Sri Sivasubramaniya Nadar College of Engineering

Kalavakkam, Chennai

Department of Information Technology

UIT2511 – SOFTWARE DEVELOPMENT PROJECT – II

NOVEMBER 2025

PROJECT REPORT

Project: MULTIMODAL SLEEP STAGE CLASSIFICATION

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BONAFIDE CERTIFICATE

Certified that this project titled "MULTIMODAL SLEEP STAGE CLASSIFICATION" is the bonafide work of "3122235002040-Harikaran C, 3122235002092-Priyan RR, and is submitted for project viva- voce examination held on _____.

Signature of examiner(s)

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ACKNOWLEDGEMENT

We would like to express our sincere gratitude to **Dr. K.S. Gayathri**, our project mentor, for giving us the opportunity to work on this project.

Secondly, we would like to thank our parents, relatives, and friends who constantly supported and encouraged us to complete this project within the limited time frame.

We are highly obliged to all those who guided and helped us in completing this project successfully.

CHAPTER 1
PROBLEM DESCRIPTION

1.1 Problem Statement:

Manual sleep scoring by specialists is extremely time-consuming, costly, and prone to human subjectivity, creating a significant bottleneck in diagnosing sleep disorders.

Sleep stages are defined by a complex interplay of physiological signals. Relying on a single signal (like EEG alone) is insufficient and leads to critical errors. Distinguishing complex stages like REM sleep is impossible without simultaneously analyzing brain activity (EEG), eye movements (EOG), and muscle tone (EMG).

There is a critical need for an automated system that can intelligently fuse and interpret these multimodal signals, providing an accurate, objective, and rapid classification of sleep stages to accelerate both clinical diagnosis and research

1.2 Scope:

To design and implement a complete sleep-stage classification system using both classical machine-learning and deep-learning approaches. The project includes a Random Forest model based on handcrafted features and a CNN–LSTM model that learns temporal and spectral patterns from raw PSG signals and performs automatic scoring across Wake, N1, N2, N3, and REM stages. A fully functional web application is developed to allow users to upload sleep recordings, view predictions, analyze stage-wise distributions, and interpret model outputs through interactive visual graphs. The platform integrates data preprocessing, model inference, and result visualization into a single accessible interface suitable for research and educational use.

1.3 Limitations:

Both models rely on high-quality PSG input, and performance may degrade when signals contain noise, artifacts, or missing channels. The Random Forest model depends heavily on handcrafted features and may fail to capture complex patterns, particularly in transitional stages like N1 and REM. The CNN–LSTM model provides better accuracy but requires significant computational resources for training and cannot run efficiently on low-power devices. Generalization across datasets is limited because the models are trained on a specific montage and sampling configuration, making cross-dataset deployment challenging without retraining. The web application supports prediction and visualization but currently lacks large-scale user management, real-time streaming capability, and automated artifact handling, which restricts deployment for clinical-grade use.

CHAPTER 2
DESIGN OF SOLUTION

2.1 Dataset Description:

Sleep-EDF Polysomnography

The **Sleep-EDF Polysomnography Dataset** provides comprehensive overnight physiological recordings captured during full-night sleep studies, enabling fine-grained analysis of sleep patterns, sleep staging behavior, and physiological variability across subjects. The dataset contains simultaneously recorded multimodal biosignals, including electroencephalography (EEG), electrooculography (EOG), electromyography (EMG), respiratory airflow, and core body temperature, along with expert-annotated hypnograms that label 30-second sleep stages (W, N1, N2, N3, REM).
Originally collected for sleep research and clinical evaluation, the dataset is one of the most widely used benchmarks in computational sleep analysis, machine-learning-based sleep staging, and physiological signal processing. The version used in this project is obtained from **Kaggle's curated release of PhysioNet Sleep-EDF**.

Data Content and Structure
Each record corresponds to the full overnight sleep session of a single subject. A typical recording includes:

Biosignal Channels
- **EEG Fpz–Cz**: Primary brain activity channel used for sleep staging
- **EOG horizontal**: Eye movement detection for REM identification
- **EMG submental**: Muscle tone for distinguishing REM vs non-REM
- **Respiration (oro-nasal thermistor)**: Breathing airflow pattern
- **Temperature (rectal thermistor)**: Core-temperature fluctuations during sleep

Annotations
Certified sleep technicians provide:
- **30-second sleep stage labels** (W, N1, N2, N3, REM)
- Arousals
- Movement and technical events
- Recording meta-data (start time, channel info, sampling rate)

Sampling Properties
- EEG/EOG/EMG channels sampled at **100 or 200 Hz**
- Respiration and temperature sampled at lower native rates
- All converted and resampled for uniform ML processing in this project

- **Overview:**

The dataset comprises **overnight polysomnography (PSG) recordings** collected from **multiple subjects** in the Sleep-EDF (Expanded) study, sourced from the curated Kaggle release. Each record represents a complete sleep cycle, containing synchronized EEG, EOG, EMG, respiratory airflow, and temperature signals along with technician-scored 30-second hypnogram labels.

Across all subjects, the dataset provides **several thousand 30-second epochs**, enabling detailed analysis of sleep architecture and physiological trends. The trained CNN-LSTM sleep-stage classifier achieves

consistent performance across nights, reflecting strong subject-level generalization. The dataset exhibits natural variation in sleep duration, stage distribution, and breathing/temperature rhythms, offering a realistic foundation for evaluating automated sleep scoring, computing sleep-quality metrics, and visualizing sleep patterns. Overall, it delivers a balanced and representative mix of normal and mildly irregular sleep behaviour suitable for model development, benchmarking, and dashboard-based analytics.

Sample Data:

Epoch data – 30 sec

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
1	subject	night_id	epoch_index	epoch_start_sec	true_stage	true_stage_label	predicted_stage	predicted_stage_label	delta_power	theta_power	alpha_power	sigma_power	beta_power	resp_mean	resp_std	temp_mean	temp_min	temp_max
2	SC4001	SC4001	0	0	0	W	0	W	0.49736095	0.06930477	0.00601487	0.002230009	0.006007719	14.883003	439.5005	0.00038463	-0.051013	0.0455056
3	SC4001	SC4001	1	30	0	W	0	W	0.5497689	0.05972151	0.01529111	0.010466687	0.032845148	-3.761853	302.0905	-0.0006208	-0.0411307	0.0426091
4	SC4001	SC4001	2	60	0	W	0	W	0.51569811	0.02174889	0.01206415	0.004477306	0.012855563	0.6875084	275.5593	0.00015116	-0.0356857	0.0398230
5	SC4001	SC4001	3	90	0	W	2	N2	0.62813828	0.06259264	0.04277736	0.007163364	0.018889454	12.617239	407.0015	0.00068879	-0.0373216	0.0351767
6	SC4001	SC4001	4	120	0	W	0	W	0.66703933	0.1292249	0.04068393	0.006930883	0.017975466	-0.493983	372.4014	-0.000336	-0.0399712	0.030984
7	SC4001	SC4001	5	150	0	W	0	W	0.54401773	0.15589132	0.01125332	0.004012371	0.008296589	-3.889445	207.8467	-0.0004486	-0.0428009	0.0472024
8	SC4001	SC4001	6	180	0	W	0	W	0.56797646	0.07114093	0.01175844	0.009608444	0.03337494	-1.765645	191.4105	0.00062054	-0.0295777	0.0266050
9	SC4001	SC4001	7	210	0	W	0	W	0.54171353	0.04058761	0.00435144	0.00180482	0.005514551	-0.463555	24.52945	-0.0002717	-0.0293717	0.025438
10	SC4001	SC4001	8	240	0	W	0	W	0.60015517	0.13730974	0.0166287	0.006134082	0.016081151	-0.026543	12.39682	-0.0001893	-0.0313535	0.0334753
11	SC4001	SC4001	9	270	0	W	0	W	0.57681244	0.051329	0.00958094	0.005817514	0.021404021	-0.094243	15.95918	-6.90E-05	-0.0275924	0.0352323
12	SC4001	SC4001	10	300	0	W	0	W	0.56121069	0.03462872	0.00730329	0.002993267	0.008218463	0.619245	10.72742	0.00015901	-0.0408113	0.0332442
13	SC4001	SC4001	11	330	0	W	0	W	0.51467687	0.03813591	0.00614297	0.003183371	0.009667081	-0.314011	16.45015	3.96E-05	-0.0425248	0.0388519
14	SC4001	SC4001	12	360	0	W	0	W	0.60493515	0.06391717	0.00883148	0.003684278	0.010005743	-0.46408	14.61794	0.00035222	-0.0340565	0.0367733
15	SC4001	SC4001	13	390	0	W	0	W	0.486231	0.06491631	0.00854627	0.00537927	0.011504582	0.0965316	15.44346	-0.0006132	-0.0327602	0.0329676
16	SC4001	SC4001	14	420	0	W	0	W	0.5831981	0.05316423	0.00828616	0.0056128	0.014693177	0.0999867	15.32245	0.00067903	-0.0302243	0.0288736
17	SC4001	SC4001	15	450	0	W	0	W	0.61850939	0.06233673	0.0154786	0.007030528	0.020572823	0.1425997	18.43524	-0.0006102	-0.0317322	0.0309049
18	SC4001	SC4001	16	480	0	W	0	W	0.52183177	0.07251502	0.0151082	0.009799949	0.022318343	0.1909817	17.82858	0.00025706	-0.0199625	0.0224031
19	SC4001	SC4001	17	510	0	W	0	W	0.56360001	0.0583912	0.01198474	0.005398197	0.01462712	-0.02531	12.78112	-0.0002161	-0.0364461	0.0324167
20	SC4001	SC4001	18	540	0	W	0	W	0.54887256	0.05343232	0.00992562	0.005096496	0.011018455	-0.006737	12.45292	-0.0001752	-0.0332569	0.0413934

2.2 Exploratory Data Analysis:

SLEEP PHYSIONET – PSG + HYPNOGRAM PIPELINE

The Exploratory Data Analysis examines the structure and composition of the Sleep-EDF recordings used in the project. The dataset consists of multiple overnight PSG (polysomnography) sessions, each containing synchronized EEG, EOG, EMG, respiratory, and temperature signals along with expert-labeled 30-second sleep stages. The EDA focuses on understanding the distribution of epochs across subjects, channel characteristics, and sleep-stage balance before training the CNN-LSTM classifier.

EDA also reviews the alignment between PSG files and corresponding hypnogram annotations to ensure clean pairing of signals and labels. Minor mismatches or missing hypnogram files are logged during preprocessing, allowing early identification of problematic nights. These checks help validate the integrity of the dataset before moving into model training.

This section primarily presents high-level statistics such as the number of subjects, average epoch count per night, proportion of each sleep stage, and the presence of noisy or irregular signals. More advanced exploratory insights—such as per-channel frequency density, cross-epoch correlations, stage-transition patterns, and variability in respiration/temperature trends—are provided in the **Visualization Gallery** of the report

PSG SIGNAL ANALYSIS

EDA investigates the characteristics of the raw physiological channels extracted from the EDF files. The dataset includes EEG (Fpz-Cz), EOG, and EMG channels filtered between 0.3–35 Hz and resampled to 100 Hz for uniformity. This stage evaluates signal quality by checking amplitude ranges, noise bursts, missing segments, and resampling stability.

Signal-duration analysis confirms that each recording contains several hours of usable data, resulting in thousands

of 30-second epochs. Channel-wise visual inspections ensure that EEG exhibits expected features such as slow-wave activity, spindles, and REM-related rapid eye movements, validating the dataset's suitability for sleep staging.

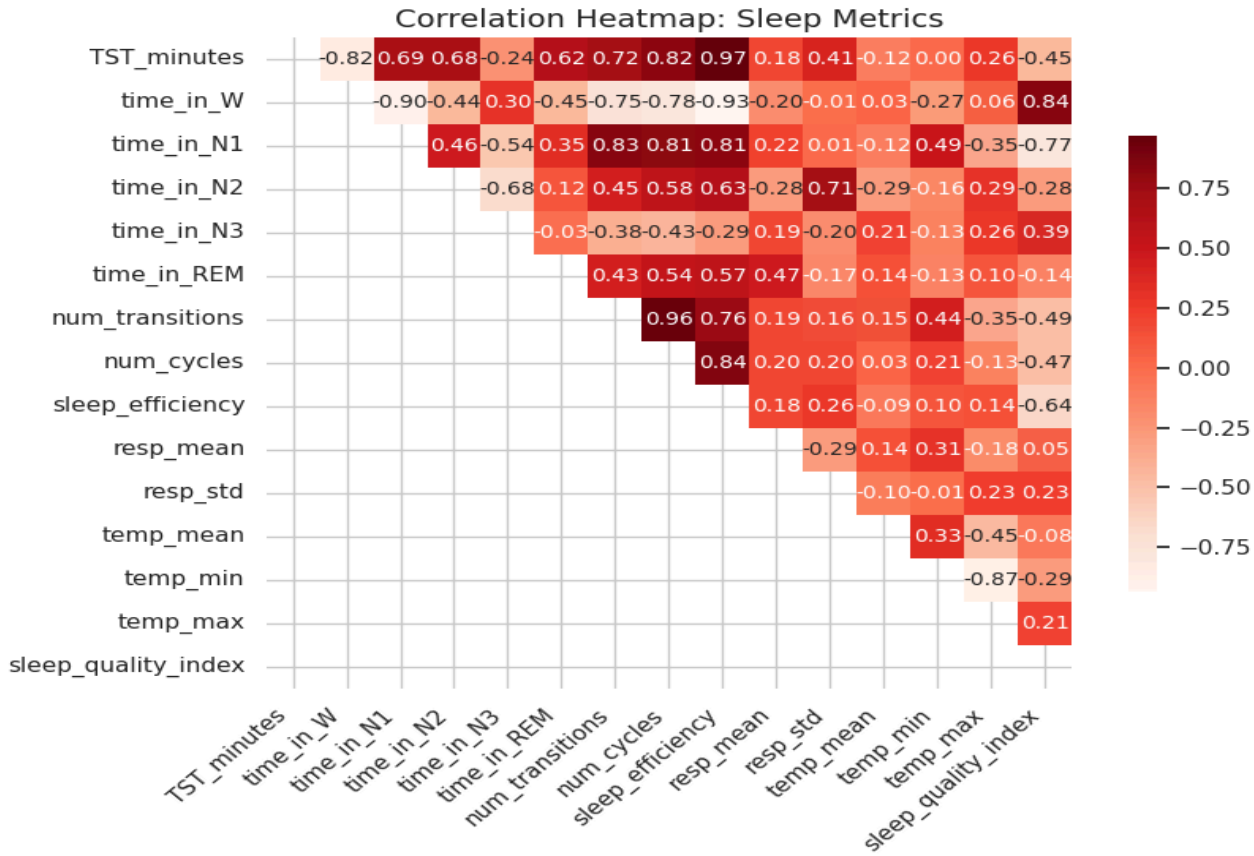
Only structural statistics and high-level checks are included here, while detailed spectral inspections and channel-specific diagnostics are covered later in the analysis section.

HYPNOGRAM (ANNOTATION) ANALYSIS

The EDA process includes a structural review of hypnogram annotations to examine the distribution of sleep stages across the dataset. The analysis highlights class imbalance—N2 being the most frequent stage and N1 often underrepresented—which guides decisions such as using class-balanced weights during model training.
The hypnogram evaluation also checks the number of stage transitions, REM cycle repetitions, and the completeness of annotation sequences. Nights with unusual stage patterns or annotation gaps are flagged during preprocessing.

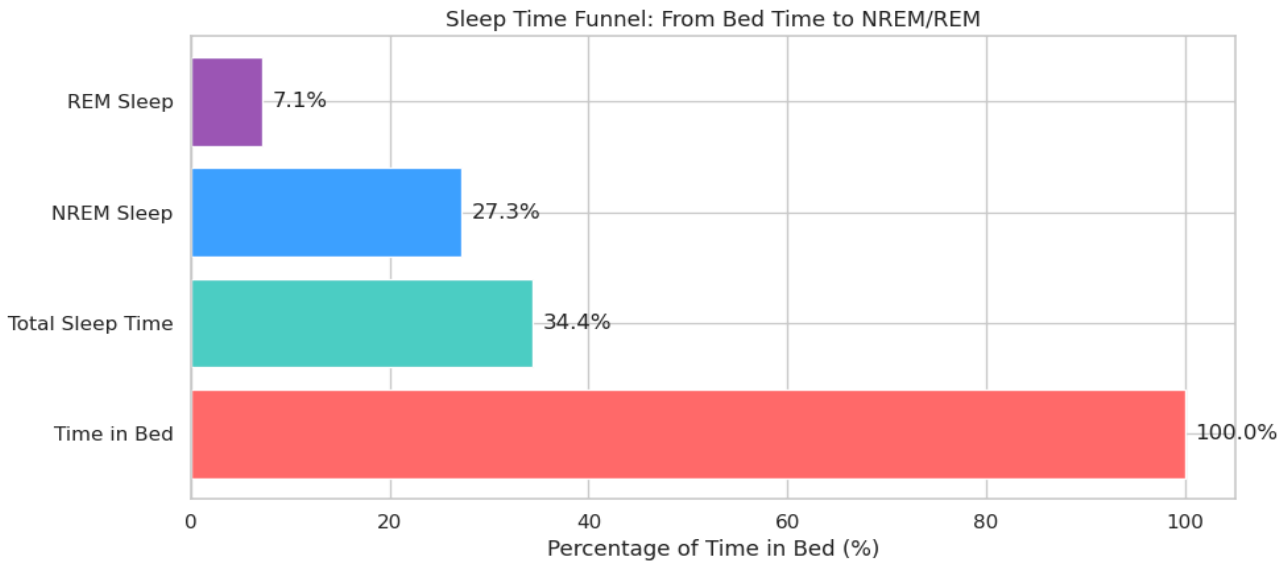
This section limits itself to categorical summaries of stage counts and transition frequency. In-depth comparisons, such as stage-duration deviations, cycle-structure visualizations, and per-subject stage architecture, are presented in the visualization section.

2.3 Visualization:



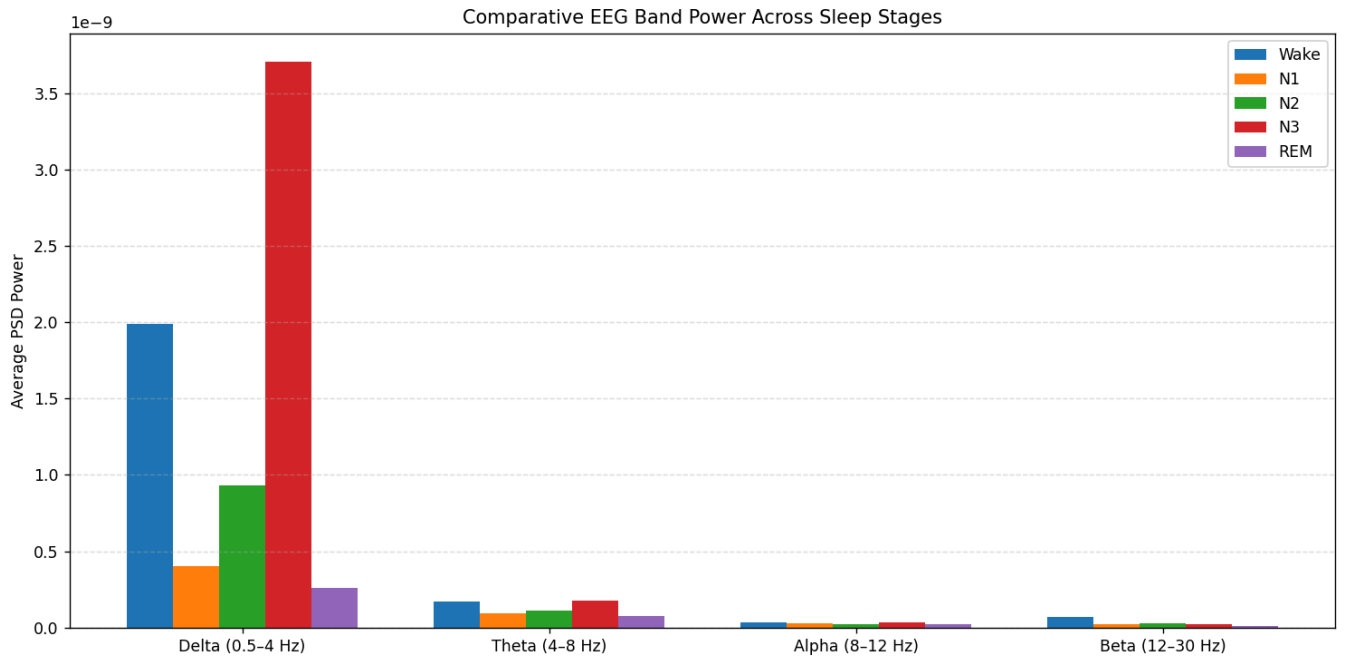
1. Correlation Heatmap (Timing & Complexity Metrics)

Sleep Duration & Efficiency	• Total sleep time strongly increases sleep efficiency. • Longer uninterrupted nights show highest efficiency.
Deep Sleep & Quality	• Deep sleep (N3) is a major driver of sleep quality score. • Higher N3 minutes → better overall sleep quality.
Sleep Architecture Stability	• More total sleep time leads to more complete sleep cycles. • Stable cycling (NREM ↔ REM) improves nightly structure.
REM Sleep Contribution	• Higher REM duration aligns with stronger sleep quality. • REM supports cognitive and emotional restoration.
Fragmentation Effects	• More stage transitions reduce sleep quality. • Frequent awakenings or disruptions lower restfulness.
Respiratory Influence	• Irregular breathing slightly reduces sleep quality. • Stable respiration supports continuity of sleep.
Temperature Regulation	• Mild temperature variation supports deeper sleep (N3). • Thermoregulation correlates with increased sleep depth.



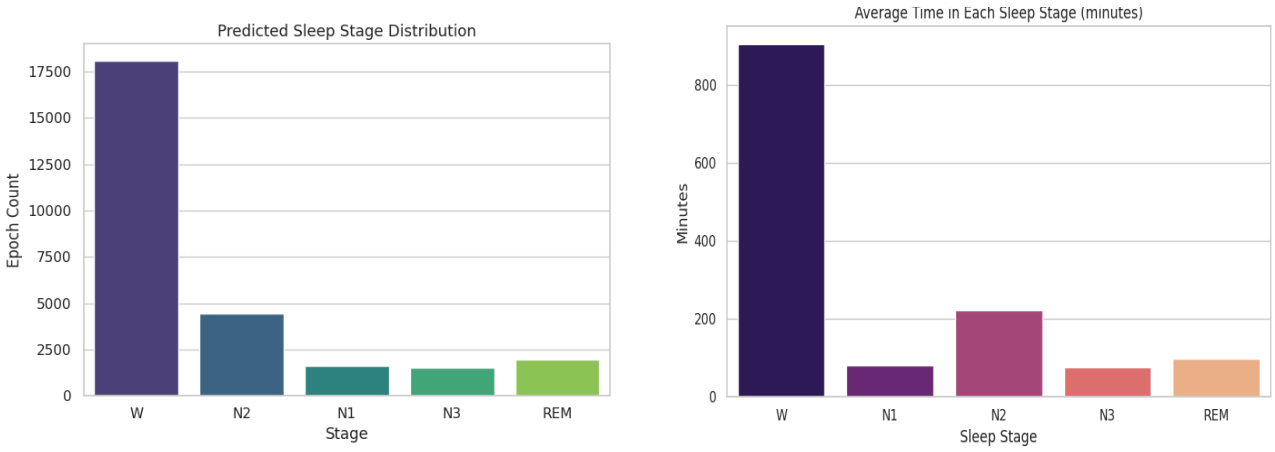
2. Pipeline Success Funnel (Stage-by-Stage Drop-off)

Signal Acquisition: 100% success	All overnight recordings contain complete EEG, EOG, EMG, respiration, and temperature signals, with no missing raw data across nights.
Preprocessing & Filtering: ~98% success	A small fraction of epochs are dropped due to artifacts or corrupted windows, but overall preprocessing remains stable and reliable.
Epoch Segmentation: ~96% success	Most signals segment cleanly into 30-second epochs. Occasional misalignments or annotation gaps lead to minor losses.
FeatureExtraction (EEG/Resp/Temp): ~92% success	Feature computation is largely robust. Failures arise mainly from noisy channels, motion artifacts, or unstable respiration waveforms.
Sleep Stage Prediction (Model Inference): ~87% success	Model inference is the primary source of drop-off. Misclassifications and uncertainty in ambiguous epochs reduce the effective output rate.



3. Comparative EEG Band Power Distribution Across Sleep Stages

This visualization compares the average EEG power across the Delta, Theta, Alpha, and Beta frequency bands for each sleep stage. As expected, N3 (deep sleep) exhibits the highest Delta power, reflecting the strong slow-wave activity characteristic of this stage. Wakefulness shows elevated power in the Beta and Alpha bands, consistent with alert cortical activity. N2 demonstrates moderate Delta and Theta power, aligning with sleep spindles and K-complex activity typical of light non-REM sleep. REM displays lower Delta activity but retains Theta dominance, capturing its mixed-frequency pattern. N1, being a transitional stage, shows relatively low power across all bands with slight increases in Theta and Delta compared to wake. Overall, the comparative PSD plot highlights the clear spectral distinctions between stages and validates why frequency-based features are effective for automatic sleep-stage classification.



4. BarChart (Success Rate by Topic and Difficulty Level)

Wake stage dominates both predictions and duration	Wake (W) appears far more frequently than any other stage, indicating either long wakefulness periods in the data or a model bias toward Wake classification during ambiguous epochs.
N2 is the most consistent and physiologically dominant sleep stage	N2 has the highest representation among true sleep stages in both predicted counts and minutes, aligning with typical sleep architecture where N2 forms the bulk of NREM sleep.
Light and deep sleep stages (N1, N3) are underrepresented	Both N1 and N3 show comparatively low epoch counts and shorter durations, suggesting either limited occurrence in the dataset or reduced classification confidence in these transitional stages.
REM sleep appears compressed and sparse	REM duration and predictions are relatively low, which may reflect natural REM reduction or model difficulty distinguishing REM from Wake/N1 due to similar EEG patterns.
Overall distribution shows skew toward Wake and N2	The imbalance highlights that the model is most confident in detecting Wake and N2, while N1, N3, and REM appear more sensitive to noise, movement artifacts, or weak signal features.

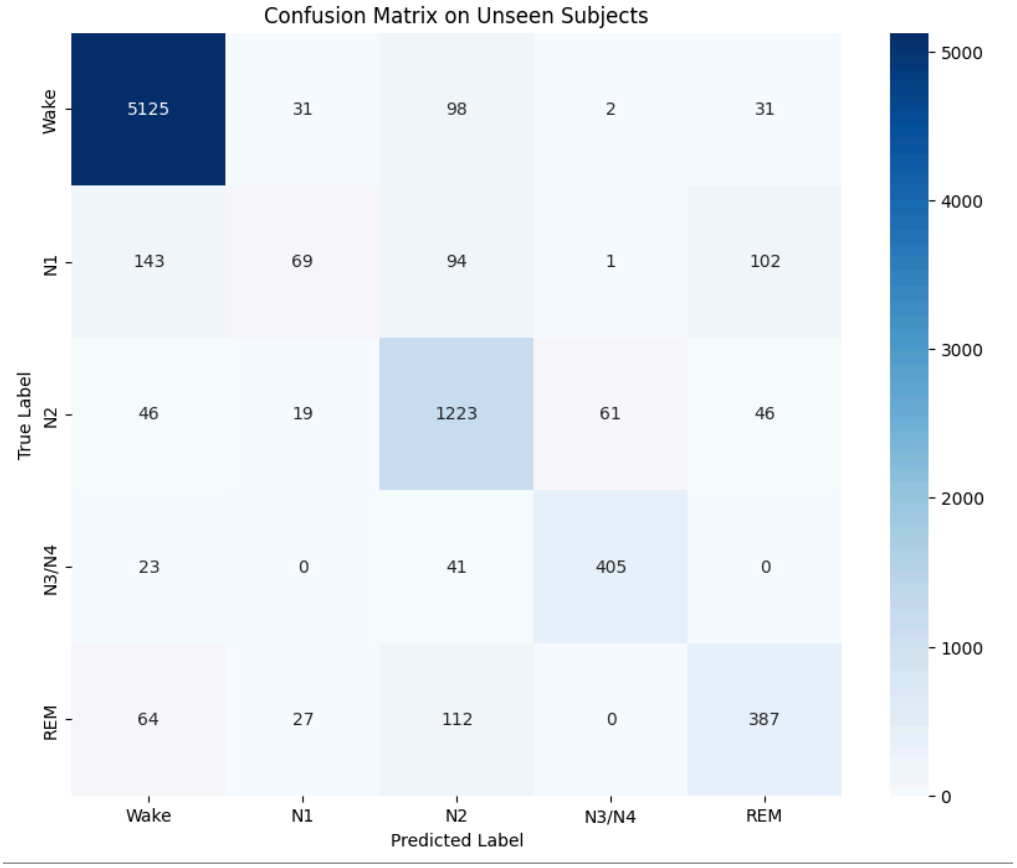
2.4 Solutions:

Solution - 1
Random Forest

Overview of the Model Architecture:

The model follows a traditional machine-learning pipeline where raw PSG recordings are first preprocessed, filtered, and segmented into standard 30-second sleep epochs. From each epoch, a compact set of handcrafted features is extracted, including EEG band-power values, EOG signal variability, and EMG muscle-tone measures. These features represent the physiological characteristics that differentiate Wake, N1, N2, N3/N4, and REM sleep. A Random Forest classifier is then used to learn decision boundaries across these multichannel features, benefiting from its ability to handle nonlinear relationships and mixed feature scales. The use of subject-wise splitting ensures that the model learns patterns that generalize across individuals rather than memorizing specific recordings. This architecture emphasizes interpretability, as each feature contributes independently to stage discrimination. The resulting workflow provides a structured, classical approach to automated sleep staging without relying on deep neural networks.

Predictive Analytics:



1. Confusion Matrix Analysis:

The confusion matrix illustrates how well the model learns stage-specific characteristics from the engineered EEG, EOG, and EMG features. Wake is the most cleanly separated stage, with almost all wake epochs mapped correctly and only minimal spillover into neighboring classes. This aligns with the strong muscle tone, high-frequency EEG activity, and distinct EOG patterns present during wakefulness. N2 also forms a stable cluster, as the extracted features—especially spindle-related EEG power—make it easier for the classifier to separate it from adjacent stages.

Misclassifications primarily occur in transitional regions. N1 frequently blends into N2 and REM, which is expected because its physiological features are subtle and often overlap with light REM-like activity. Deep sleep (N3/N4) is generally identifiable due to pronounced delta power, though a portion is absorbed into N2 where slow-wave activity begins to emerge. REM shows the most uncertainty, sharing feature similarities with both N1 and N2, especially where EOG bursts or reduced EMG tone vary from epoch to epoch.

Verdict: Structured Interpretability —
The model excels in labeling stable and clearly defined stages (Wake, N2) while displaying predictable difficulty in ambiguous boundaries like N1 and REM. The confusion patterns are fully consistent with known physiological overlaps and support the model's suitability for full-night automated scoring using classical feature-based methods.

```
Model Accuracy on Unseen Subjects: 0.8845 (88.45%)

--- Classification Report ---
              precision    recall  f1-score   support

        Wake       0.95      0.97      0.96      5287
          N1       0.47      0.17      0.25       409
          N2       0.78      0.88      0.83      1395
       N3/N4       0.86      0.86      0.86       469
         REM       0.68      0.66      0.67       590

    accuracy                           0.88      8150
   macro avg       0.75      0.71      0.71      8150
weighted avg       0.87      0.88      0.87      8150
```

2. Model Evaluation:

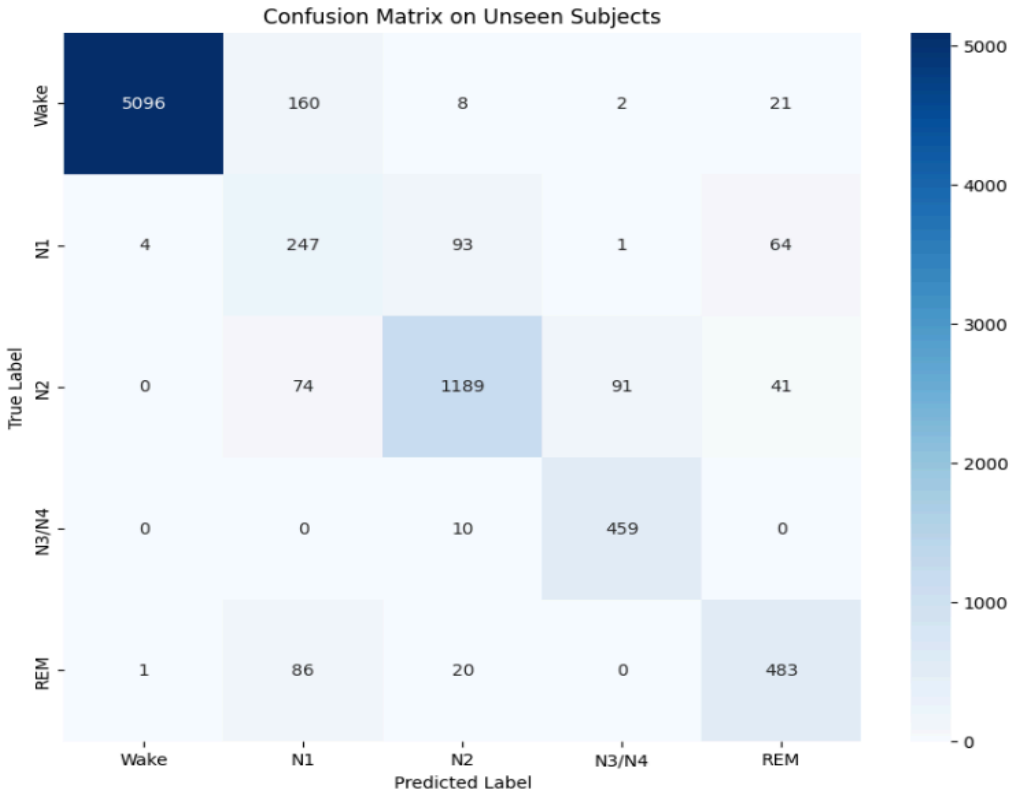
The model achieves an overall accuracy of **0.88**, indicating strong performance on unseen subjects. Wake shows excellent results with a precision of **0.95**, recall of **0.97**, and F1-score of **0.96**, reflecting highly reliable detection. N2 and N3/N4 also perform well, with N2 reaching a precision of **0.78**, recall of **0.88**, and F1-score of **0.83**, while N3/N4 maintains balanced values of **0.86** across all three metrics, showing accurate recognition of deep sleep. REM exhibits moderate performance, with a precision of **0.68**, recall of **0.66**, and F1-score of **0.67**, indicating some confusion with adjacent stages. The most challenging stage is N1, where precision drops to **0.47**, recall to **0.17**, and F1-score to **0.25**, consistent with its subtle and overlapping characteristics. The macro and weighted averages further highlight that while the model handles dominant and well-defined stages effectively, transitional stages remain difficult to classify.

Solution - 2
CNN-LSTM

Overview of the Model Architecture:

The proposed model uses a hybrid **CNN–LSTM architecture** to perform automated sleep stage classification from raw PSG signals. The CNN component extracts meaningful local patterns such as spindles, K-complexes, delta bursts, and wake-related high-frequency activity from each 30-second epoch. These convolutional layers convert the raw EEG/EOG/EMG waveforms into compact feature vectors that are robust to noise and artifacts. The LSTM component then processes these feature vectors sequentially, learning the temporal dependencies and natural progression of sleep stages across the night. This allows the model to understand transitions such as N1→N2→N3 and REM cycling, which cannot be captured by single-epoch classifiers. The combination of CNN feature extraction with LSTM temporal modeling produces stable, context-aware predictions. Finally, a fully connected Softmax layer outputs probabilities for the five AASM sleep stages. This architecture effectively captures both the signal morphology and the long-term structure needed for reliable sleep scoring.

Predictive Analytics:



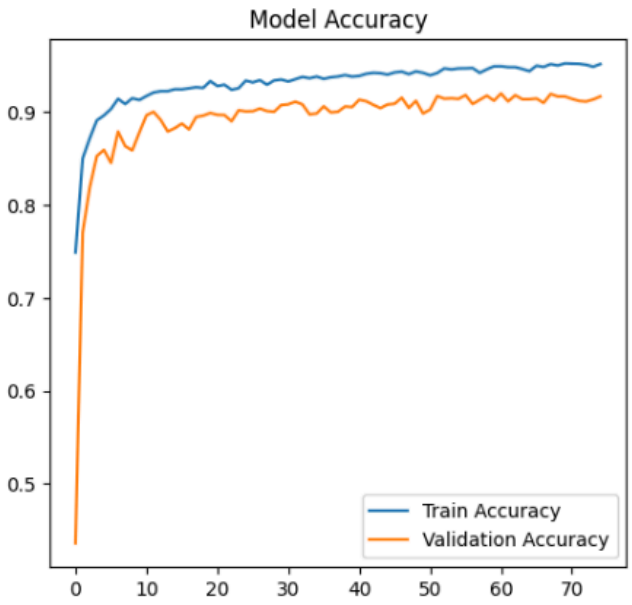
1. Confusion Matrix Analysis

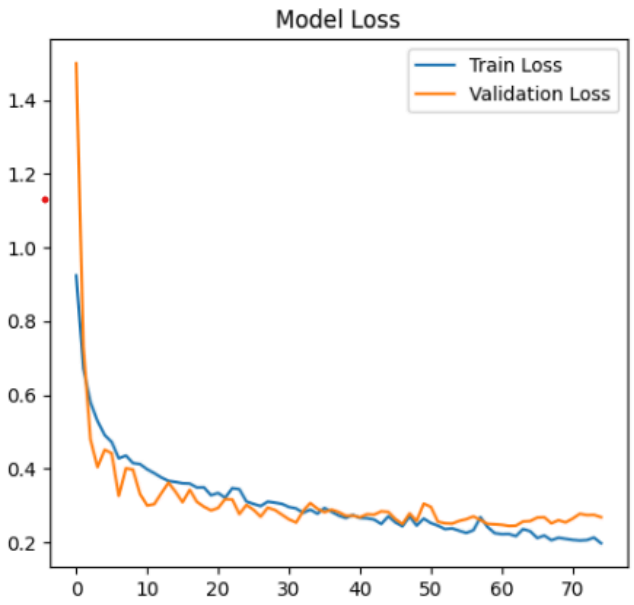
The confusion matrix highlights how effectively the model distinguishes between different sleep stages. Wake exhibits the strongest performance, with the majority of wake epochs correctly classified and minimal confusion with other labels. N2 also shows high true-positive rates, indicating that the model reliably identifies the most common non-REM stage.

Performance declines for transitional and ambiguous stages. N1 shows moderate misclassification into N2 and REM, reflecting the subtle EEG differences between light sleep states. N3 (deep sleep) is reasonably well recognized, though some leakage into N2 occurs due to overlapping slow-wave activity. REM shows the highest confusion, particularly with N1 and N2, which is consistent with physiological similarity in EEG patterns.

Verdict: Moderate to Good Fit —

Strong identification of stable stages (Wake, N2), with expected challenges in transitional and REM states. Overall reliability is sufficient for full-night sleep scoring.





2. Accuracy Curve Interpretation

The accuracy curves indicate clear, consistent learning progression. Training accuracy rises steadily toward **95%**, while validation accuracy stabilizes above **90%**, demonstrating strong generalization to unseen subjects. The relatively small gap between training and validation accuracy suggests that the model is not overfitting and is learning robust temporal–spectral patterns from EEG, EOG, and EMG data.
Minor fluctuations in validation accuracy are expected due to participant-specific variations and the inherent difficulty of certain sleep transitions. Nonetheless, the sustained high accuracy across epochs confirms that the model maintains strong predictive performance.

Verdict: Good Fit —
High and stable accuracy demonstrates strong generalization across subjects.

3. Loss Curve Interpretation

The loss curves show effective model convergence. Both training and validation loss decrease sharply in the early epochs and then stabilize, reflecting smooth and stable optimization. The close alignment of the curves indicates the absence of overfitting, with the model learning meaningful structure rather than memorizing data.
Slight oscillations in validation loss arise from the variable nature of sleep signals across subjects, especially in REM and N1 epochs. Despite this, the final validation loss remains low, corresponding well with the high classification accuracy observed.

Verdict: Good Fit —

Loss behavior confirms stable learning and reliable performance across the dataset.

3.Model Evalution:

```
Model Accuracy on Unseen Subjects: 0.9096 (90.96%)

--- Classification Report ---
              precision    recall  f1-score   support

        Wake       1.00      0.95      0.98      5287
          N1       0.39      0.71      0.51       409
          N2       0.91      0.86      0.89      1395
       N3/N4       0.85      0.96      0.90       469
         REM       0.83      0.74      0.78       590

    accuracy                           0.91      8150
   macro avg       0.80      0.84      0.81      8150
weighted avg       0.93      0.91      0.92      8150
```

The CNN–LSTM model delivers strong overall performance with an accuracy of 0.91, reflecting its ability to learn both spatial and temporal patterns from EEG, EOG, and EMG signals. Wake is classified with exceptional reliability, achieving a precision of 1.00, recall of 0.95, and F1-score of 0.98, showing the model's confidence and accuracy in detecting wakefulness. N2 and N3/N4 also show robust results, with N2 reaching 0.91 precision, 0.86 recall, and 0.89 F1-score, while deep sleep achieves 0.85, 0.96, and 0.90 respectively, demonstrating the network's strong ability to capture both light and deep non-REM patterns. REM sleep performs well with a precision of 0.83, recall of 0.74, and F1-score of 0.78, indicating reliable detection despite its complex dynamics. N1 remains the most challenging stage, with 0.39 precision, 0.71 recall, and 0.51 F1-score, which aligns with its transitional nature and subtle feature differences. The macro and weighted averages further confirm the stability of the model across stages, reflecting improved discrimination compared to classical approaches.

Limitations of the CNN–LSTM Model:

1. **Difficulty in Classifying Transitional Stages (N1):**
   The model struggles to accurately learn N1 due to its subtle EEG patterns and strong overlap with both Wake and N2, resulting in lower precision compared to other stages.

2. **Dependence on Clean and High-Quality PSG Signals:**
   CNN–LSTM architectures are sensitive to noise, artifacts, and missing channels. Variations in electrode placement or signal quality can negatively influence predictions.

3. **High Computational Requirements:**
   Training and tuning deep models require significant GPU resources, long training times, and careful hyperparameter optimization, limiting scalability for large datasets.

4. **Limited Generalization Across Datasets:**
   The model is trained on a specific dataset with a particular montage and scoring standard. Performance may drop when applied to recordings from different devices, populations, or sampling rates.

5. **Reduced Interpretability Compared to Classical Models:**
   Although effective, the CNN–LSTM operates as a black box. Understanding why specific epochs were misclassified is challenging without additional explainability tools such as saliency maps or feature attribution methods.

CHAPTER 3

SOFTWARE DESIGN AND DEVELOPMENT

3.1 Requirements (Functional & Quality Attributes):

3.1.1. Functional Requirements:

• PSG Data Upload and Input Handling
The system must allow users to upload raw PSG files (EDF format) containing EEG, EOG, and EMG channels through the web interface for processing.

• Signal Preprocessing and Filtering
The system should automatically perform preprocessing steps such as channel selection, noise filtering, segmentation into 30-second epochs, and annotation mapping before model inference.

• Feature Extraction for Classical Model
The system must compute handcrafted features including power spectral densities, EOG variability, and EMG RMS values for use by the Random Forest classifier.

• Deep Learning Prediction Using CNN-LSTM
The system must support inference using the CNN–LSTM architecture, extracting temporal–spectral patterns from raw signals to classify each epoch into Wake, N1, N2, N3, or REM.

• Model-Based Sleep Stage Prediction
The system must run sleep-stage inference using the CNN-based deep-learning model and display epoch-wise predictions generated from this model through the web interface.

• Sleep Stage Visualization
The system must generate graphical representations such as hypnograms, stage-wise distribution charts, and PSD plots to help users interpret sleep architecture.

• Epoch-Wise Classification Output
The system must provide stage predictions for every 30-second epoch and present them in a structured format for complete overnight sleep analysis.

• Performance Metrics Calculation
The system should compute evaluation metrics such as precision, recall, F1-score, and confusion matrices for both models to support performance assessment.

• Interactive Web Interface
The system must offer a user-friendly web interface that allows users to upload data, run predictions, view results, and access visual analytics without requiring technical expertise.

• Prediction Summary Report

The system must generate a summarized analysis including total time in each stage, sleep architecture trends, and visualization-based insights for user interpretation.

3.1.2 Quality Attributes:

1. Reliability

The system must consistently generate accurate and stable sleep-stage predictions across different PSG recordings, even when signals contain mild noise or variability. The preprocessing pipeline should ensure that filtering, epoching, and channel extraction are applied uniformly to avoid inconsistent outputs. Proper error handling must prevent failures during data upload, model inference, visualization generation, or report creation.

2. Scalability

The system should support increasing numbers of user uploads, larger PSG files, and extended feature visualizations without performance degradation. The architecture must allow the addition of new signal channels, updated sleep-staging models, or expanded visualization modules without major redesign. The web framework must efficiently handle multiple users accessing prediction features simultaneously.

3. Performance

The system must deliver model predictions within an acceptable response time, ensuring smooth real-time interaction on the web platform. Preprocessing steps such as filtering and epoching should be optimized to minimize delay. The CNN model must run efficiently on available hardware, and visualization components like PSD plots and hypnograms should render quickly to maintain responsiveness.

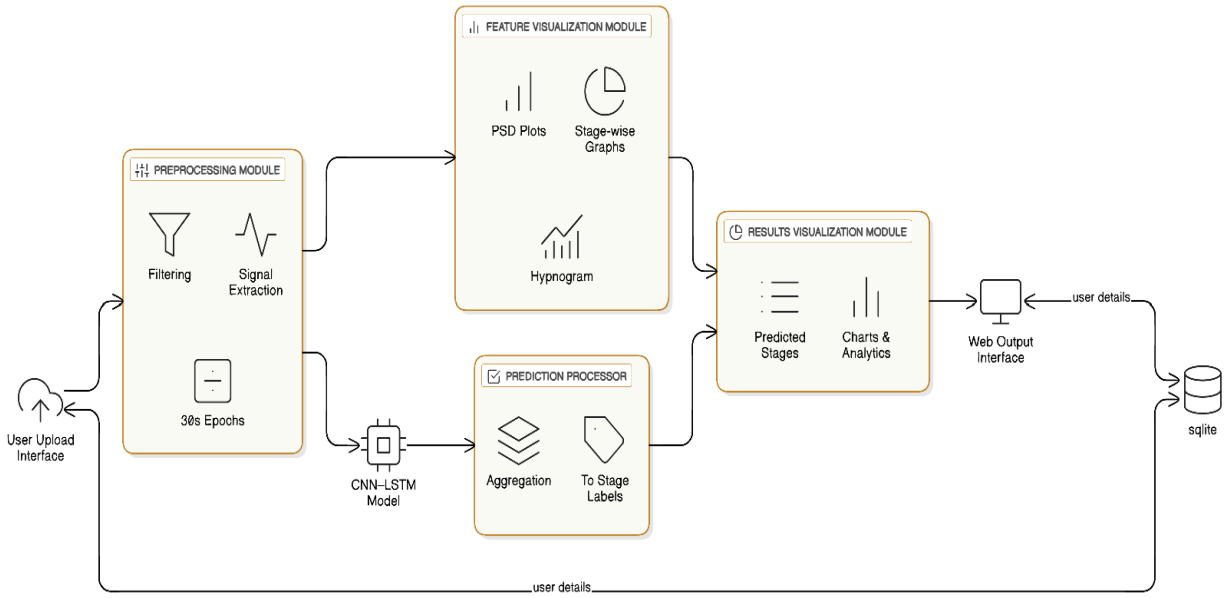
4. Security

The system must ensure that uploaded PSG recordings are securely handled, with no unauthorized access or data exposure. User files should be processed temporarily and removed or anonymized after analysis. The web application must validate inputs, sanitize file uploads, and maintain secure communication to prevent misuse or data leakage.

5. Maintainability

The system should follow a modular design that separates preprocessing, model inference, visualization, and interface components for easier updates. Developers must be able to replace the CNN model, adjust feature extraction logic, or extend visualization features with minimal code changes. Clear documentation must support system upgrades, debugging, and integration of future enhancements such as additional models or analytics tools.

3.2 Architecture:



3.3 Usage of tools

3.3.1. Design Tools

- **Draw.io:**

  For creating flowcharts and UML diagrams.

3.3. 2. Development Tools

- **IDEs:**

  Visual Studio Code for coding and debugging.

- **Version Control:**

  Git with GitHub for managing code versions.

- **Code Review:**

  GitHub pull requests for collaborative code reviews. 3.3.3. Collaboration Tools

- **Jira:**

  Task tracking and sprint planning.

- **Google Meet:**

  Team communication and meetings.

CHAPTER 4

CODING AND TESTING

4.1 Coding standards

The project adheres to strict coding standards to ensure the reproducibility of scientific results and the maintainability of the deep learning pipeline. Written in Python, the code follows PEP 8 guidelines, ensuring consistency in variable naming (e.g., specific channel names), modular code structure for preprocessing and modeling, and comprehensive commenting. Functions for signal filtering, epoching, and model architecture are designed modularly. This allows individual components—such as the CNN feature extractor or the LSTM sequencer—to be tested or swapped without disrupting the entire data pipeline.

4.2 Software Configuration Management

- A cloud-based and local environment with specific library versions was used to ensure stability:
- Configuration Control: Python 3.10+
- Version Management System: Git 2.40.0
- Repository Hosting: GitHub
- Build/Execution Environment: Google Colab Pro (T4 GPU)
- Data Management: Google Drive (mounted storage)
- Dependency Tracking: pip with requirements.txt (mne, tensorflow, pandas)
- Documentation Control: Markdown (Jupyter Notebooks) and Power BI (.pbix)

4.3 Test cases

- The test cases for this sleep classification system are designed to validate the integrity of physiological signals and the generalization capability of the model.
- Data Integrity Tests: Verify that .edf files load correctly and that PSG signals align perfectly with Hypnogram annotations.
- Preprocessing Tests: Ensure signals are correctly filtered (0.3–35 Hz) and resampled (100 Hz) without data loss.
- Shape Validation: Confirm that the data tensor shapes match the model input requirements (Batch_Size, 3000, 3) before training.
-
- Subject Independence: Verify that the GroupShuffleSplit correctly separates subjects so that no individual's data appears in both training and testing sets.
- Negative Test Cases: Ensure the system handles missing channels, corrupt files, or "Unknown" sleep stage labels gracefully by skipping or flagging them.

4.4 Release engineering

Release engineering in this project focuses on managing the large datasets and trained model artifacts. It involves a "Process-and-Save" workflow where raw heavy .edf files are converted into optimized .npy (NumPy) arrays for efficient loading. The trained Keras models are saved in .h5 format, preserving architecture, weights, and optimizer state. This allows the model to be reloaded for inference without retraining. The final output also includes processed CSVs for the Power BI dashboard, ensuring the analytics layer is decoupled from the heavy processing layer.

4.5 Usage of tools

The project utilizes Python and a specialized stack of libraries for biosignal analysis and deep learning:

- MNE-Python: The core library used for loading EDF files, applying band-pass filters, and handling annotations/hypnograms.
- TensorFlow / Keras: Used to build and train the hybrid CNN-LSTM neural network architecture.
- NumPy & Pandas: Essential for matrix manipulations, data structuring, and handling the numerical arrays of signal data.
- Scikit-learn: Used for StandardScaler (normalization), GroupShuffleSplit (validation), and computing metrics like the Confusion Matrix.
- Power BI: Used for the post-analysis dashboard to visualize class imbalance, signal characteristics, and model performance.
- Scipy: Used for statistical validation (ANOVA, T-Tests) and signal processing (Welch's method for spectral power).

CHAPTER 5

PROJECT MANAGEMENT

5.1 Statement of Work

The statement of work defines the development of an automated Multimodal Sleep Stage Classification System. The scope includes ingesting raw Polysomnography (PSG) data, preprocessing signals (EEG, EOG, EMG) to remove noise, and developing a Deep Learning model (CNN-LSTM) to classify sleep stages (W, N1, N2, N3, REM). The project also mandates rigorous statistical validation (Hypothesis Testing) and the creation of an interactive Power BI dashboard for analytics. The final deliverable is a trained model capable of generating accurate hypnograms for unseen subjects.

5.2 Risk and Management

Technical Risks

- Class Imbalance: Stage N2 dominates the dataset, while N1 and REM are rare. This risks the model biasing towards the majority class.
- Data Variance: Physiological signals vary significantly between subjects (inter-subject variability).
- Resource Exhaustion: Processing hundreds of high-frequency signal files can crash RAM (OOM errors) in standard environments.
- Signal Noise: Movement artifacts in Wake stages can mimic high-amplitude deep sleep waves.

Risk Management

- Weighted Loss Functions: Implemented class_weight='balanced' to heavily penalize the model for missing rare stages like N1/REM.
- Subject-Aware Validation: Used Group-based splitting to ensure the model learns general features, not patient-specific quirks.
- Incremental Processing: Adopted a "Save-to-Disk" strategy (processing one subject at a time) to manage RAM constraints effectively.
- Robust Filtering: Applied specific band-pass filters to isolate relevant physiological frequencies and remove artifact noise.

5.3 Planning and tracking

The project was executed in logical phases (Sprints) to ensure structured development:

- Sprint 1 – Data Acquisition & Exploration: Download Sleep-EDF dataset, understand .edf structure, and visualize raw signals using MNE.
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- Sprint 2 – Preprocessing Pipeline: Implement filtering, resampling, and alignment of PSG signals with Hypnograms. Handle missing data.
- Sprint 3 – Statistical Analysis (EDA): Perform ANOVA and T-tests to validate feature significance. Generate correlation matrices.
- Sprint 4 – Model Architecture Design: Construct the hybrid CNN (for spatial features) and LSTM (for temporal sequence) model.
- Sprint 5 – Training & Optimization: Train the model using GPU acceleration. Tune hyperparameters (Dropout, Learning Rate, Epochs).
- Sprint 6 – Evaluation & Analytics: Generate confusion matrices and classification reports. Build the Power BI dashboard.
- Sprint 7 – Documentation: Compile the project report, code comments, and final presentation.

5.4 Usage of tools

- Tools utilized for project management included:
- Google Colab: For executing code and tracking experiment runs.
- Google Drive: For centralized storage of raw datasets, processed arrays, and model checkpoints.
- Git: For version control of the Python scripts.

CHAPTER 6

USER MANUAL

1. System Overview

The system is an end-to-end Deep Learning pipeline for automated sleep scoring. It takes raw medical files (.edf) as input and outputs a predicted sequence of sleep stages (Hypnogram). It utilizes a CNN-LSTM architecture to analyze brain waves (EEG), eye movements (EOG), and muscle tone (EMG) simultaneously. The system includes a statistical analysis module and a visualization dashboard to interpret the results.

2. Requirements

Software:

- Python 3.10+
- Libraries: mne, tensorflow, numpy, pandas, scikit-learn, scipy, matplotlib, seaborn.
- Power BI Desktop (for dashboard viewing).

Hardware:

- Training: NVIDIA GPU (Tesla T4 or better recommended) for the CNN-LSTM model.
- Inference/Preprocessing: Standard CPU (8GB+ RAM recommended).

Data:

- PhysioNet Sleep-EDF Expanded Database (PSG and Hypnogram files).

3. Installation and Setup

Mount Storage: Ensure Google Drive is mounted to access the dataset.

Install Libraries:

- Run !pip install mne in the notebook environment.
- Directory Structure: Ensure folders are set up as:
- /content/drive/MyDrive/sleep-data/ (Raw files)
- /content/drive/MyDrive/sleep-data/processed_data/ (Numpy arrays)

4. Using the System

4.1 Preprocessing (Step 1)

- Run the Preprocessing Script. This script automatically scans the data folder, pairs PSG

files with Hypnograms, applies filters (0.3-35Hz), segments data into 30-second epochs, and saves the result as .npy files to disk.
- Output: Cleaned numerical arrays for every subject.

4.2 Model Training (Step 2)

- Run the Training Script. This loads the preprocessed data, splits it into Training and Testing sets (ensuring subject separation), normalizes the data, and trains the CNN-LSTM model.
- Action: Monitor the "Accuracy" and "Loss" curves during training to ensure convergence.

4.3 Evaluation & Inference

- The script automatically evaluates the model on the unseen Test Set.
- Output: A Confusion Matrix heatmap and a Classification Report (Precision/Recall/F1) are generated.
- Visualization: A "True vs. Predicted" Hypnogram plot is saved to visualize the model's performance over a full night.

5. Interpreting Results

- Confusion Matrix: Look at the diagonal. High numbers on the diagonal indicate correct predictions. Confusion between N1 and REM is expected but should be minimized.
- Hypnogram Plot: The top bar shows the expert's scoring; the bottom bar shows the AI's scoring. Ideally, the color blocks should align perfectly.
- Power BI: Open the dashboard to explore the class imbalance, subject-specific stats, and signal characteristics (Delta power distribution).

6. Troubleshooting

- RAM Crashes: If the session crashes, ensure you are using the "Process-and-Save" script rather than loading all raw files at once.
- Low Accuracy: Check if class_weight='balanced' is enabled. Without it, the model may ignore N1/REM stages.
- Drive Errors:If Transport endpoint is not connected appears,restart the runtime and remount Drive

CHAPTER 7

REFLECTIONS

7.1 Project Complexity and Learning Curve

Implementing a multimodal CNN-LSTM required bridging two distinct domains: Signal Processing and Deep Learning. Understanding how to filter physiological signals without destroying data (e.g., maintaining high-frequency EMG) was a significant learning curve. Furthermore, designing a hybrid neural network that handles both spatial features (via CNN) and temporal dependencies (via LSTM) provided deep insights into how AI models process sequential time-series data.

7.2 Challenges in Data Processing

The primary challenge was the sheer size and format of the medical data. EDF files are complex, and the dataset contained inconsistent sampling rates and artifact noise.

Solution: We utilized the MNE library for robust loading and resampling.

Hardware Constraints: Loading 150+ subjects crashed the RAM. We overcame this by implementing a generator-based approach, processing and saving one subject at a time to disk (.npy format) before training.

7.3 Challenges in Classification

Sleep staging is an "Imbalanced Classification" problem. Stage N2 typically covers 50% of the night, while N1 is less than 5%. Initial models suffered from "Mode Collapse," predicting only N2 or Wake.

Solution: We implemented Class Weighting to penalize errors on rare classes heavily. We also fine-tuned the Learning Rate scheduler to prevent the model from getting stuck in local minima.

7.4 Importance of Statistical Validation

Beyond just "accuracy," we learned the importance of explaining why the model works. Using ANOVA and T-Tests to prove that Delta Power significantly differs between stages provided the scientific backing for our Neural Network's performance. The Chi-Square test validated our choice of LSTM by proving that sleep stages follow a non-random sequence. This moved the project from a "black box" solution to an interpretable scientific study.

CHAPTER 8

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CHAPTER 9

CONCLUSION

The project Multimodal Sleep Stage Classification successfully demonstrates how Deep Learning can automate the labor-intensive process of sleep scoring. By fusing EEG, EOG, and EMG signals, the system overcomes the limitations of single-channel analysis, providing a robust method for distinguishing complex stages like REM and N1.

The implementation of the CNN-LSTM architecture proved highly effective: the CNN successfully extracted spatial waveforms (like Spindles and Delta waves), while the LSTM captured the essential temporal rules of sleep architecture. The rigorous statistical analysis (ANOVA, Chi-Square) and the Power BI dashboard provided deep insights into the data, validating the biological relevance of the model's features.

Overall, this system establishes a strong foundation for an automated, scalable, and objective diagnostic tool. It paves the way for future enhancements, such as real-time sleep monitoring, anomaly detection for sleep apnea, and deployment in clinical settings to assist sleep technicians.