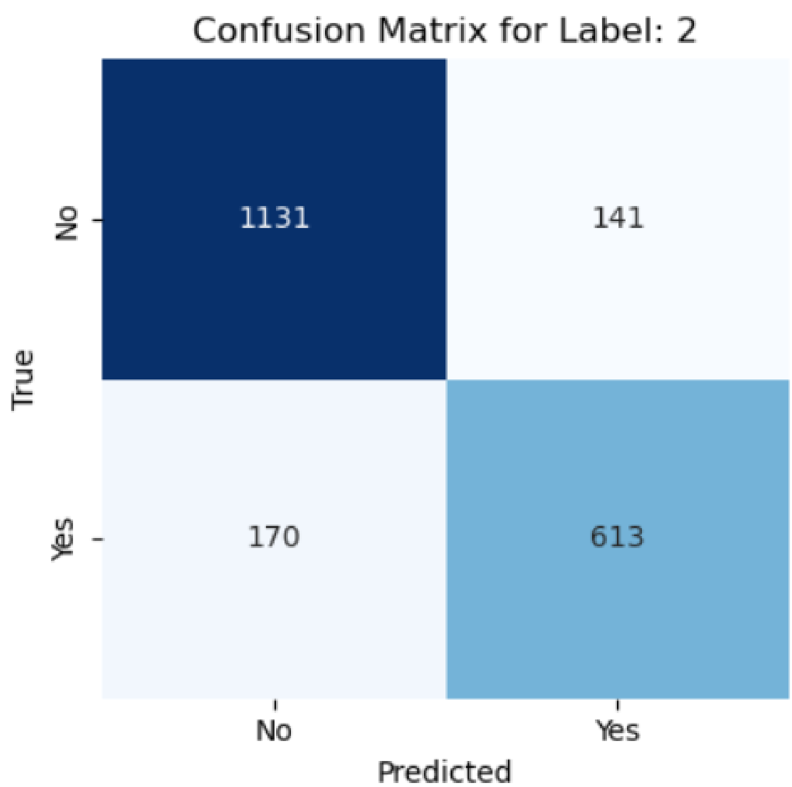

ROC Curve - Multi-label Classification
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
H (AUC = 0.90)
HA (AUC = 0.93)
OA (AUC = 0.98)
X (AUC = 0.93)
CA (AUC = 0.92)
CAA (AUC = 0.91)
L (AUC = 0.93)
LA (AUC = 0.96)
A (AUC = 0.90)
W (AUC = 0.96)
1 (AUC = 0.88)
2 (AUC = 0.92)
3 (AUC = 0.97)
4 (AUC = 0.97)
R (AUC = 0.98)


Accuracy per Label
H
HA
OA
X
CA
CAA
L
LA
A
W
1
2
3
4
R
0.0
0.2
0.4
0.6
0.8
1.0
Accuracy

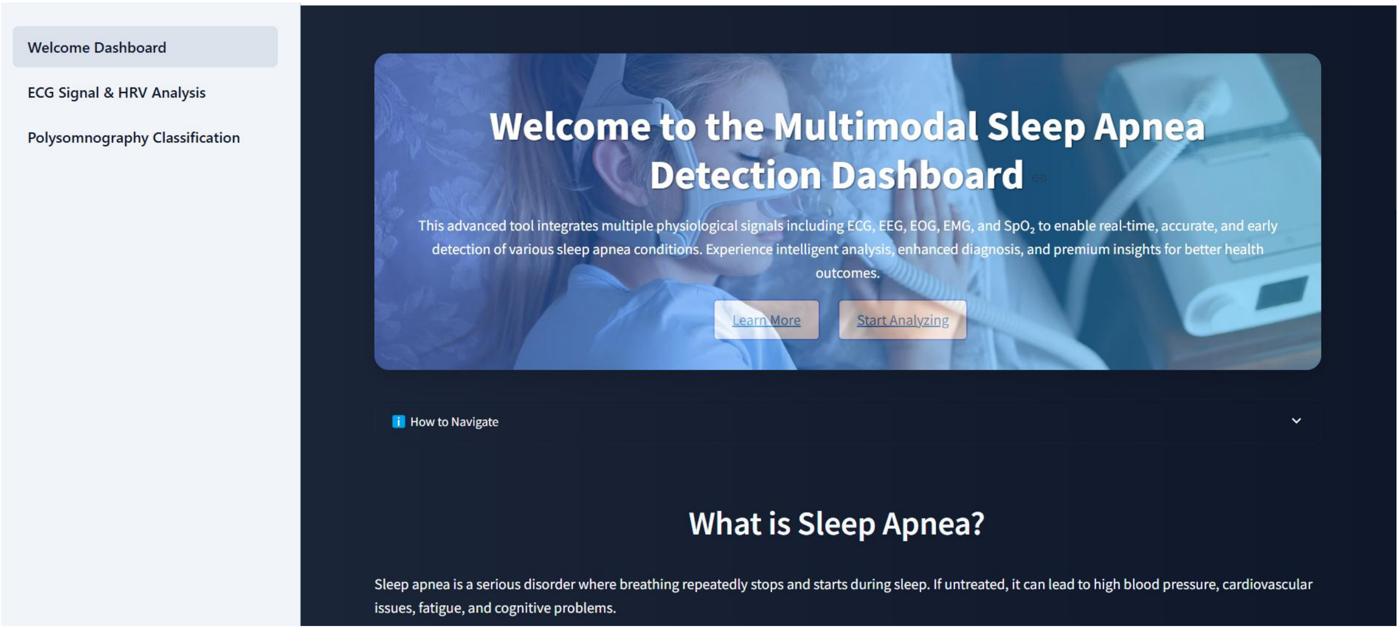
```
  H | Accuracy: 0.9139 |
 HA | Accuracy: 0.9367 |
 OA | Accuracy: 0.9713 |
  X | Accuracy: 0.9027 |
 CA | Accuracy: 0.9742 |
CAA | Accuracy: 0.9796 |
  L | Accuracy: 0.9684 |
 LA | Accuracy: 0.9849 |
  A | Accuracy: 0.8735 |
  W | Accuracy: 0.8949 |
  1 | Accuracy: 0.8745 |
  2 | Accuracy: 0.8487 |
  3 | Accuracy: 0.9635 |
  4 | Accuracy: 0.9898 |
  R | Accuracy: 0.9703 |
```



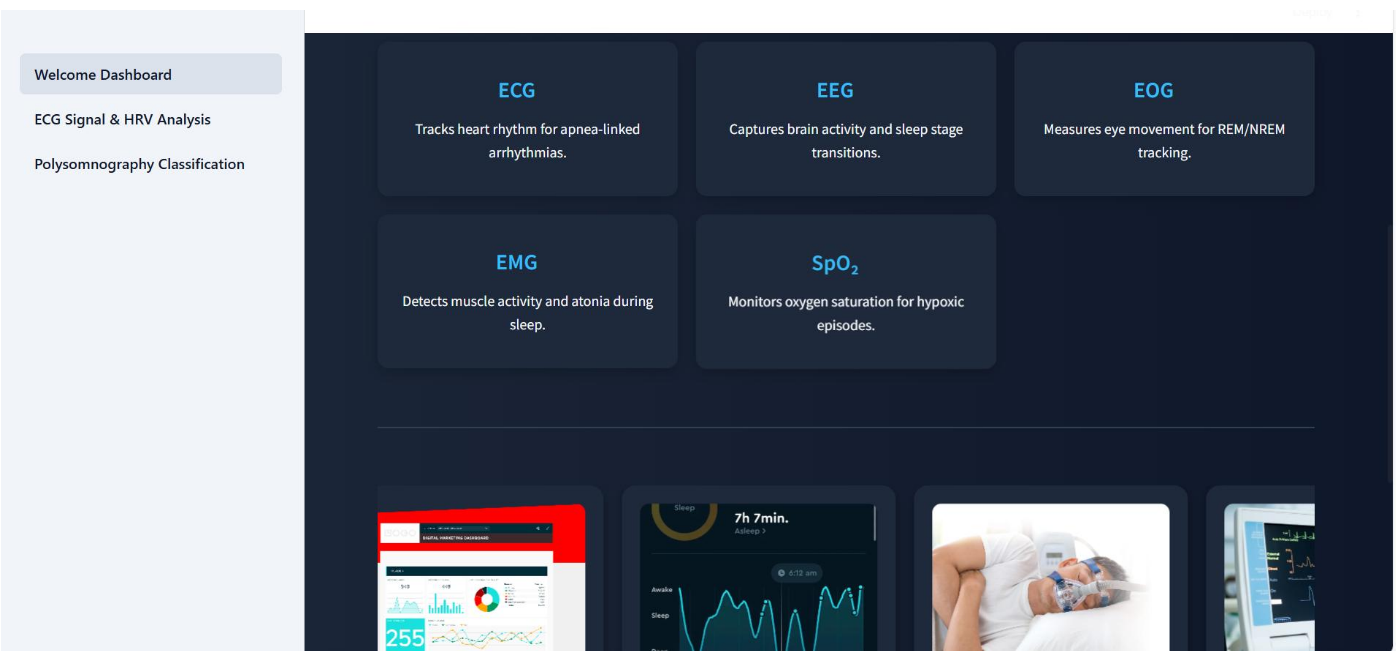

Confusion Matrix for Label: W
No
Yes
True
1318
115
101
521
No
Yes
Predicted


Confusion Matrix for Label: 2
No
Yes
True
1131
141
170
613
No
Yes
Predicted

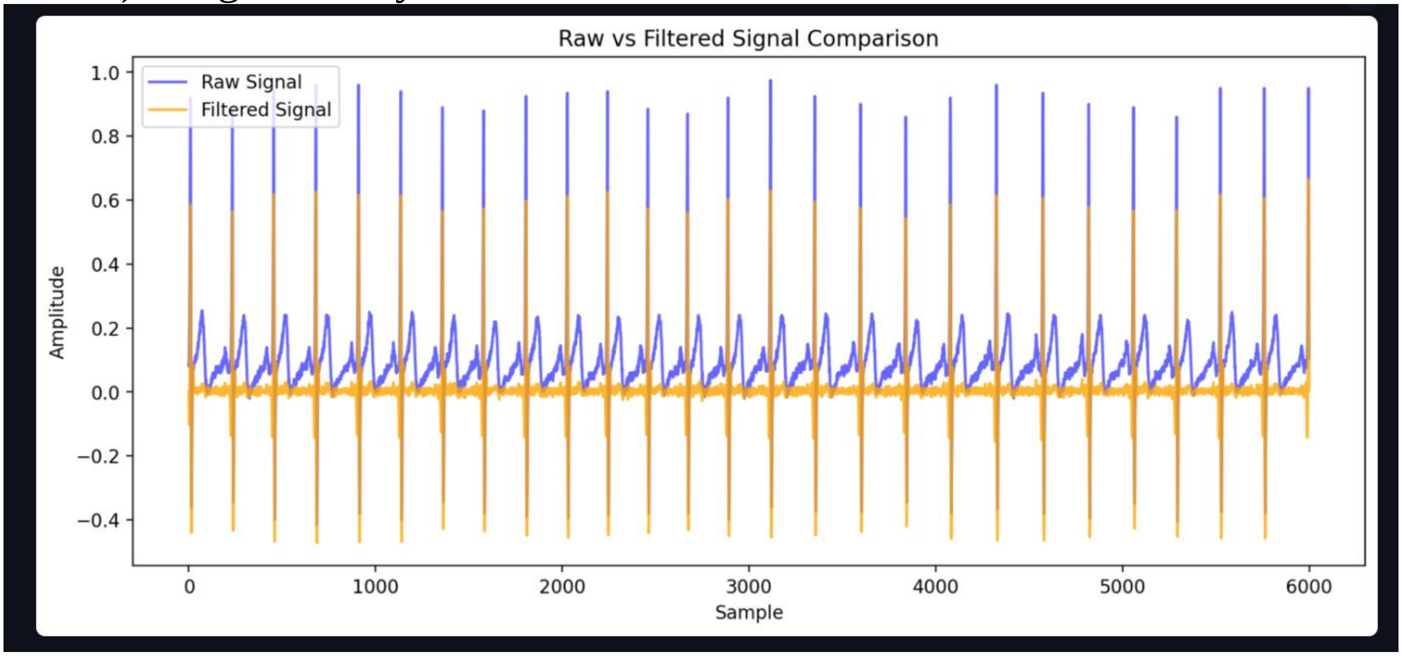
i) Front Page

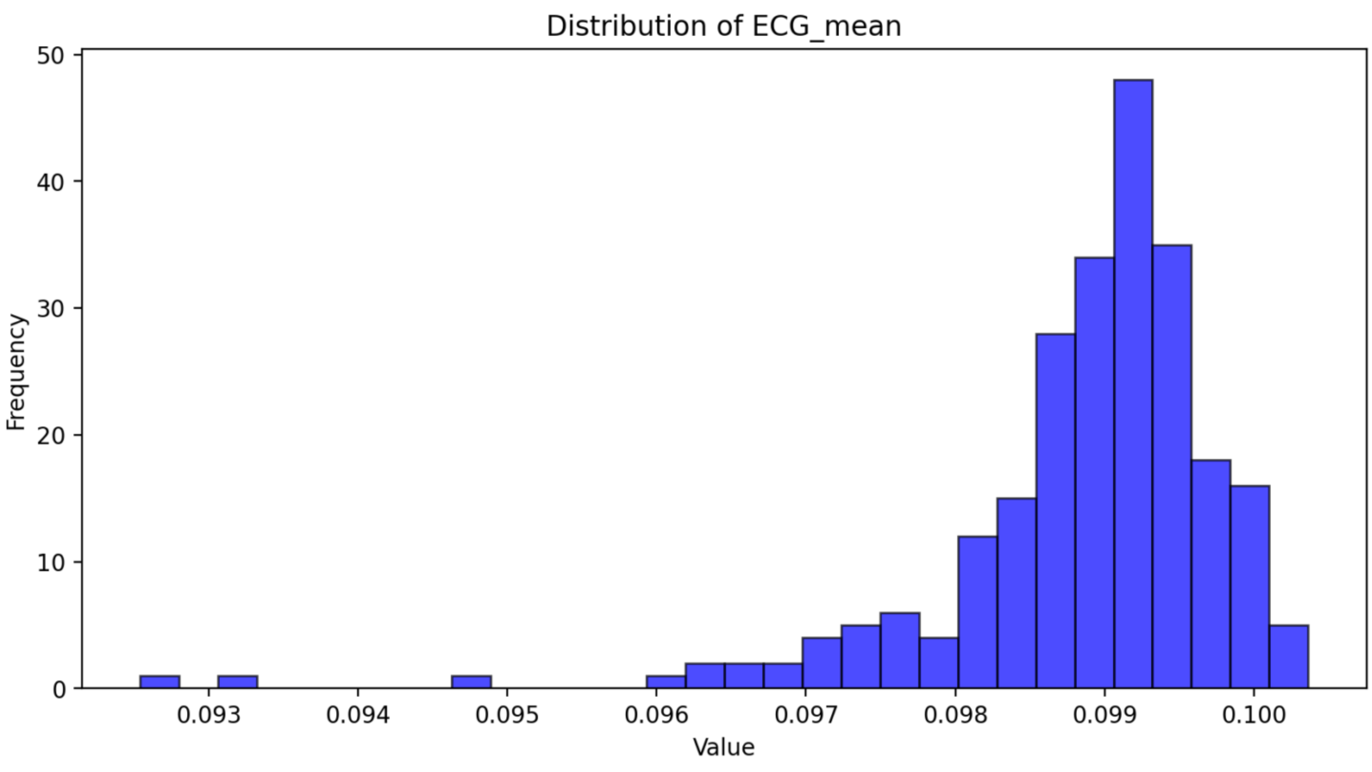


ii) Dashboard



iii) Signal Analysis





iv) Classification Information

2	0.7143	0.5556	0.625	18
3	0	0	0	9
4	0.7333	0.7857	0.7586	14
R	1	0.5	0.6667	4
micro a	0.7956	0.6987	0.744	156
macro	0.3275	0.2837	0.2979	156
weight	0.7167	0.6987	0.703	156
sample	0.7083	0.6656	0.653	156

v) Statistical Analysis

	count	mean	std	min	25%	50%	75%	max
ECG_mean	10274	-0.1329	0.2967	-0.8287	-0.1816	-0.0319	0.0855	0.2755
ECG_std	10274	0.1681	0.058	0.0038	0.1205	0.1695	0.1981	1.2759
ECG_max	10274	0.9875	0.4715	-0.518	0.598	0.886	1.266	7.575
ECG_min	10274	-0.7069	0.3624	-7.08	-0.946	-0.698	-0.445	0.072
ECG_power	10274	0.0325	0.0343	0.00001	0.0148	0.0295	0.0403	1.5721
BP_mean	10274	101.1935	13.9284	-1.2716	94.1931	101.7855	109.5028	327.8915
BP_std	10274	20.3211	6.2383	0.1165	17.1645	19.7727	22.7455	168.7588
BP_max	10274	161.4458	26.6891	-0.3952	144.7511	158.6416	174.1954	547.884
BP_min	10274	69.0483	17.2752	-282.9612	59.9	71.0768	79.1711	190.4292
BP_power	10274	391.7685	162.1677	0.013	290.5754	366.0166	468.6342	4778.084

	count	mean	std	min	25%	50%	75%	max
EEG (C4-A1)_mean	10274	0.0004	0.0085	-0.0254	0	0	0	0.0313
EEG (C4-A1)_std	10274	0.0035	0.0075	0	0	0	0.0035	0.0617
EEG (C4-A1)_max	10274	0.0171	0.037	0	0	0	0.0146	0.2406
EEG (C4-A1)_min	10274	-0.015	0.0348	-0.2345	-0.0095	0	0	0.0076
EEG (C4-A1)_power	10274	0.00004	0.0001	0	0	0	0.00001	0.0021
Resp (sum)_mean	10274	-0.0004	0.0138	-0.2517	0	0	0	0.364
Resp (sum)_std	10274	0.0248	0.1073	0	0	0	0	1.4324
Resp (sum)_max	10274	0.0505	0.2258	0	0	0	0	2.3725
Resp (sum)_min	10274	-0.0488	0.2225	-2.2072	0	0	0	0
Resp (sum)_power	10274	0.0006	0.0056	0	0	0	0	0.3734

IX. CONCLUSION

In this project, a robust ensemble learning framework was developed for multi-label classification of sleep apnea events using physiological signals from the Sleep-EDF database. By extracting both time-domain and frequency-domain features from segmented biosignals, the model effectively captured important physiological patterns indicative of various sleep disorders.

The stacked ensemble approach, combining Random Forest, Multilayer Perceptron (MLP), XGBoost, and LightGBM models under a meta-level Random Forest classifier, demonstrated significant improvements over standalone models. The system achieved a **high accuracy of 93.64%** and a **weighted F1-score of 0.67**, showcasing strong overall predictive performance. Notably, the model achieved high F1-scores across major classes (W, 2, R) while also substantially improving detection rates for underrepresented apnea events such as CAA, CA, and LA.

The success of the ensemble can be attributed to several key factors:

- The diverse learning paradigms captured complementary aspects of the signal data.
- The use of GPU-accelerated models enabled faster convergence and efficient handling of large feature sets.
- Meta-level aggregation through a Random Forest increased overall stability, interpretability, and resilience to overfitting.

Importantly, the model maintained consistent performance across all 17 classes, with only minor recall reductions in the rarest categories (H, HA, 1). This highlights the ensemble's ability to generalize well even under conditions of significant class imbalance — a common challenge in biomedical datasets.

While the system performed strongly overall, some challenges remain, such as occasional misclassification of minority classes and the computational complexity involved in tuning multiple base learners and meta-learners. Future work could focus on:

- Incorporating temporal modeling techniques (e.g., LSTMs or transformers) to better capture sequential dependencies across sleep stages.

- Applying advanced data augmentation strategies to further balance minority classes.

- Exploring lightweight deployment techniques for real-time, wearable-device integration.

In conclusion, the proposed ensemble-based multi-label classification framework represents a powerful and scalable solution for automated sleep apnea detection, offering both high accuracy and strong generalization capabilities across diverse physiological signal patterns.

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