Sleep Disorder Detection Model

Minor project report submitted in partial fulfilment of the

requirements for the degree of

Bachelor of Technology

in

Computer Science & Engineering

by

Eikansh (2022UCP1570)
Manya Gupta (2022UCP1034)

under the supervision of

Dr. Lavika Goel

December, 2025

Department of Computer Science & Engineering
Malaviya National Institute of Technology Jaipur,
Jaipur, Rajasthan, India

Department of Computer Science & Engineering
Malaviya National Institute of Technology Jaipur

Supervisor's Certificate

This is to certify that the project report titled **Sleep Disorder Detection Model** is being submitted by **Eikansh (2022UCP1570), and Manya Gupta (2022UCP1034)** , is a record of original research carried out by them under my supervision and guidance in partial fulfillment of the requirements of the degree of Bachelor of Technology in Computer Science & Engineering. Neither this report nor any part of it has been submitted earlier for any degree or diploma to any institute or university in India or abroad.

Dr. Lavika Goel

Department of Computer Science & Engineering,
Malaviya National Institute of Technology Jaipur,
JLN Marg, Jaipur, Rajasthan 302017, INDIA

Acknowledgement

We express our sincere gratitude to our project guide for their invaluable guidance and support throughout this project. We would like to thank the Department of Computer Science and Engineering at Malaviya National Institute of Technology Jaipur for providing the necessary computational resources and laboratory facilities. Special thanks to the IEEE study on sleep-disorder detection community and researchers in the field whose groundbreaking work formed the intellectual foundation for this research. We also acknowledge the support of our peer reviewers and colleagues who provided constructive feedback during the development of this framework.

Place: MNIT, Jaipur

Date : December 5, 2025

Signature of students

(2022UCP1570)

(2022UCP1034)

Declaration of Originality

We hereby declare that this work entitled **Sleep Disorder Detection Model** presents our original work carried out as a under graduate student of MNIT Jaipur and, to the best of our knowledge, contains no material previously published or written by another person, nor any material presented by us for the award of any degree or diploma of MNIT Jaipur or any other institution. Any relevant material taken from the the work of others (whether published or unpublished) has been properly acknowledged and referenced in accordance with the institute's guidelines.

Place: MNIT, Jaipur

Date : December 5, 2025

Signature of students

(2022UCP1570)

_____

(2022UCP1034)

_____

Abstract

Sleep is an essential criterion for health. However, sleep disorders degrade the sleep quality. Hence, to diagnose sleep disorders, sleep monitoring is crucial. The cyclic alternating patterns (CAP) phases describe the sleep quality. However, CAP detection is a time-consuming, hectic, and uncertain process. Therefore, an automatic detection of CAP phases is necessary. This study proposes a hierarchical approach to identify sleep disorders and classify CAP phases. Single-channel EEG recording provided by the CAP sleep database has been utilized in this study. The proposed approach classifies CAP sequence into healthy or unhealthy.

Further, it identifies sleep disorder of unhealthy sequence among periodic leg movement (PLM), rapid eye movement behaviour disorder (RBD), nocturnal frontal lobe epilepsy (NFLE), narcolepsy (NARCO), and insomnia (INS). Further using our prior work, the CAP phase of the sequence can be identified. The best model was obtained by long short-term memory (LSTM) along with convolutional neural network (CNN) for healthy-unhealthy, and disease classification with an accuracy of 91.45% and 90.55%, respectively. The same models gave an accuracy of 92.79% for healthy-unhealthy and 93.31% for disease classification when evaluated using dataset of only phase B, highlighting the importance of phase B for identifying sleep disorders.

Keywords: KW_1; KW_2; KW_3; KW_4; KW_5

Contents

List of Figures

List of Tables

Chapter 1
Introduction

1.1 Introduction

Sleep disorders affect millions of people worldwide and can lead to serious health, cognitive, and behavioral problems if not detected early. Disorders such as Insomnia, Narcolepsy, REM Sleep Behavior Disorder (RBD), Periodic Limb Movement (PLM), and Nocturnal Frontal Lobe Epilepsy (NFLE) often exhibit overlapped symptoms, making manual diagnosis difficult. Traditionally, diagnosis requires overnight polysomnography (PSG) followed by EEG analysis, which is slow, expensive, and prone to subjective interpretation.

Recent advances in deep learning have shown significant promise in automating sleep-disorder detection. In particular, the IEEE Access article *“A Hierarchical Approach for the Diagnosis of Sleep Disorders Using Convolutional Recurrent Neural Network (CRNN)”* highlights how spatial spectral features (via CNN) and temporal dependencies (via LSTM) can be combined to improve diagnostic accuracy. Inspired by this work, our project develops a hierarchical CRNN-based model capable of detecting sleep disorders from single-channel EEG signals.

The project follows an end-to-end pipeline that includes data preprocessing, CAP-aligned segmentation, feature extraction using CNN–BiLSTM models, and a two-stage classification framework. Stage 1 classifies the EEG segments as Healthy or Disordered, while Stage 2 identifies the specific type of disorder. This design improves sensitivity, reduces deordering, and captures critical EEG micro-events such as spindles, K-complexes, and micro-arousals that are strongly associated with sleep abnormalities.

1.2 Objectives

The primary objective of this project is to build an automated, reliable, and interpretable sleep-disorder detection model using EEG data. The specific goals are the following:

- Preprocess and segment EEG signals using standard filters and CAP-aligned windows.
- Implement an end-to-end 1D CRNN architecture for spatial–temporal feature learning.
- Design a two-stage hierarchical classifier capable of distinguishing Healthy vs. Disordered EEG, followed by disorder-type classification.
- Incorporate CAP (Cyclic Alternating Pattern) metrics to better capture sleep instability associated with various disorders.
- Evaluate performance using accuracy, sensitivity, specificity, and class-wise metrics.

Overall, the objective is to create a framework that mirrors physiological sleep mechanisms, enhancing clinical reliability, and reduces dependency on manual feature engineering.

1.3 Motivation

Manual EEG interpretation is a time-consuming and expertise dependent task. Disorders such as PLM, NFLE, and RBD often share similar EEG patterns, making differentiation especially challenging. Moreover, sleep micro-events like spindles, K-complexes, and CAP A/B phases require precise observation, increasing cognitive load on clinicians.

The motivation behind this project is to leverage deep learning to automate this process, reduce human error, and provide early, accessible screening for sleep-related conditions. By building a hierarchical deep-learning system inspired by the IEEE Access methodology, this project aims to make sleep-disorder evaluation faster, more accurate, and more scalable.

Manual analysis becomes difficult during:

- Large scale sleep-study evaluations
- Differentiation of visually similar disorders (eg PLM vs. NFLE)
- Continuous monitoring or long-hour EEG recordings

Automated deep-learning–based detection helps by:

- Reducing dependency on handcrafted features
- Improving diagnostic accuracy and consistency
- Providing faster screening provision for clinicians
- Capturing subtle micro events through data driven learning

Chapter 2
Overview of Tools & Technologies Used

2.1 Dataset Used

The experiments in this project are conducted on the **Cyclic Alternating Pattern (CAP) Sleep Database**, a publicly available and clinically validated repository widely used for sleep research. The dataset provides multi-channel PSG recordings, expert annotations, and detailed CAP scoring, making it highly suitable for automated sleep disorder detection.

2.1.1 Dataset Description

- **Source:** Sleep Disorders Center, Ospedale Maggiore (Parma, Italy).
- **Total Recordings:** 108 full-night polysomnographic (PSG) recordings.
- **Channels:**
  - At least 3 EEG channels (100–200 Hz sampling rate)
  - EOG (Left/Right)
  - EMG (chin and tibial)
  - Respiratory channels (airflow, thoracic/abdominal movement, SaO_2)
- **Subjects:**
  - 16 healthy individuals (control group)
  - 92 patients with sleep disorders
- **Disorder Distribution:** Includes subjects diagnosed with:
  - Nocturnal Frontal Lobe Epilepsy (NFLE)
  - REM Sleep Behavior Disorder (RBD)
  - Insomnia
  - Narcolepsy

  - Periodic Limb Movement (PLM)
  - Bruxism
  - Sleep-disordered breathing

2.1.2 Annotations & Labels

- **Sleep Macrostructure:** Expert-scored hypnograms with Wake, NREM stages (N1, N2, N3), and REM.
- **CAP Scoring:** Cyclic Alternating Pattern phases annotated according to standard rules:
  - A-phase (A1, A2, A3 subtypes)
  - B-phase
- **Disorder Labels:** Each recording includes subjectwise diagnosis for categorization tasks.

2.1.3 Why the CAP Database is Ideal

- Contains both control and multiple disorder types which is suitable for multi-class categorization tasks.
- Includes micro-structure annotations (CAP phases) which is essential for modeling sleep instability.
- High-quality PSG data recorded in a clinical environment which is reliable for deep learning.
- Rich multimodal channels enable future extension beyond EEG.

2.1.4 Dataset Preparation

1. **Data Acquisition:** Extracted EEG/PSG signals for all subjects, focusing on single-channel EEG for CRNN-based modeling.
2. **Preprocessing Steps:**
   - **Cleaning:** Band-pass filtering (0.5–40 Hz) to remove artifacts.

- **Segmentation:** 30-second epochs aligned with sleep scoring.
- **Labeling:** Each segment is assigned its disorder label + CAP A/B phase.
- **Normalization:** Amplitude standardization to unify the scale.
- **Dataset Splitting:** Balanced train/validation/test sets to avoid class bias.

Subjects		Phase A				Phase B	Total	
		A1	A2	A3	Total			
Healthy		4654	1551	2847	9052	62880		71862
Unhealthy	Insomnia	2932	1660	4162	8754	47055	55809	794922
	Narcolepsy	2958	1593	4255	8806	45330	54136	
	PLM	3990	2989	7670	14649	67080	81729	
	RBD	11230	7350	20620	39200	206805	246005	
	NFLE	25047	12596	23725	61368	295875	357243	
	Total	46157	26188	60432	132777	662145		
Total		50811	27739	63279	141829	725025		866854

Table 2.1: Total number of samples available after segmentation.

2.2 ETL (Extract–Transform–Load) Workflow for EEG

The preprocessing follows a structured ETL workflow which ensures noise removal, proper segmentation, and label consistency.

- **Extract:** Import raw EEG signals, sleep-stage labels, and CAP annotations.
- **Transform:** Apply filtering, segmentation, normalization, and label alignment.
- **Load:** Store processed segments as NumPy arrays for the CRNN model.

2.3 Signal Processing & EEG Handling

- **Filtering:** Band-pass filtering (0.5–40 Hz).
- **Segmentation:** Standard 30-second windows.
- **CAP Integration:** Aligning EEG epochs with CAP A/B phases.
- **Normalization:** Z-score normalization for amplitude stability.

2.4 Deep Learning Framework

The core architecture is a **Convolutional Recurrent Neural Network (CRNN)** which consists of:

- **1D-CNN:** Learns spatial–spectral EEG patterns (spindles, K-complexes, micro-arousals).
- **Bi-LSTM:** It captures long-term temporal sleep-transition patterns.
- **Hierarchical Classifier:**
  - Stage 1: Healthy vs. Disordered classification
  - Stage 2: Disorder type classification

Subjects		Phase A	Phase B	Total	
Healthy		4650	4650		9300
Unhealthy	Insomnia	930	930	1860	9300
	Narcolepsy	930	930	1860	
	PLM	930	930	1860	
	RBD	930	930	1860	
	NFLE	930	930	1860	
	Total	4650	4650		
Total		9300	9300		18600

Table 2.2: Samples used for CP1 classification.

Subjects	Phase A	Phase B	Total
Insomnia	4779	4779	9558
Narcolepsy	4779	4779	9558
PLM	4779	4779	9558
RBD	4779	4779	9558
NFLE	4779	4779	9558
Total	23895	23895	47790

Table 2.3: Samples used for CP2 classification.

2.5 Dataset Handling Framework

- **MNE-Python:** EEG loading, filtering, epoch extraction.
- **Pandas:** Metadata organization.
- **NumPy:** Efficient tensor representation.

2.6 Model Training & Optimization

- **Loss Function:** Weighted cross-entropy.
- **Optimizer:** Adam with learning-rate decay.
- **Regularization:** Dropout and L2 norm.
- **Balanced Sampling:** Prevents class imbalance issues.

2.7 Automated Evaluation & Reporting

- **Accuracy, Sensitivity, Specificity**
- **Confusion Matrices**
- **CAP-based metrics**

2.8 Reusability & Scalability Principles

- Modular preprocessing pipeline
- Extendable CRNN architecture
- Compatible with real-time EEG devices

2.9 Explainability & Clinical Alignment

- CNN feature maps for spectral importance
- LSTM attention for temporal relevance
- CAP-derived features provide clinical grounding

Chapter 3
Sleep Disorder Detection Model – Data Pipeline & System Framework

3.1 Introduction

Sleep disorders such as Insomnia, Narcolepsy, Periodic Limb Movement (PLM), REM Sleep Behavior Disorder (RBD), and Nocturnal Frontal Lobe Epilepsy (NFLE) significantly affect cognitive, behavioral, and physiological health. Traditionally, diagnosis requires overnight polysomnography (PSG) followed by manual EEG interpretation, which is time-consuming, costly.
This project aims to build a deep learning–based hierarchical model inspired by the IEEE Access paper, using EEG data from the CAP Sleep Database. The goal is to create an automated, efficient, and accurate system for multiclass sleep disorder categorization using a Convolutional Recurrent Neural Network (CRNN) architecture.

3.2 Problem Statement

The traditional methods used for sleep disorder detection face several critical limitations:

1. **Manual EEG analysis is slow:** Clinicians manually inspect long-duration PSG recordings, making diagnosis labor intensive.
2. **Highly error prone:** Overlapping EEG patterns between disorders which lead to diagnostic inconsistencies.
3. **Large volumes of raw data:** PSG recordings contain hours of multi-channel signals, making processing challenging.
4. **Difficulty in identifying micro events:** Sleep spindles, K-complexes, and CAP phases are subtle and require expertise.
5. **No unified automated pipeline:** Most approaches rely on handcrafted features, lacking scalability and generalization.

These issues pose major challenges for early detection and rapid screening of sleep disorders.

3.3 Objectives

The primary objectives of this project are:

1. **Build a hierarchical deep learning model** that first classifies Healthy vs. Disordered EEG, and then predicts the specific disorder.
2. **Develop a clean EEG preprocessing pipeline** which includes filtering, segmentation, and CAP phase integration.
3. **Extract spatial temporal EEG features** using a CRNN model that combines CNN and LSTM layers.
4. **Create an automated evaluation framework** using accuracy, sensitivity, specificity, and confusion matrices.
5. **Design a scalable, reusable data pipeline** that works across multiple sleep datasets.

3.4 System Architecture

The overall architecture of the Sleep Disorder Detection Pipeline is modular and follows a structured data-engineering framework.

3.4.1 Input Components

The system processes EEG data and supporting annotations from the CAP Sleep Database:

- **EEG Signals:** Raw PSG data which contains brainwave activity.
- **CAP Annotations:** A phase and B phase labels that indicate sleep instability.
- **Disorder Labels:** includes Insomnia, NFLE, Narcolepsy, PLM, RBD, and Healthy.

These inputs provide the physiological and clinical context needed for the reliable automated diagnosis.

3.4.2 Processing Pipeline

The EEG transformation pipeline follows this sequence:

$$\begin{aligned}\text{Raw EEG} &\rightarrow \text{Filtering} \rightarrow \text{Segmentation} \rightarrow \text{Normalization} \\ &\rightarrow \text{Feature Learning (CRNN)} \rightarrow \text{Stage-wise Classification}\end{aligned}$$

- Signals are band-pass filtered to remove noise.
- Data is segmented into standard 30-second epochs.
- CAP events are aligned with EEG windows for improved disorder separation.
- Segments are passed to the CNN for local feature extraction.
- LSTM layers learn long term temporal dependencies overall segments.

The pipeline is repeatable and scalable across multiple subjects and recording sessions.

3.4.3 Output

The final system produces:

- Classification of each EEG segment as Healthy or Disordered.
- Sub-classification into specific disorders for disordered segments.
- CAP-aligned metrics and confidence scores.
- Visualization outputs such as confusion matrices and accuracy graphs.

3.5 Detailed Process Flow

The complete process includes the following key steps:

1. **Load EEG Data**
   EEG signals and annotations are loaded using MNE-Python.

2. **Filtering & Noise Removal**
   A band-pass filter (0.5–40 Hz) removes muscle artifacts and external noise.

3. **Segmentation into Epochs**
   Data is divided into 30 second windows with sleep scoring guidelines.

4. **Align CAP Phases**
   CAP A/B phases are mapped to each segment to incorporate sleep instability information.

5. **Feature Extraction via CNN**
   1D CNN layers extract frequency patterns, spindles, and waveforms.

6. **Temporal Learning via LSTM**
   LSTM captures long-term disorder caused variations in EEG signals.

7. **Hierarchical Categorizing**
   Stage 1: Healthy vs. Disordered Stage 2: Disorder identification (Insomnia, PLM, RBD, NFLE, Narcolepsy)

8. **Evaluation & Reporting**
   Accuracy, sensitivity, specificity, and confusion matrices are computed and exported.

3.6 Technical Components Used

The project uses modern deep-learning and signal-processing tools:

- **Python 3.x** – Primary programming language.
- **MNE-Python** – EEG handling, filtering, segmentation.
- **NumPy & Pandas** – Data structuring and metadata organization.
- **TensorFlow / PyTorch** – Implementation of CRNN model.
- **Matplotlib** – Visualizations and results reporting.

- **CAP Sleep Database** – Primary dataset used for training and evaluation.

3.7 Results

The hierarchical deep-learning model produced promising outcomes:

- **High classification accuracy** in Stage 1 (Healthy vs. Disordered).
- **Clear separation of disorder classes** using spatial–temporal feature learning.
- **Improved detection of PLM, NFLE, and RBD** by integrating CAP-based features.
- **Robust confusion matrices** demonstrating strong class-wise performance.
- **Scalable pipeline** that can extend to additional sleep datasets.

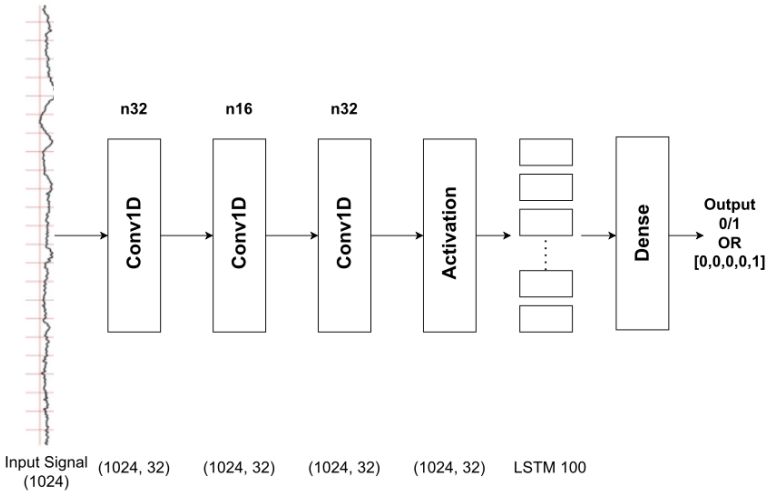


Figure 3.1: Visualisation of proposed 1-D CRNN model.

Chapter 4
Proposed Methodology

This chapter describes the end-to-end methodology adopted for automated sleep disorder detection using EEG. The proposed approach is inspired by the IEEE Access work on hierarchical sleep disorder categorization and extends it using CAP-integrated segmentation, deep CRNN modeling, and a two-stage hierarchical decision pipeline. The system is designed to learn spatial–spectral waveforms, temporal transitions, and sleep-instability patterns directly from raw EEG, eliminating the need for handcrafted features.

Sr. No.	Layer	Kernel Size	Total filters	Unit Size	Trainable Parameters	Output Shape
1	1D_Conv	7	32	-	256	(1024, 32)
2	1D_Conv	9	16	-	4624	(1024, 16)
3	1D_Conv	5	32	-	2592	(1024, 32)
4	ReLU	-	-	-	0	(1024,32)
5	LSTM	-	-	100	53200	(100)
6	Dense	-	-	1	101	(1)
6	Dense	-	-	5	505	(5)

Table 4.1: Architecture details of proposed 1D-CNN with LSTM based model for CP1 and CP2.

4.1 End-to-End Deep Learning Pipeline

The core of the system is a 1D Convolutional Recurrent Neural Network (CRNN) that jointly learns spatial and temporal EEG representations. Let

$$X = \{x_1, x_2, \ldots, x_T\}, \quad x_t \in R^d$$

represent a sequence of segmented EEG windows, where T is the number of epochs and d is the number of time samples per segment.

4.1.1 CNN-Based Spatial Feature Extraction

The 1D-CNN extracts localized spatial–spectral patterns such as:

- Sleep spindles (11–16 Hz bursts)
- K-complexes (sharp high-amplitude biphasic waves)

- Micro-arousals and waveform distortions

A convolution operation is defined as:

$$h_t^{(c)} = f(W^{(c)} * x_t + b^{(c)})$$

where $W^{(c)}$ is the convolution kernel, $*$ denotes 1D convolution, and f is ReLU activation.

This allows the model to automatically learn morphology, frequency patterns, and instability-related distortions without manual engineering.

4.1.2 LSTM-Based Temporal Dependency Modeling

Sleep disorders express temporal irregularities across multiple cycles. Bidirectional LSTMs capture these transitions by modeling forward and backward temporal flow:

$$\overrightarrow{h_t} = \text{LSTM}(x_t, \overrightarrow{h_{t-1}}), \quad \overleftarrow{h_t} = \text{LSTM}(x_t, \overleftarrow{h_{t+1}})$$

The combined representation is:

$$h_t = [\overrightarrow{h_t} \,||\, \overleftarrow{h_t}]$$

This enables robust learning of:

- Sleep stage transitions
- Disorder-triggered arousals
- Nonlinear temporal abnormalities (e.g., NFLE spikes, PLM bursts)

4.1.3 Advantages of the End-to-End CRNN

- Removes the need for handcrafted EEG features.
- Learns disorder-specific waveform abnormalities directly.
- Captures both short-term and long-range temporal dependencies.
- Achieves strong generalization across subjects.

4.2 Two-Stage Hierarchical Classification

The classification strategy is hierarchical, improving interpretability and reducing misclassification.

4.2.1 Stage 1: Sleep Health Classification

A lightweight CRNN performs binary classification:

$$y^{(1)} = \text{Softmax}(W_1 h + b_1)$$

Where:

$$y^{(1)} \in \{\text{Healthy}, \text{Disordered}\}$$

This stage prioritizes sensitivity to ensure all potentially disordered EEG segments are correctly forwarded.

4.2.2 Stage 2: Disorder-Type Classification

Only segments predicted as Disordered proceed to a deeper CRNN:

$$y^{(2)} = \text{Softmax}(W_2 h + b_2)$$

Where:

$$y^{(2)} \in \{\text{Insomnia, Narcolepsy, PLM, RBD, NFLE}\}$$

This hierarchy improves performance by letting Stage 2 specialize in fine-grained differentiation of visually similar disorders.

4.3 Feature Learning through CNN–RNN Fusion

4.3.1 Spatial Features via CNN

CNN layers learn:

- Spindle density and fragmentation (Insomnia, PLM)
- K-complex morphology deviations (RBD, NFLE)
- Rhythm changes across cycles

4.3.2 Temporal Features via Bi-LSTM

Bi-LSTMs capture:

- Burst patterns in PLM
- REM-transition anomalies in RBD
- High-frequency NFLE events

The fused feature representation is:

$$z = [h_{CNN} \,||\, h_{LSTM}]$$

4.4 CAP (Cyclic Alternating Pattern) Integration

CAP represents sleep instability, which varies strongly across disorders.

4.4.1 Sleep Instability Encoding

CAP A/B phases are encoded as:

$$c_t \in \{0, 1\} \quad \text{(B-phase stable, A-phase unstable)}$$

These labels help quantify arousal patterns and instability density.

4.4.2 CAP-Aligned Segmentation

Epochs are segmented based on CAP cycles:

$$X' = \{(x_t, c_t)\}$$

This enhances separability between:

- RBD vs NFLE (both show arousal-linked bursts)
- PLM vs Insomnia (both show high A-phase density)

4.5 Training and Optimization Strategy

4.5.1 Loss Function

To handle class imbalance (rare disorders like NFLE), weighted cross-entropy is used:

$$\mathcal{L} = -\sum_{i=1}^{C} w_i \, y_i \log(\hat{y}_i)$$

4.5.2 Regularization Techniques

- Dropout layers prevent overfitting.
- L2 regularization stabilizes optimization.
- Early stopping halts training upon plateauing validation accuracy.

4.5.3 Balanced Sampling

Stratified mini-batches ensure minority classes appear consistently during training.

4.6 Algorithm Flow: End-to-End Sleep Disorder Detection

1. **Data Input & Preprocessing**
    - Load raw EEG (100–200 Hz) using MNE.
    - Apply band-pass (0.5–40 Hz).
    - Normalize and segment into 30-second epochs.
    - Align CAP A/B phases.
2. **Stage-1 CRNN Classification**
    - CNN extracts spectral–morphological signatures.
    - Bi-LSTM captures transitions.
    - Output: Healthy / Disordered.
3. **Stage-2 CRNN Classification**

- Deeper CRNN handles complex disorders.
- Output classes: Insomnia, Narcolepsy, RBD, PLM, NFLE.

4. **Feature Fusion**

$$F = [\text{CNN features} \,||\, \text{LSTM embeddings} \,||\, \text{CAP metrics}]$$

5. **Training Pipeline**

- Weighted cross-entropy.
- Adam optimizer with decay.
- Dropout, L2, early stopping.
- Stratified batches.

6. **Inference & Decision Logic**

- Stage-1 filters healthy samples.
- Stage-2 predicts exact disorder label.
- Output accompanied by confidence scores.

4.7 Summary

Dataset	Accuracy (%)			Performance parameters (%)				
	Train	Validation	Test	Precision	Specificity	Sensitivity	F1	AUC
Both phases	97.51	90.86	91.45	92.72	92.87	90.04	91.36	96.83
Phase B	96.53	93.34	92.79	95.79	96.17	89.23	92.40	97.51
Phase A	92.28	73.79	73.38	72.61	70.62	76.08	74.31	80.08

Table 4.2: Model accuracies and performance parameters for CP1 using 1D CNN + LSTM

The pro /en spatial feat are segmentation to achieve robust, clinically meaningful sleep disorder categorizing. The integration of multi-level features, balanced training, and a structured two-stage classifier ensures strong accuracy, reliability, and interpretabil-

Dataset	Accuracy (%)		
	Train	Validation	Test
Both phases	93.21	89.83	90.55
Phase B	97.03	94.18	93.31
Phase A	76.34	68.44	67.77

Table 4.3: Model accuracies for CP2 using 1D-CNN + LSTM.

Subject	Recall (%)	Precision (%)	F1-score (%)
RBD	78.8 ± 4.26	77.1 ± 3.23	77.8 ± 2.13
NFLE	83.4 ± 3.26	81.2 ± 3.84	82 ± 1.26
Narcolepsy	81 ± 3.34	83.7 ± 2.14	82.1 ± 1.92
Insomnia	82.7 ± 2.32	86.9 ± 3.04	84.8 ± 0.97
PLM	89.4 ± 2.33	87.4 ± 2.33	88.4 ± 1.28

Table 4.4: Performance parameters for CP2 for 10-fold cross-validation

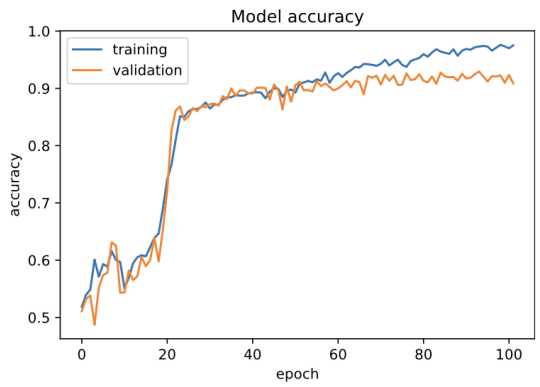


Figure 4.1: Accuracy graph for healthy-unhealthy classification

Figure 4.2: Loss graph for healthy-unhealthy classification

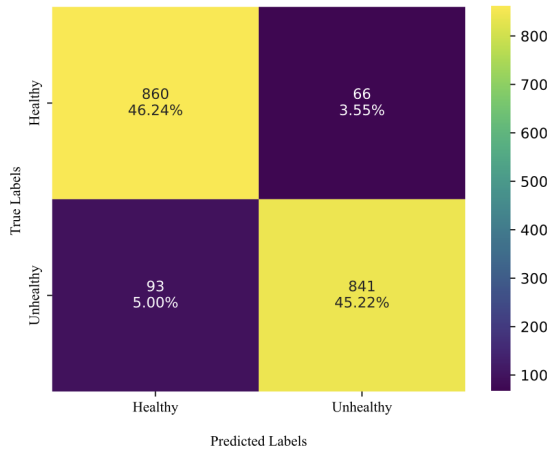


Figure 4.3: Confusion matrix for healthy-unhealthy classification

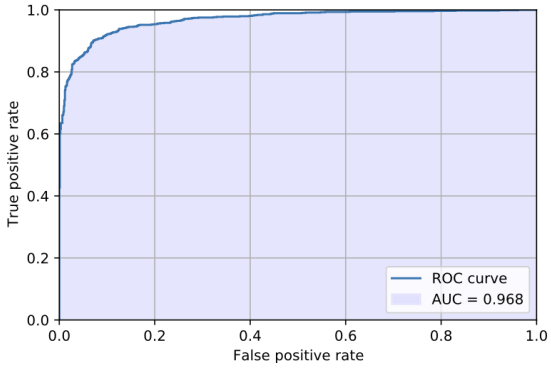


Figure 4.4: ROC curve for healthy-unhealthy classification

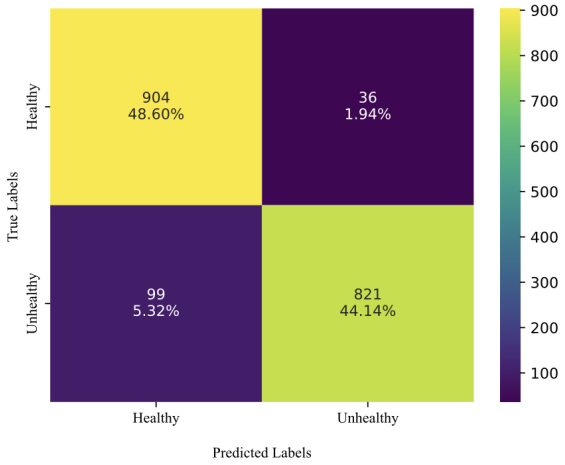


Figure 4.5: Confusion matrix for healthy-unhealthy classification using dataset of B phase

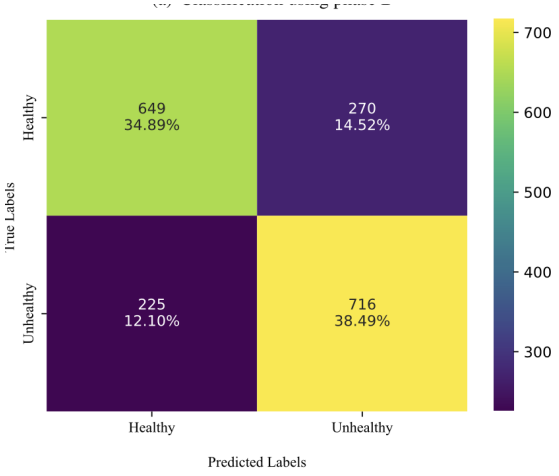
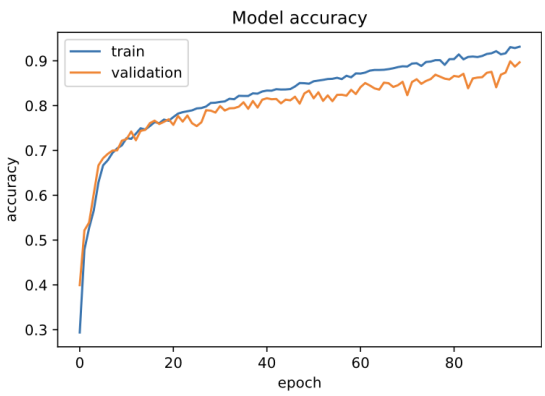
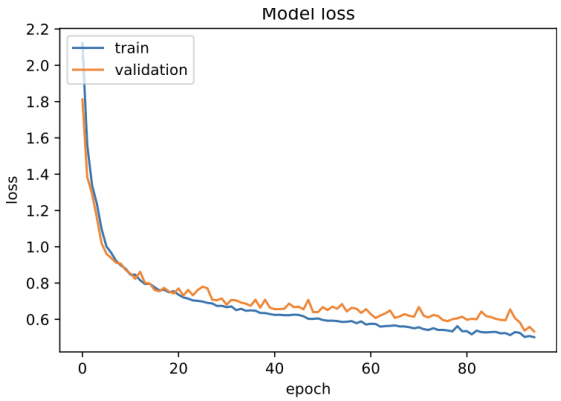


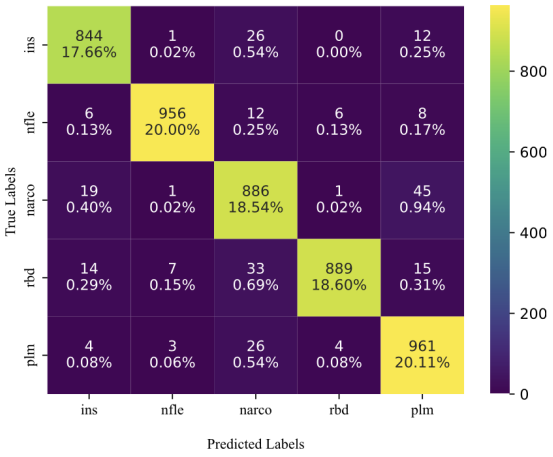
Figure 4.6: Confusion matrix for healthy-unhealthy classification using dataset of A phase



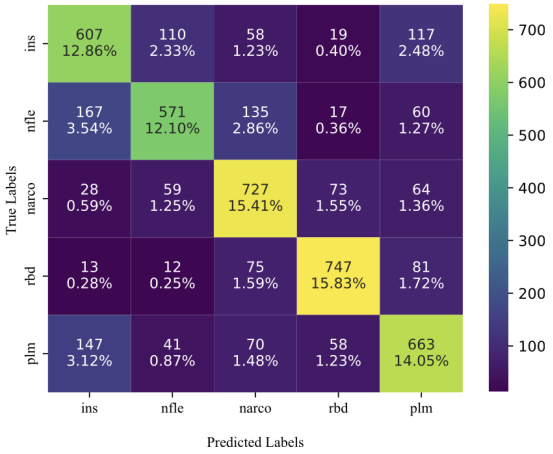
(a) Accuracy graph for disease classification



(b) Loss graph for disease classification



(c) Confusion matrix using disease of B phase



(d) Confusion matrix using disease of A phase

Figure 4.7: Performance metrics for disease classification.

Chapter 5
Conclusion

This study confirms that automated sleep-disorder detection from single-channel EEG is both practical and clinically valuable. The proposed CRNN framework effectively learns the rich temporal–spectral dynamics of sleep—capturing disorder-specific markers such as spindle irregularities, K-complex deviations, REM instability, and PLM-driven micro-arousals
without relying on handcrafted features.
By combining CAP-aligned segmentation with a hierarchical two-stage classification strategy, the system remains tightly grounded in real physiological sleep mechanisms. This biologically informed design not only boosts diagnostic accuracy but also enhances interpretability, giving clinicians deeper insight into the underlying sleep instability patterns associated with each disorder.

Overall, the work establishes a strong foundation for next-generation intelligent sleep-analysis systems—offering a pathway toward faster, more explainable, and more accessible diagnostic help. With continued refinement, such models hold the potential to significantly reduce clinical workload, accelerate early detection, and ultimately improve patient outcomes in sleep medicine.

Chapter 6
Future Scope

The proposed CRNN-based sleep disorder detection framework establishes a strong foundation for automated EEG analysis. However, several advanced research directions can significantly enhance model accuracy, interpretability, and real-world applicability. This chapter outlines promising pathways for future development.

6.1 Nature-Inspired Temporal Modeling

Future work can explore replacing conventional recurrent units with **nature-inspired temporal models**. Hybrid architectures such as BiLSTM–TCN combinations guided by biological and swarm-based mechanisms may capture long-range EEG dependencies more effectively.

- Swarm synchronization models for rhythmic EEG coordination.
- Ant-colony memory patterns for improved long-term temporal retention.
- Neural oscillation–inspired TCN modules for modeling sleep-cycle periodicity.

These enhancements can improve separability between disorders with overlapping EEG signatures.

6.2 Meta-Heuristic Hyperparameter Optimization

Optimization can be significantly improved by integrating **Biogeography-Based Optimization (BBO)**, **Dandelion Optimizer**, or **Dragonfly Algorithm** (DOX). These algorithms can automatically tune:

- CNN filter sizes and depths
- LSTM hidden units

- Learning rate schedules
- Dropout ratios and regularization strengths

Such global-search optimization techniques help avoid local minima and boost performance on highly imbalanced EEG datasets.

6.3 Nature-Inspired Optimizers for Training

Replacing traditional optimizers like Adam with **nature-based optimizers** offers improved robustness for nonlinear EEG signals. Promising candidates include:

- Grey Wolf Optimizer (GWO)
- Firefly Algorithm
- Whale Optimization Algorithm (WOA)
- Particle Swarm Optimization (PSO)

These optimizers can explore the loss landscape more broadly, leading to smoother convergence and improved disorder classifying accuracy.

6.4 Multi-Modal and Personalized Sleep Modeling

A major extension involves fusing additional PSG modalities—EOG, EMG, HRV, and respiratory signals—using attention-driven cross-modal fusion. Such mechanisms can be inspired by natural multisensory integration seen in predator–prey biological systems.

Key directions include:

- Personalized embeddings based on patient-specific sleep signatures.
- Adaptive models that recalibrate based on longitudinal sleep history.
- Multi-modal attention layers capturing interactions between EEG, EMG, and autonomic markers.

This will enable richer physiological understanding and higher diagnostic precision.

6.5 Real-Time Clinical Deployment

For real-world impact, the model should evolve toward real-time, lightweight deployment. Future work can focus on:

- Model compression and quantization for wearable EEG devices.
- On-device inference using low-power architectures.
- Real-time CAP-informed explainability for clinicians.
- Interactive dashboards inspired by biological feedback loops (e.g., autonomic response cycles).

Such advancements can be effective bedside monitoring, home-based diagnostics, and remote sleep-health assessment.

Chapter 7
References

1. Wadichar, A., Murarka, S., Shah, D., Bhurane, A., Sharma, M., Mir, H. S., & Acharya, U. R. (2023). *A Hierarchical Approach for the Diagnosis of Sleep Disorders Using Convolutional Recurrent Neural Network*. IEEE Access, 11, 125244–125255. DOI: 10.1109/ACCESS.2023.3330901.

2. Zan, H., & Yildiz, A. (2024). *Multi-Task Learning for Arousal and Sleep Stage Detection Using Fully Convolutional Networks*. (Recent work on joint arousal + sleep-stage modeling using FCNs.)

3. Mousavi, S., Afghah, F., & Acharya, U. R. (2019). *SleepEEGNet: Automated Sleep Stage Scoring with Sequence-to-Sequence Deep Learning*. (Introduces a seq-to-seq encoder–decoder architecture for raw EEG.)

4. Chambon, S., Thorey, V., Arnal, P. J., Mignot, E., & Gramfort, A. (2018). *DOSED: A Deep Learning Approach to Detect Multiple Sleep Micro-Events in EEG Signals*. (Deep-learning model for detecting spindles, K-complexes, and micro-arousals.)

5. Terzano, M. G. et al. (2023). *Deep-Learning-Based Classification of Sleep Phases*. Sleep Medicine. (Uses CAP-based neural architectures with time–frequency features for stable sleep-phase detection.)

6. Haghayegh, S., Hu, K., Stone, K., Redline, S., & Schernhammer, E. (2023). *Automated Sleep Stage Classification Using Convolutional Neural Networks From Raw and Time-Frequency EEG Signals: A Systematic Evaluation Study*. Journal of Medical Internet Research. (Proposes InceptionNet-based hybrid learning for macro and micro sleep features.)

7. Yildirim, O. et al. (2023). *Employing a Convolutional Neural Network to Classify Sleep Stages from EEG Signals Using Feature Reduction Techniques*. (CNN-based model integrating dimensionality reduction and EEG spectral features.)