Department of Information & Communication Technology

Major Project

Automated Sleep Apnea Prediction Using Deep Learning for Improved Health

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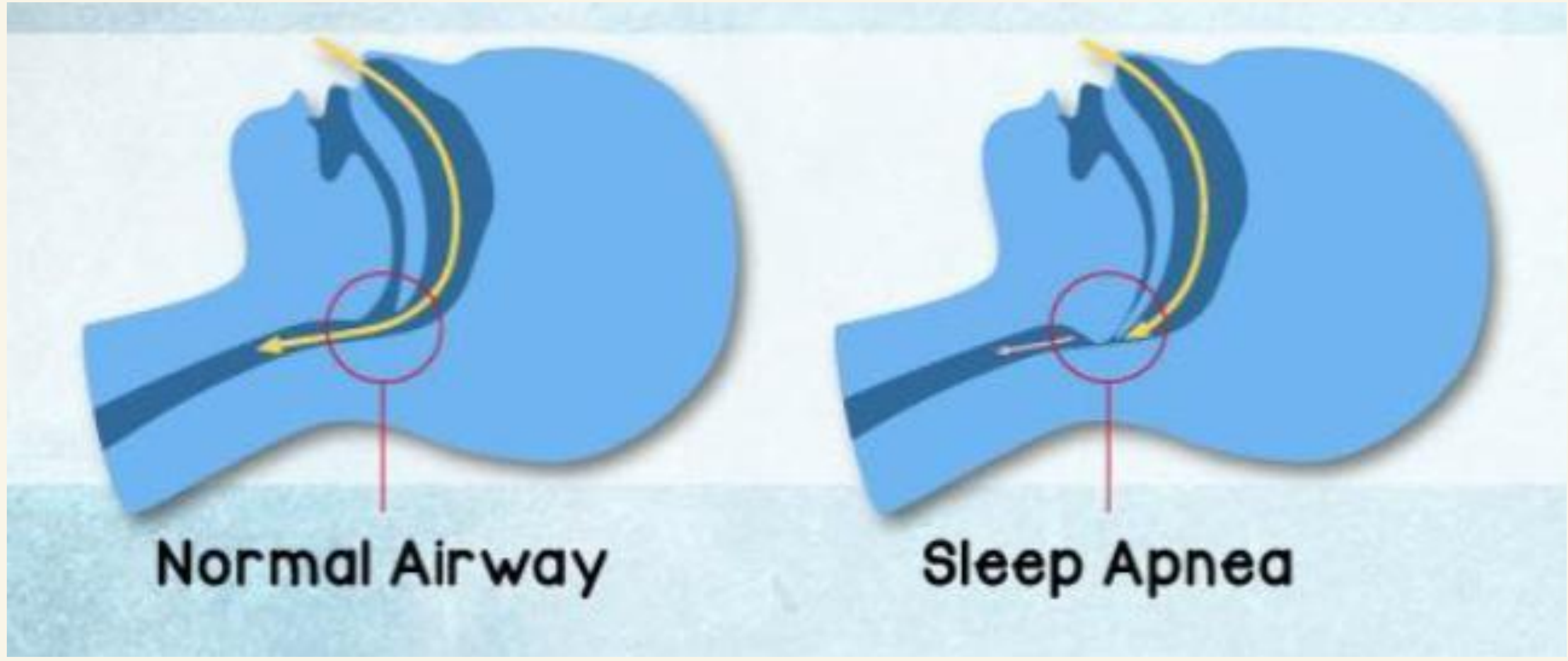
Outline:

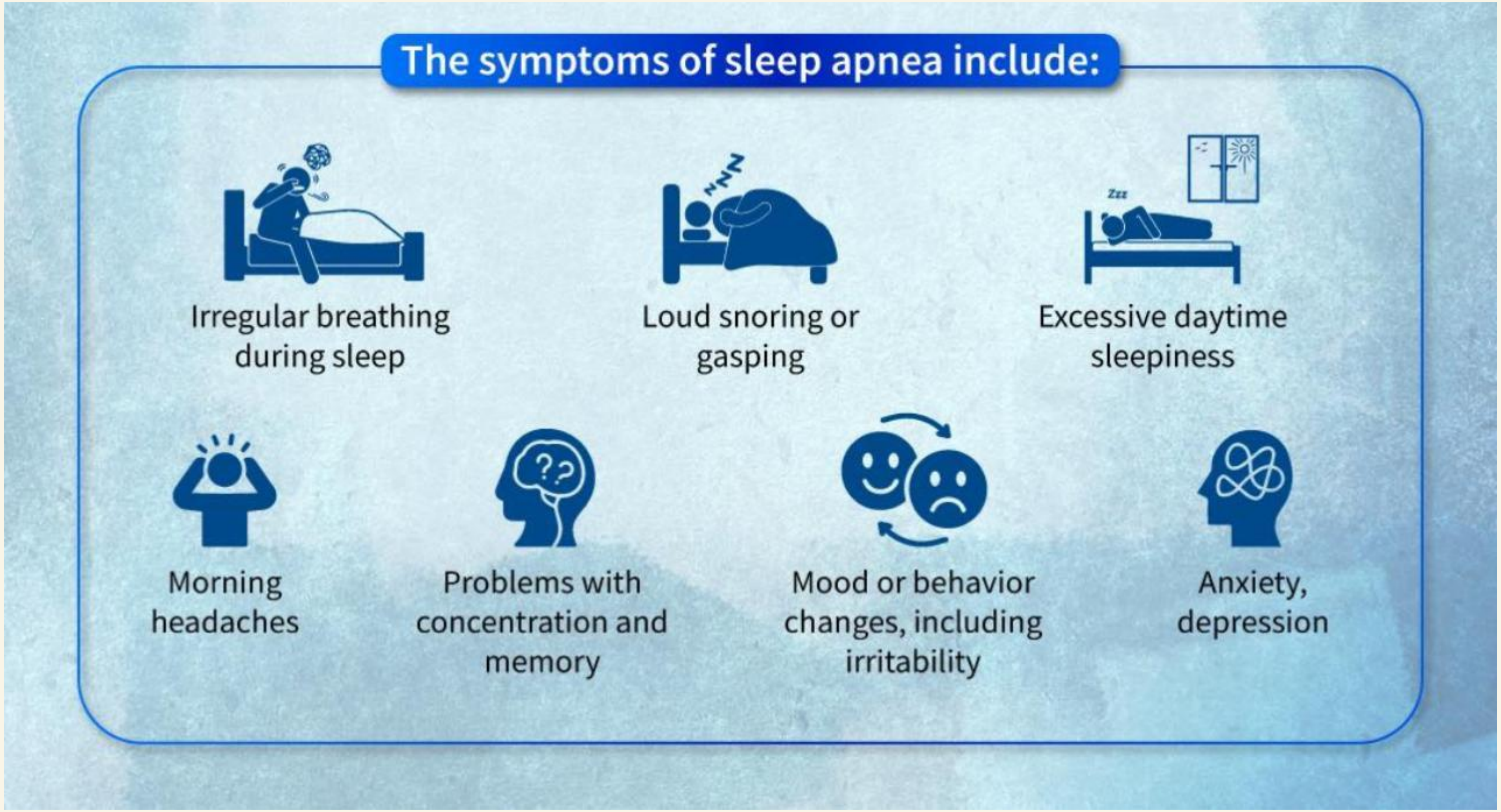
1. Introduction
2. Literature Review
3. Problem Statement
4. Objectives
5. Proposed Methodology
6. Results
7. Conclusion

Introduction:

- Sleep Apnea (SA) is a serious sleep disorder characterized by repeated interruptions in breathing during sleep.
- These breathing pauses typically last 10–20 seconds, causing oxygen desaturation and sleep disturbances.
- SA affects approximately 15% of men and 5% of women, increasing the risk of severe health conditions.
- SA is associated with severe health risks, including cardiovascular diseases, stroke, seizures, and neurological disorders.

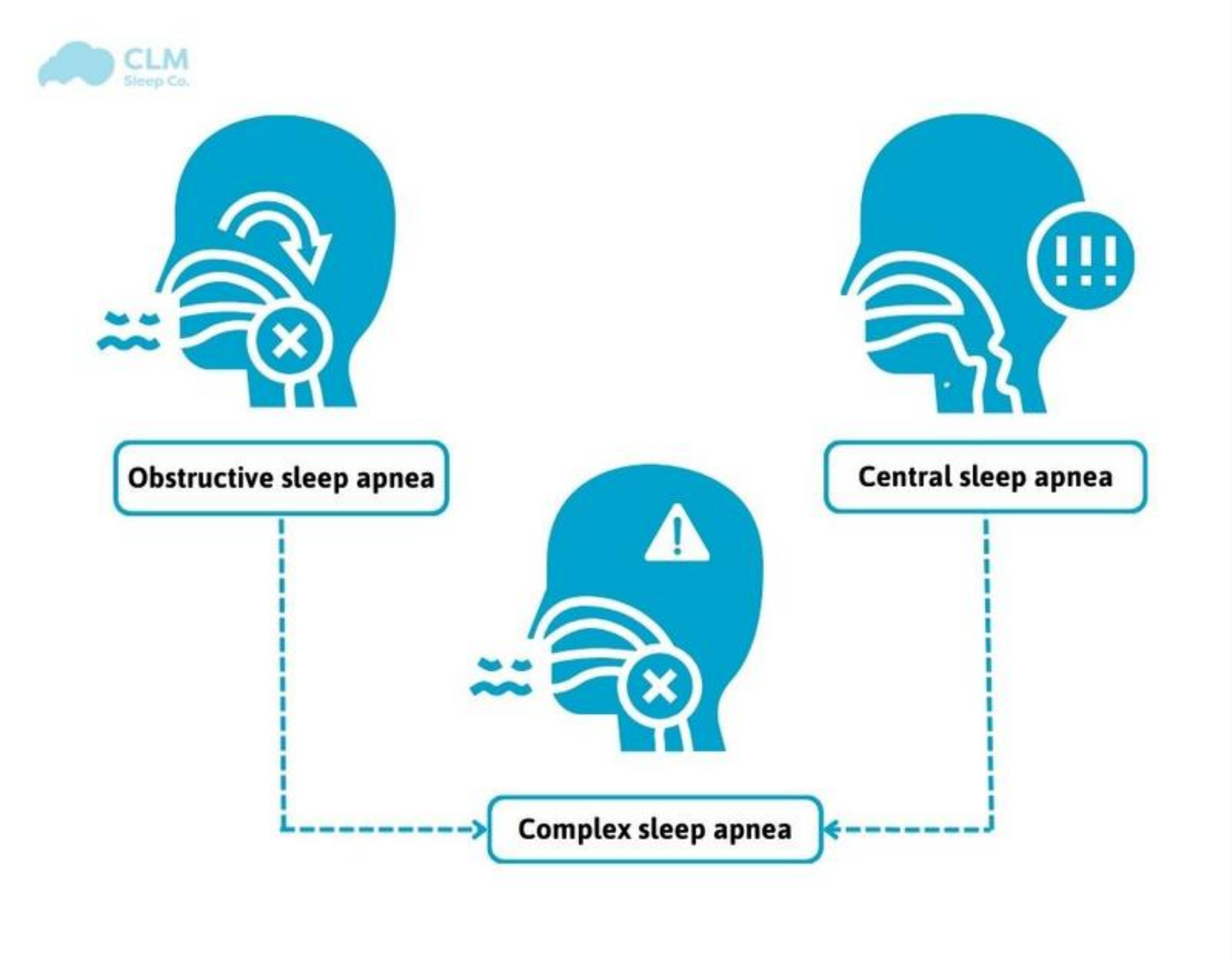


Introduction:



Introduction:

- There are three main types of SA:
  - Obstructive Sleep Apnea (OSA):
    - Caused by physical blockage of the upper airway during sleep.
    - Associated with snoring, gasping, and oxygen desaturation.
  - Central Sleep Apnea (CSA):
    - Caused by the brain's failure to send proper signals to the breathing muscles.
    - Leads to pauses in breathing without airway obstruction.
  - Mixed Sleep Apnea (MSA):
    - A combination of OSA and CSA.
    - Includes both physical obstruction and neurological miscommunication.



Literature Review:

Author	Signal Type	Model	Accuracy
Mahmud et al.	EEG	FCNN Bi-LSTM	93.25%
Alam et al.	EEG	Linear Support Vector Machine (LSVM)	94.81%
R. Gupta.	EEG	Decision Tree	95.10%
V. Vimala	EEG	Support Vector Machine	95%
Banluesombatkul, N.	ECG	1D CNN + LSTM + DNN	79.45%
Sharma, M.	ECG	Support Vector Machine	90.87%
Vaquerizo-Villar, F.	EEG	Convolutional Neural Network	86.9%

Literature Review:

Author	Signal Type	Model	Accuracy
Korkalainen et al.	EEG	Convolutional Neural Networks + Recurrent Neural Networks	82.9%
Yeh, C. Y.	EEG	1-D Convolutional Neural Network	85.8%
Pinho, A.	ECG	Artificial Neural Network + Support Vector Machine	82.12%
Wang, L	ECG	Deep residual neural network (LeNet-5 CNN)	94.4%
Sharma, H.	ECG	K-nearest neighbour classifier	87.5%

Research Gaps:

- **Butterworth Filter works on EEG/ECG signals for noise removal, while RRI Works on ECG signals with QRS detection for HRV analysis.**
- **Discrete Wavelet Transform (DWT) used for time-frequency analysis by breaking a signal into segments at different frequency bands, capturing both time and frequency information.**
- **Convolutional Neural Networks (CNNs) and Long-Short-Term Memory (LSTM) networks are commonly used to classify sleep apnea. In addition to deep learning models, several machine learning algorithms are also used.**
- **Adam optimizer is the most commonly used optimization algorithm in deep learning studies.**

Problem Statement:

Sleep apnea is a common sleep problem where a person's breathing stops and starts during sleep. This can lower oxygen levels and cause tiredness during the day. The current method to detect sleep apnea, called polysomnography, is accurate but expensive, time-consuming, and not comfortable for many people. So, there is a need for an easy, fast, and low-cost system that can find and classify sleep apnea using body signals like heart rate and breathing, making it easier to diagnose and treat.

Objectives:

Develop a deep learning model to detect and classify sleep apnea events using physiological signals (e.g., EEG, ECG, SpO_2) with high accuracy, enabling early diagnosis. The model aims to identify potential sleep apnea risks before severe symptoms arise, allowing timely intervention to prevent cardiovascular or metabolic complications.

Proposed Methodology:

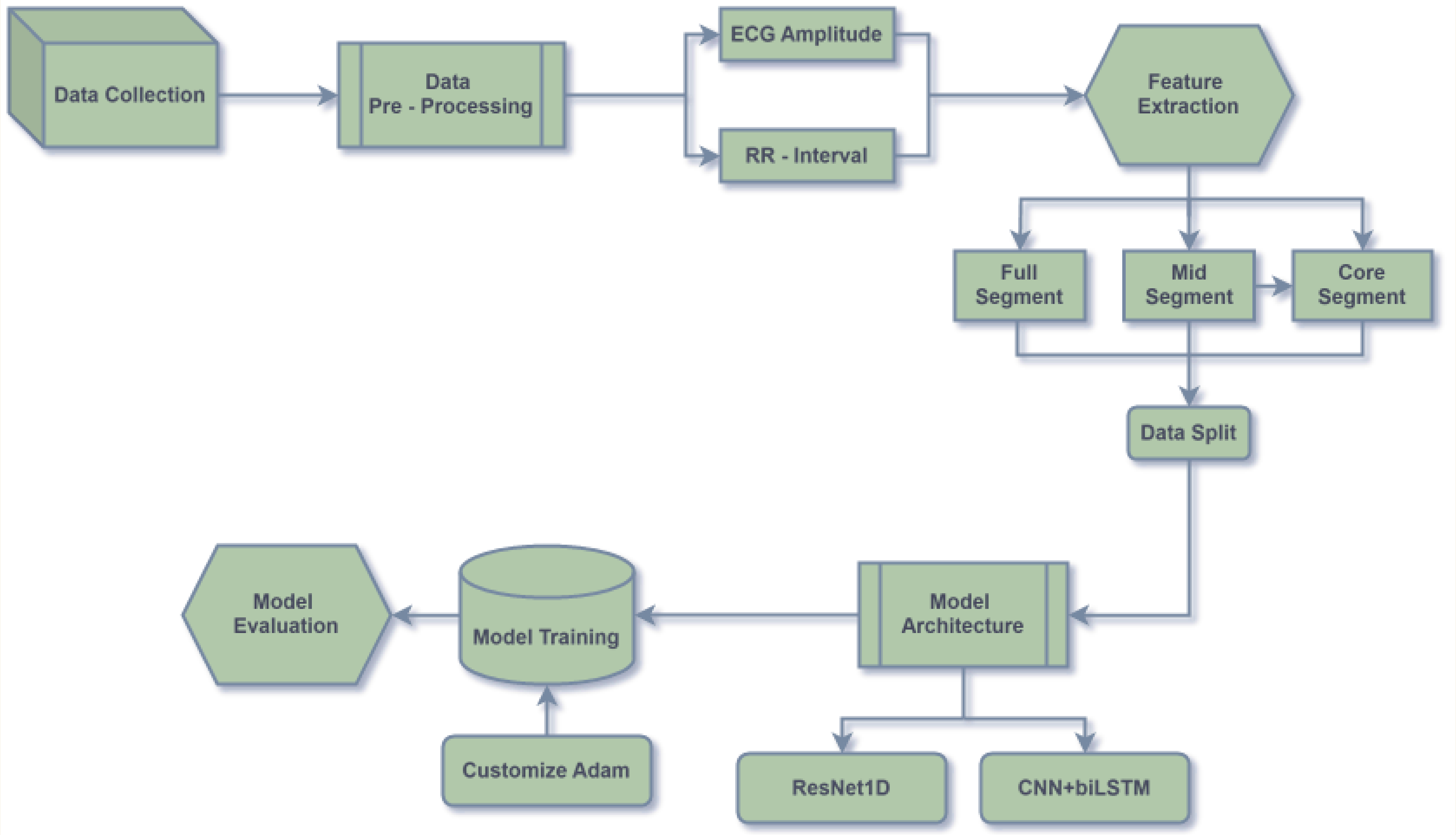


Fig 1. Proposed Overall Methodology Diagram

Dataset Description:

- The Apnea-ECG Database, sourced from PhysioNet, includes 70 long-term ECG recordings, each about 8 hours in length.
- Sampling rate: 100 Hz.
- Dataset Split:
  - Training Set (35 records): a01–a20, b01–b05, c01–c10.
  - Testing Set (35 records): x01–x35.
  - Recording duration: Ranges from <7 hours to ~10 hours.
- File Types in the Dataset:
  - .apn files: Binary annotations marking the presence/absence of apnea per minute
  - .dat files: Contain raw binary ECG signal data.

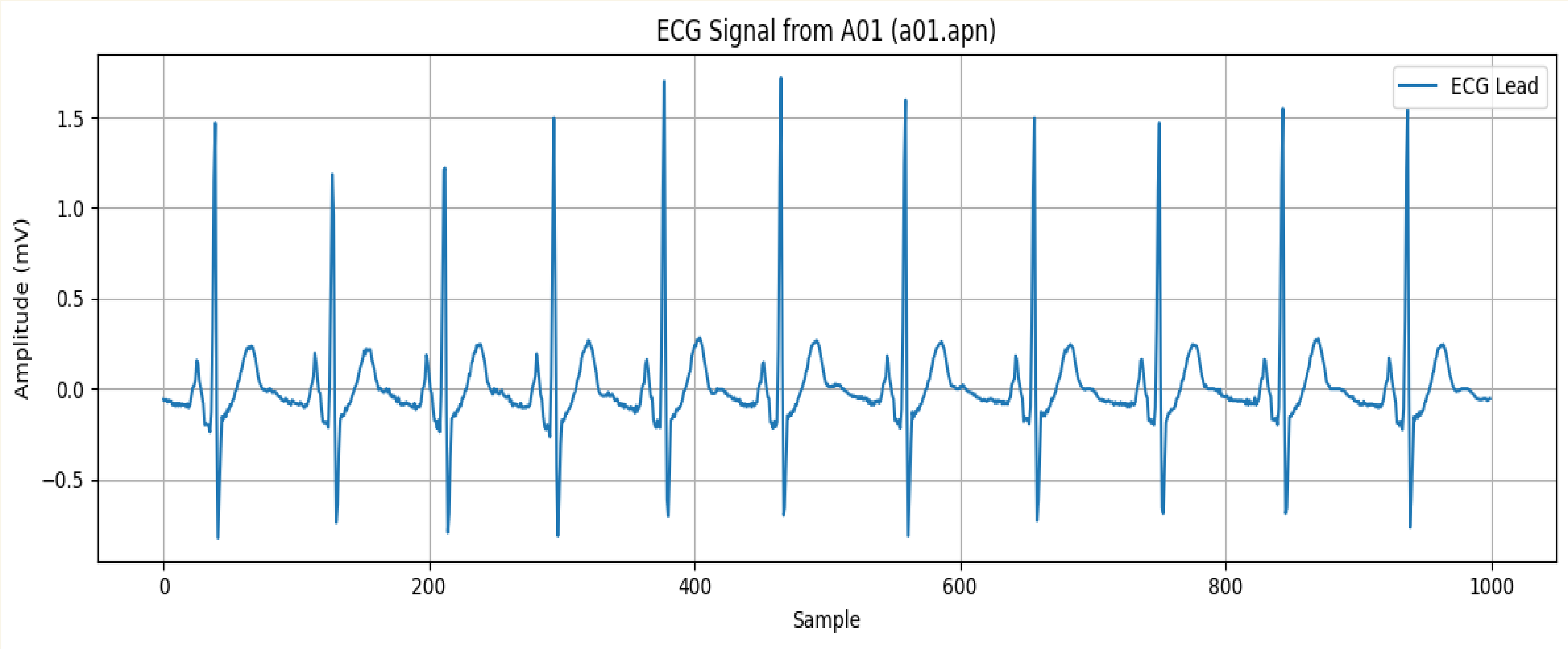


Fig 2. ECG signal segment from subject A01 (a01.apn)

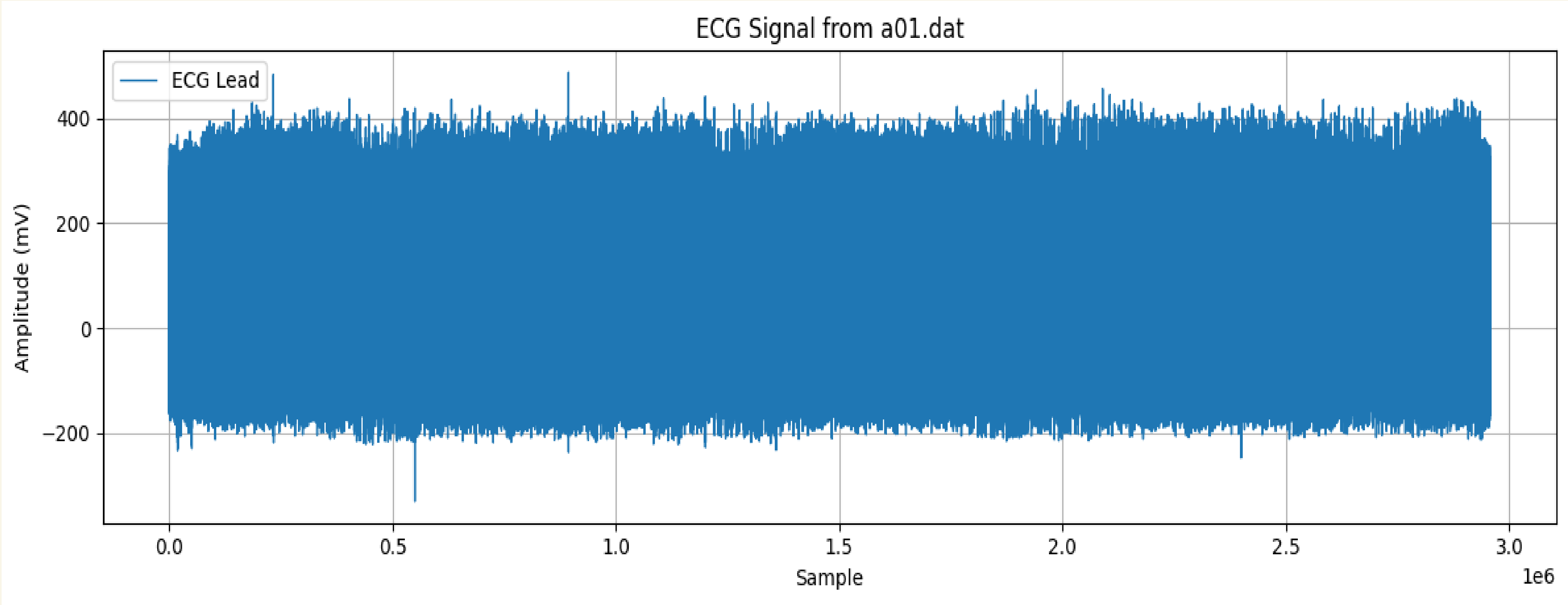


Fig 3. ECG signal from subject A01 (a01.dat)

Data Pre-Processing :

Before feeding data into the model, preprocessing is crucial to improve learning and accuracy.

1. RR Interval Calculation

- **RR intervals are the time gaps between two R-peaks in the ECG signal.**

2. ECG Amplitude Normalization

- **ECG signal strength can vary due to electrode placement or patient differences.**
- **Normalization helps the model focus on patterns, not raw values.**

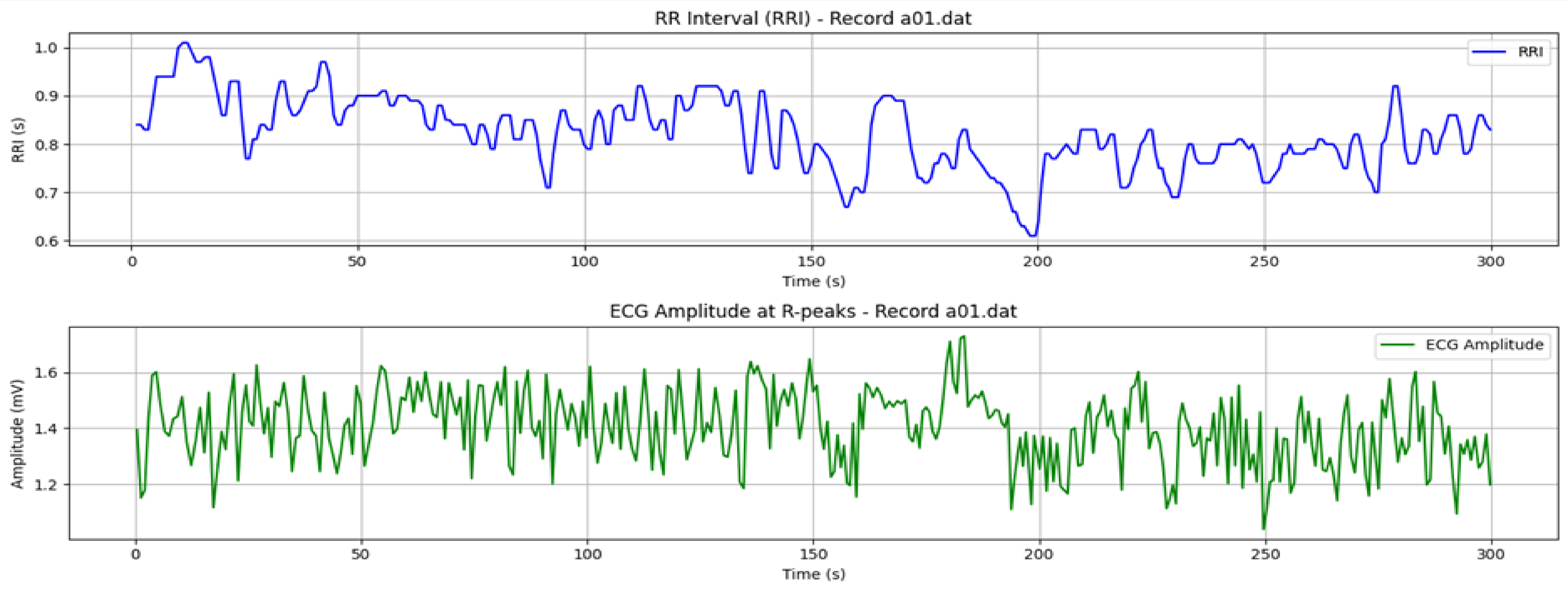


Fig 4. RR Interval and ECG Amplitude from record a01.dat

Feature Extraction:

After preprocessing, the ECG amplitude and RR interval signals are used to extract useful features. These features help the model learn the difference between normal and apnea sleep stages.

Steps:

- **Full-length Signal Pair Extraction:**

$$\text{Feature}_1 = \left[\text{RRI}_{\text{interp}}, \text{AMPL}_{\text{interp}}\right]$$

- **Middle Segment Extraction:**

$$\text{Feature}_2 = RRI_{interp}[180 : 720], AMPL_{interp}[180 : 720]$$

- **Center Segment Extraction:**

$$\text{Feature}_3 = RRI_{interp}[360 : 540], AMPL_{interp}[360 : 540]$$

Model Architecture:

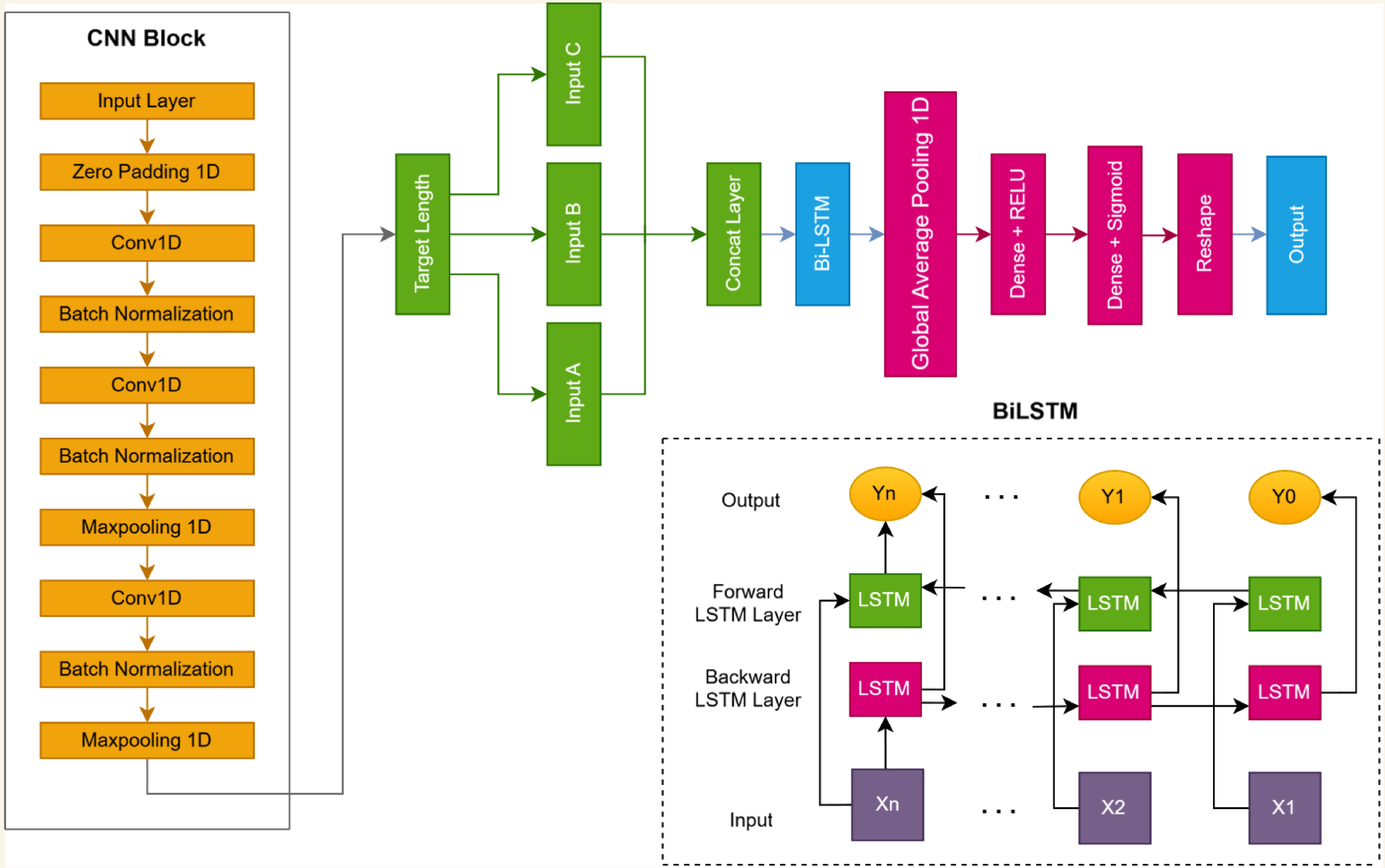


Fig 5. Model Architecture of CNN+biLSTM

Model Architecture:

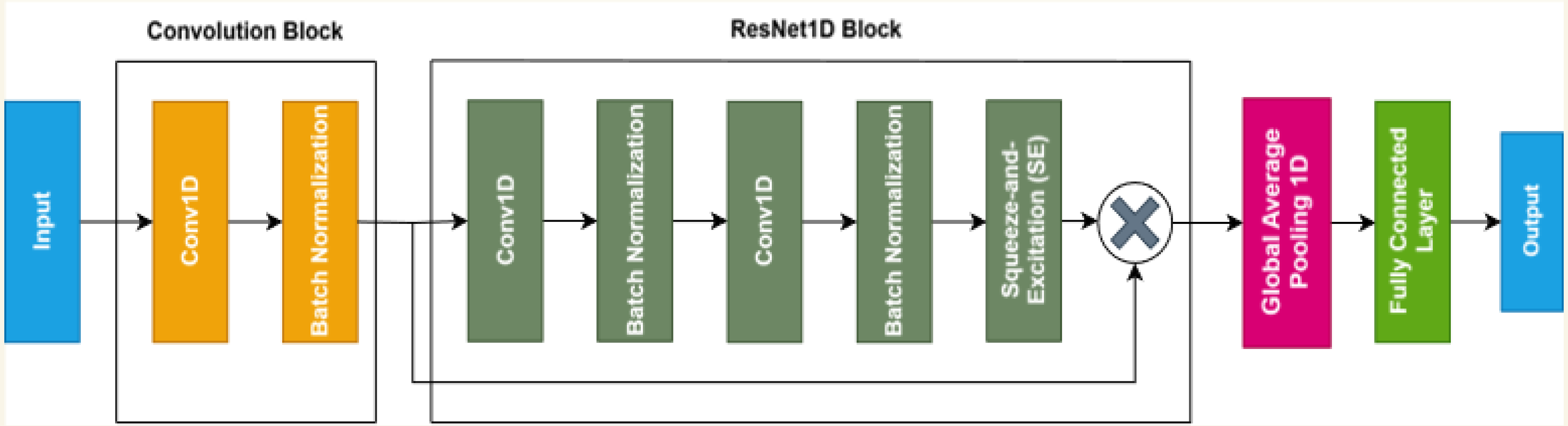


Fig 6. Model Architecture of ResNet-1D

Results using CNN+biLSTM:

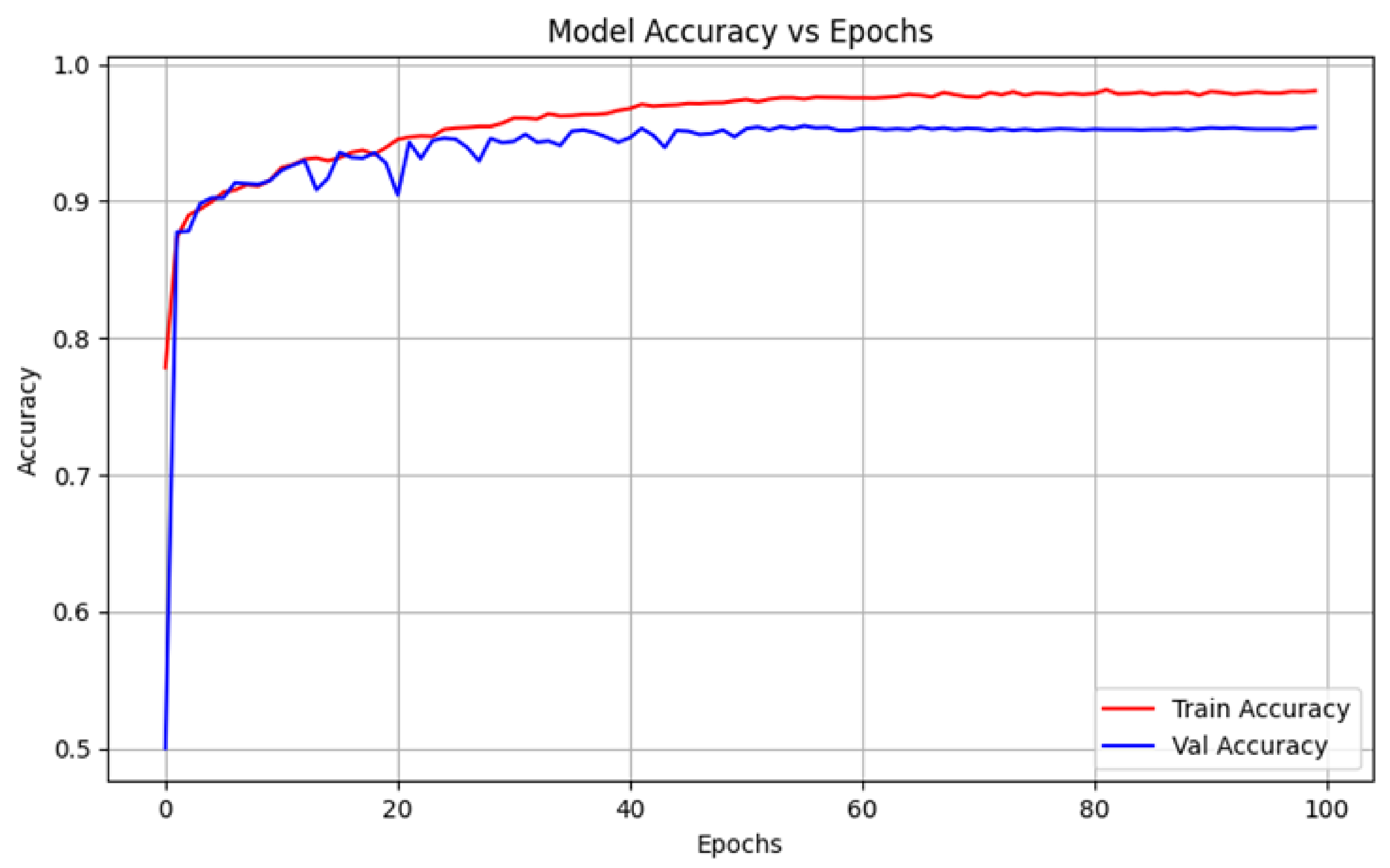


Fig 7. Model Accuracy vs Epochs

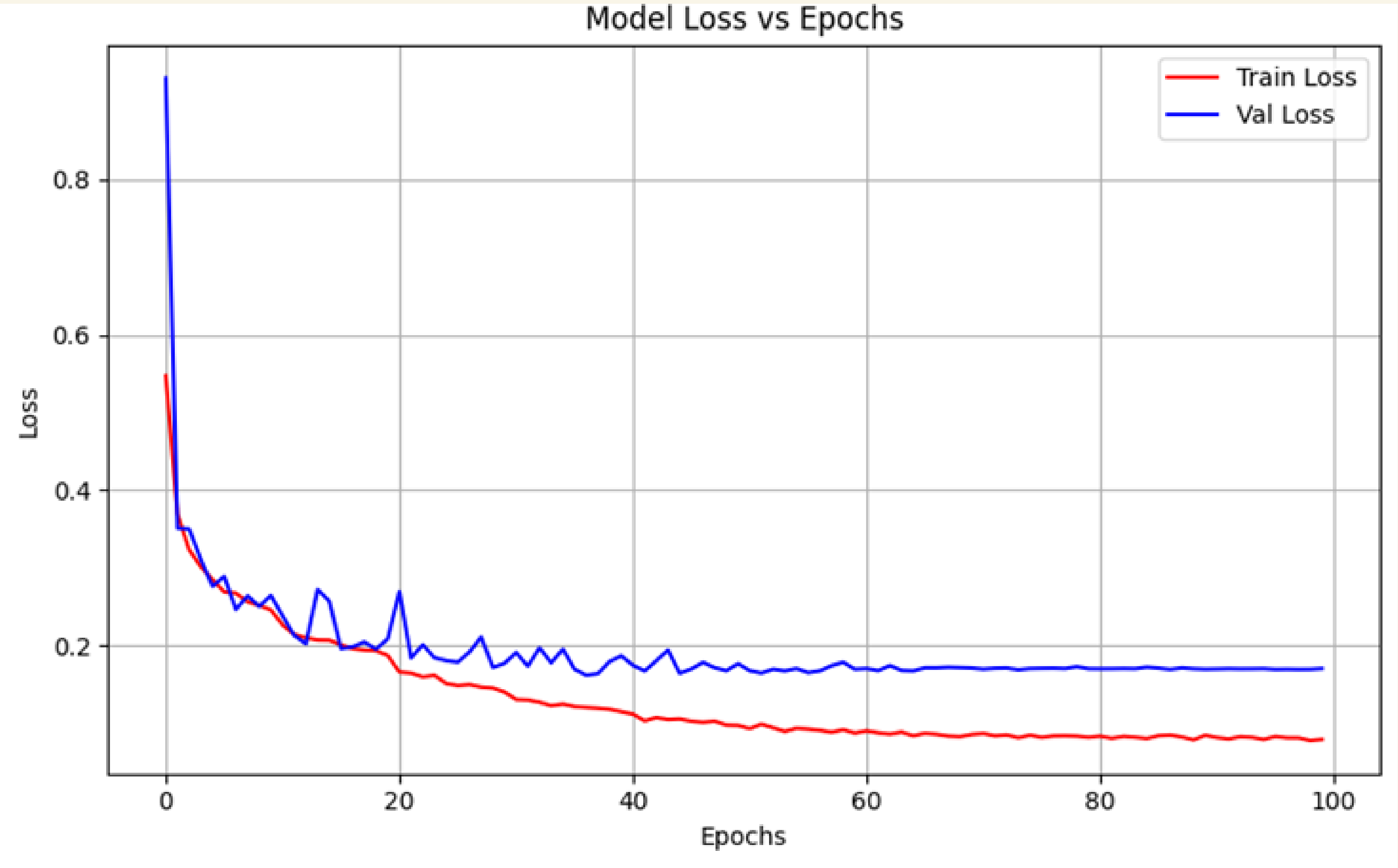


Fig 8. Model Loss vs Epochs

Training Accuracy: 98.07%
Validation Accuracy: 95.39%

Results using CNN+biLSTM:

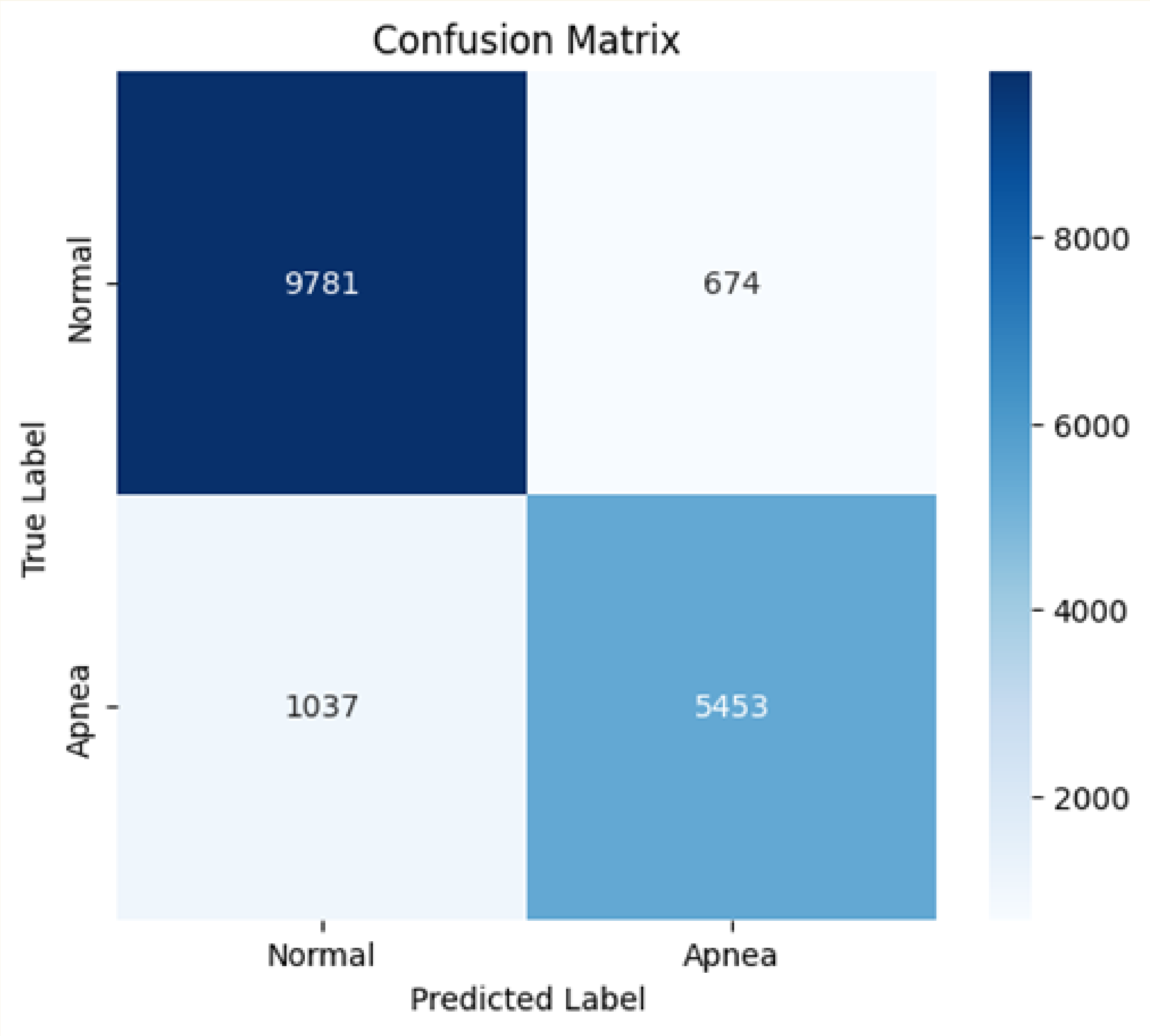


Fig 9. Confusion Matrix

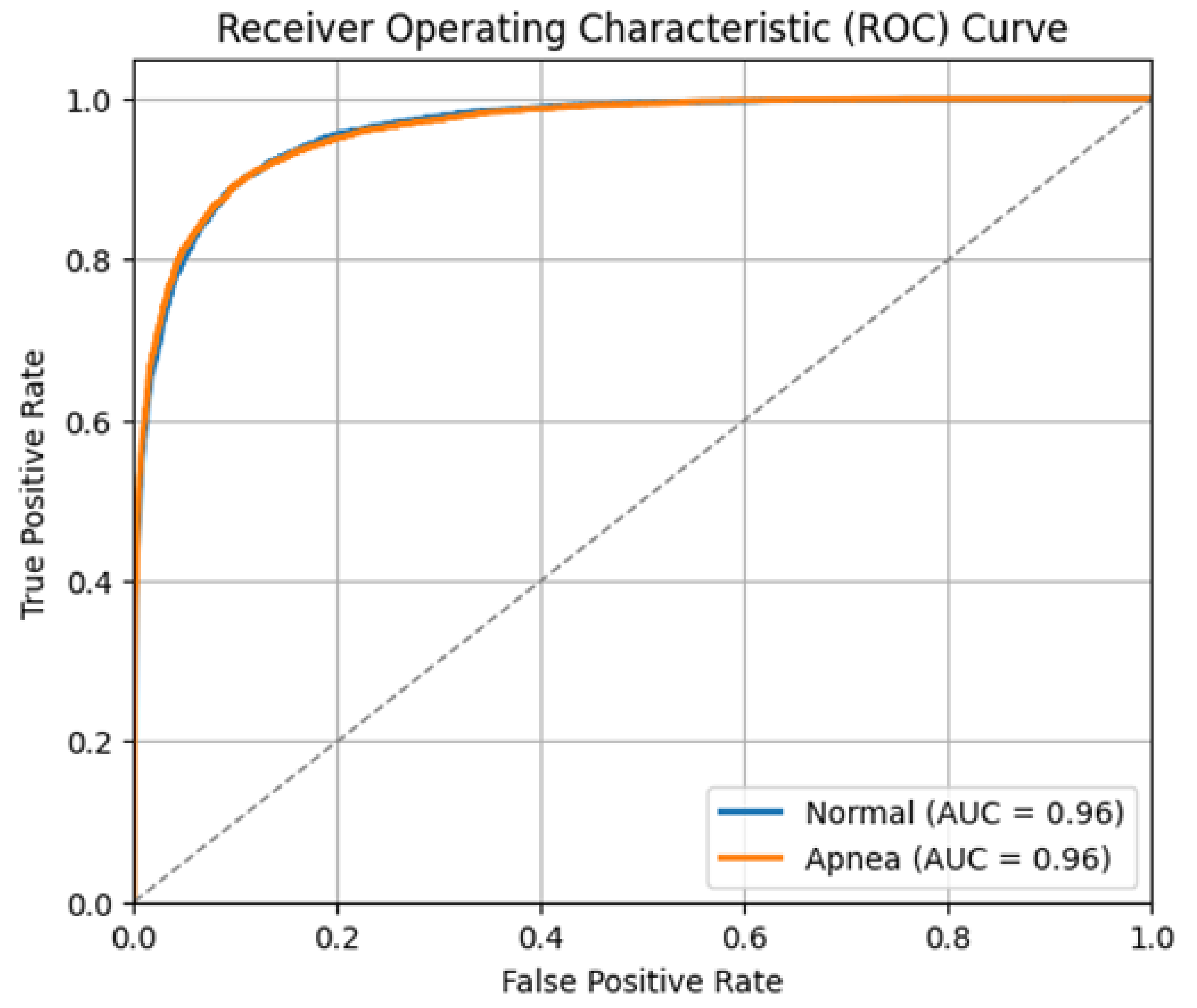


Fig 10. ROC curve

Results using CNN+biLSTM:

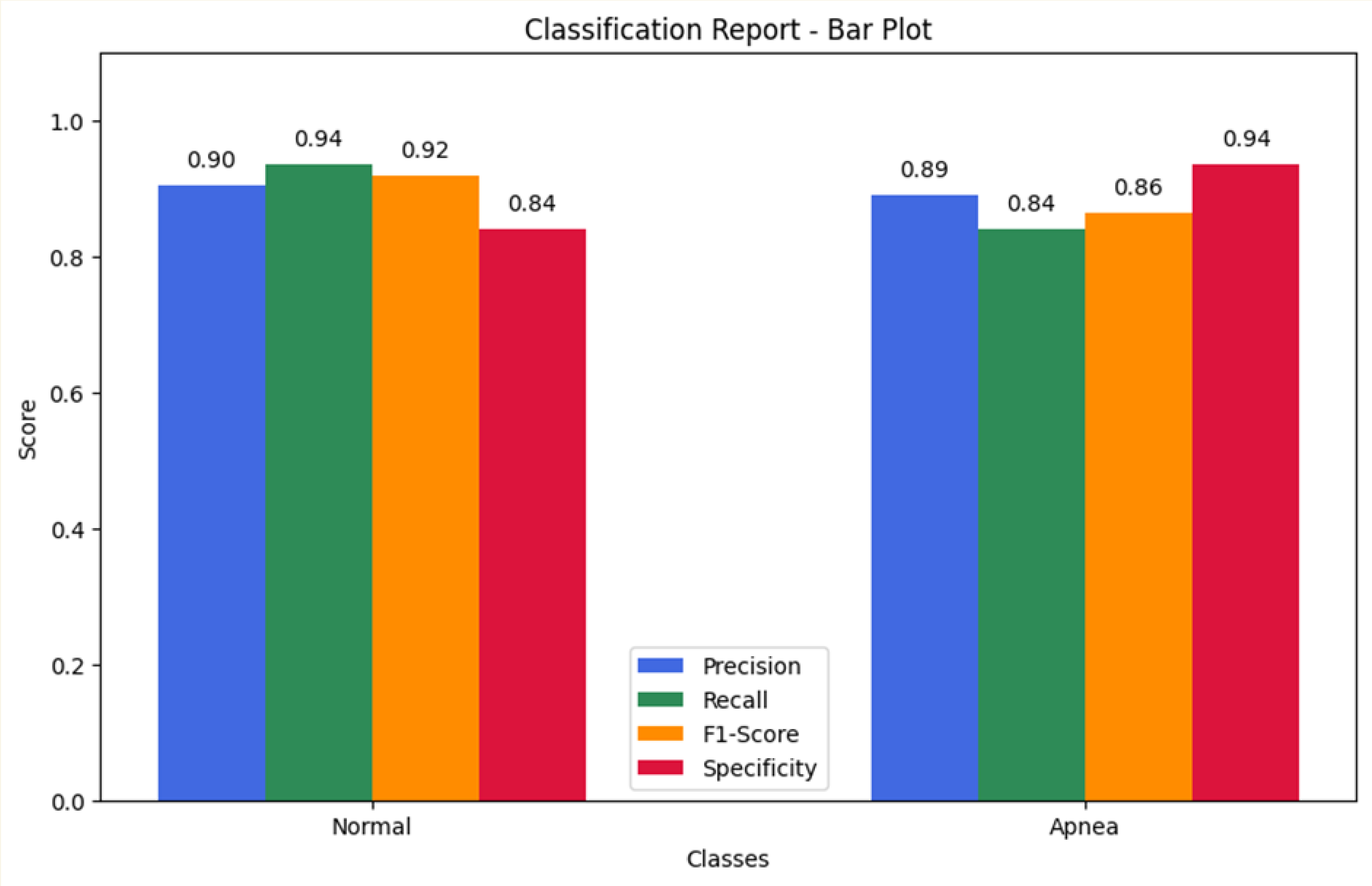


Fig 11. Classification Report of Sleep Apnea

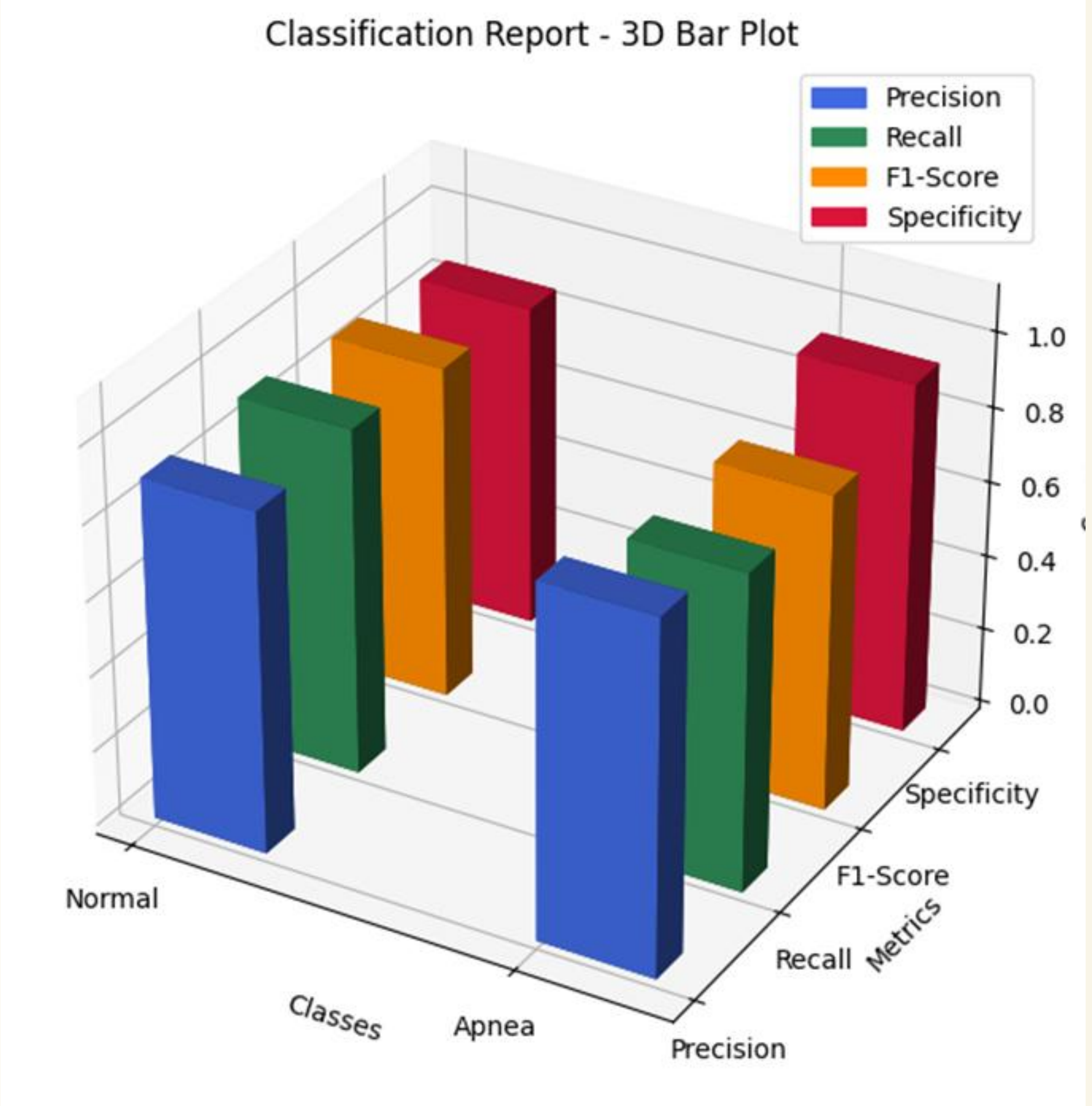


Fig 12. Classification Report of Sleep Apnea-3D plot

Results using ResNet-1D:

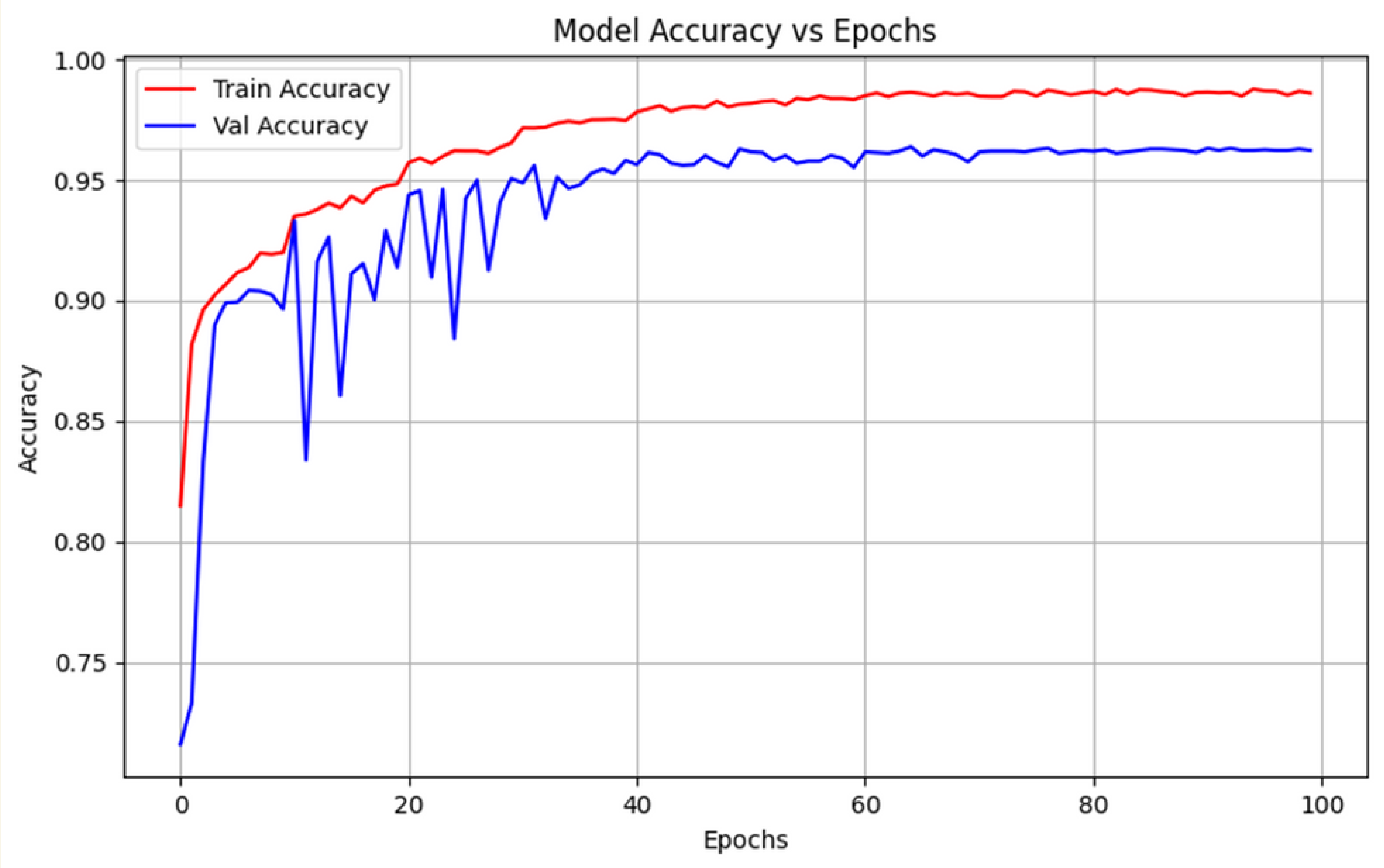


Fig 13. Model Accuracy vs Epochs

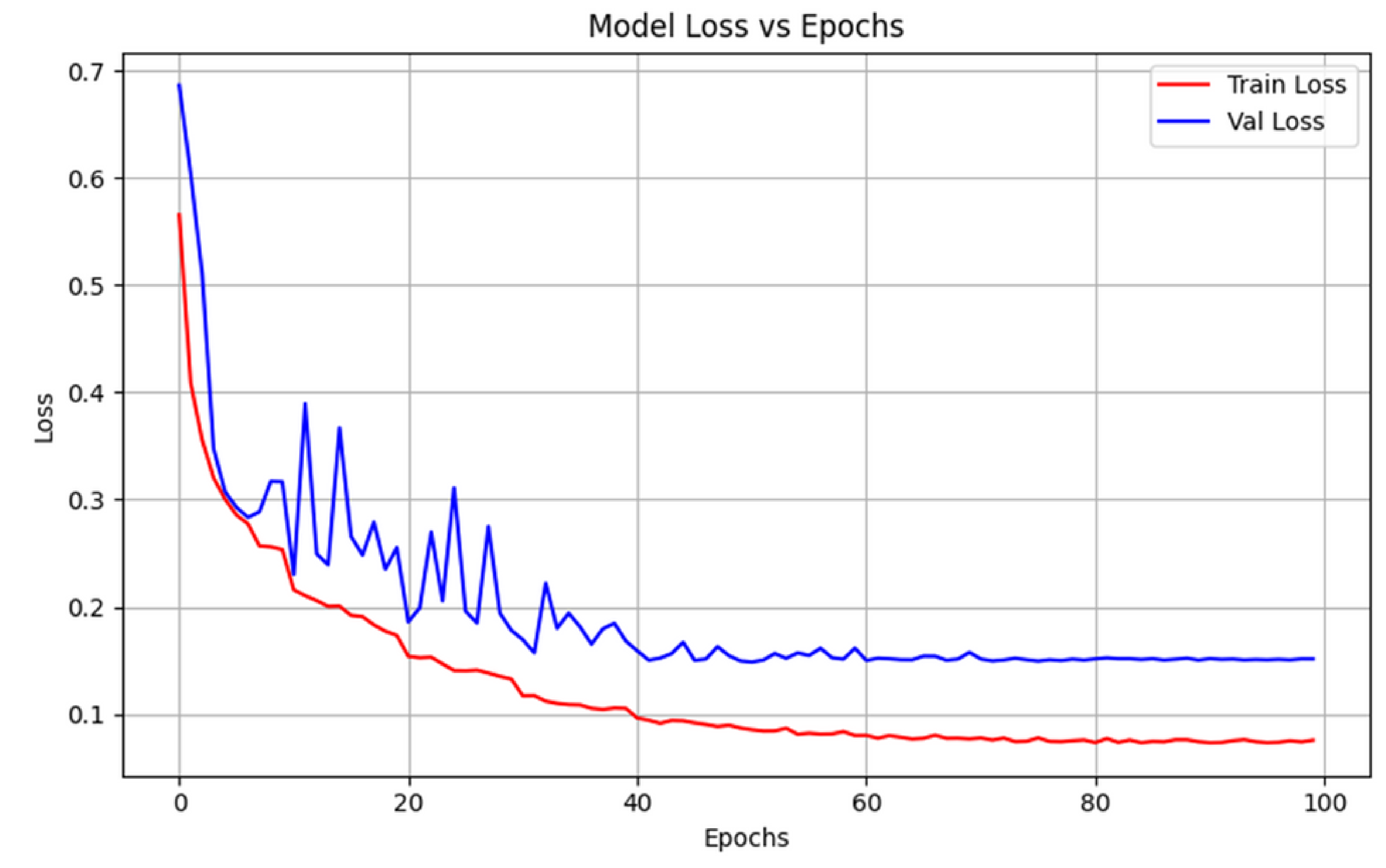


Fig 14. Model Loss vs Epochs

Training Accuracy : 98.94%
Validation Accuracy : 96.10%

Results using ResNet-1D:

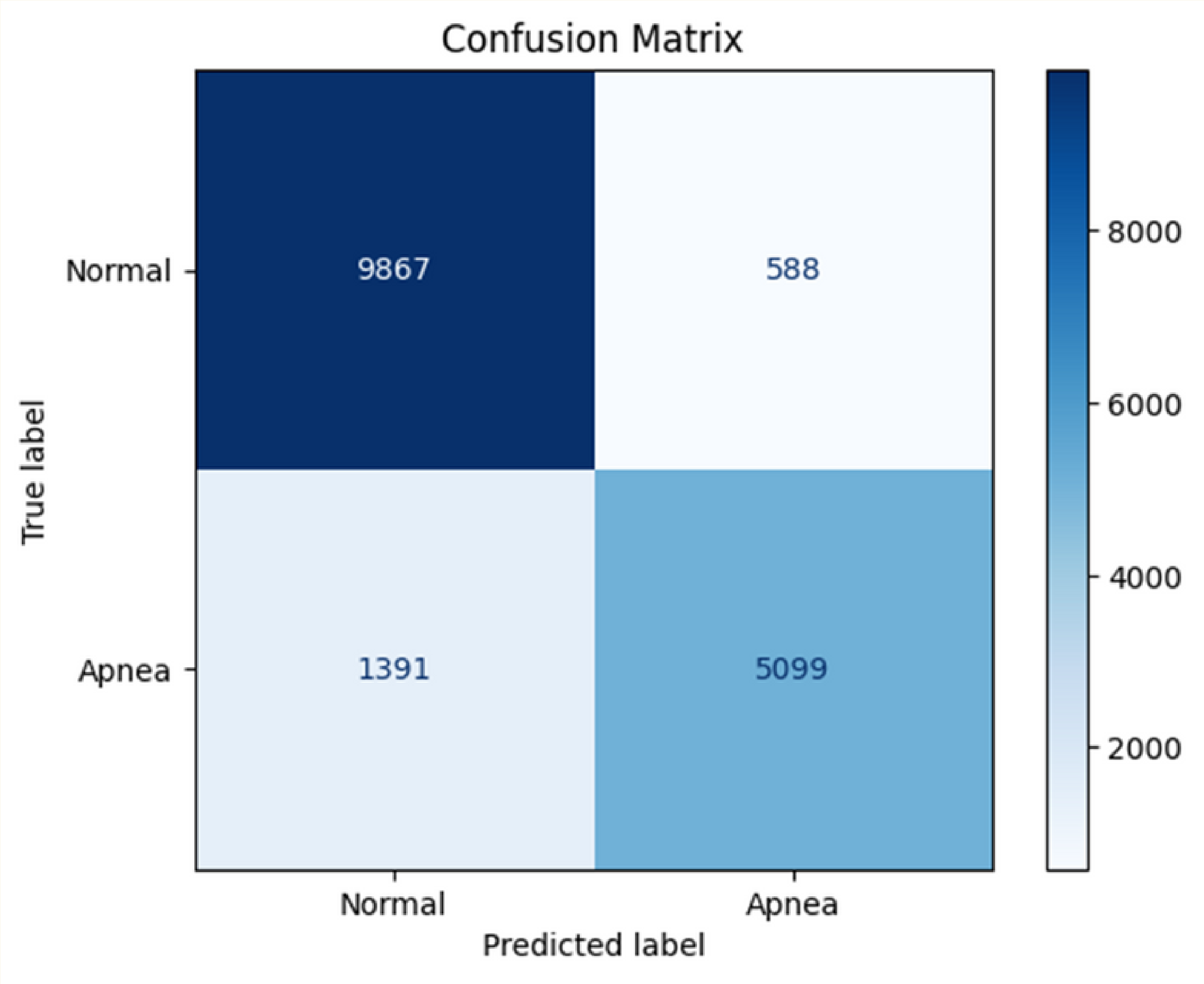


Fig 15. Confusion Matrix

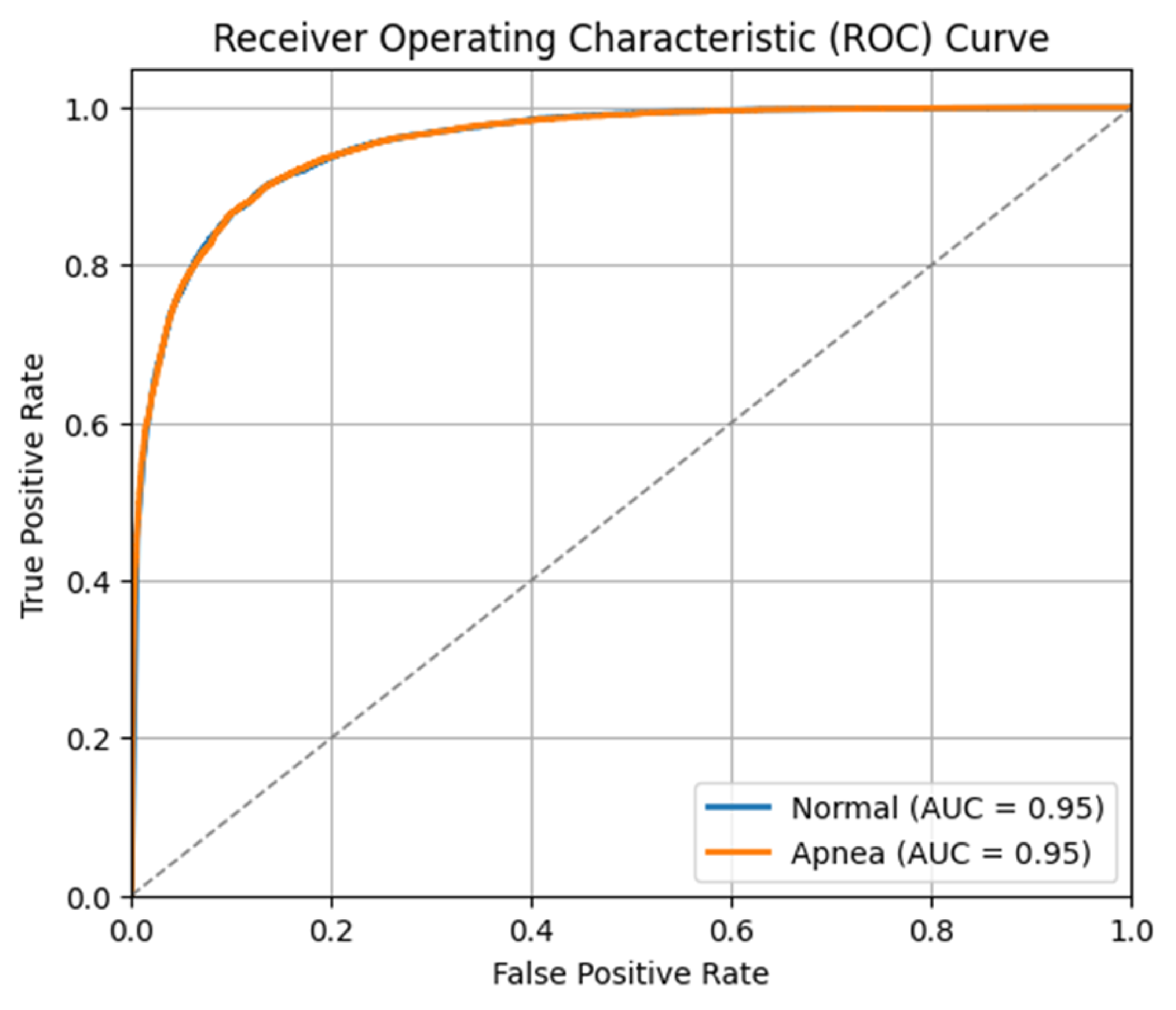


Fig 16. ROC curve

Results using ResNet-1D:

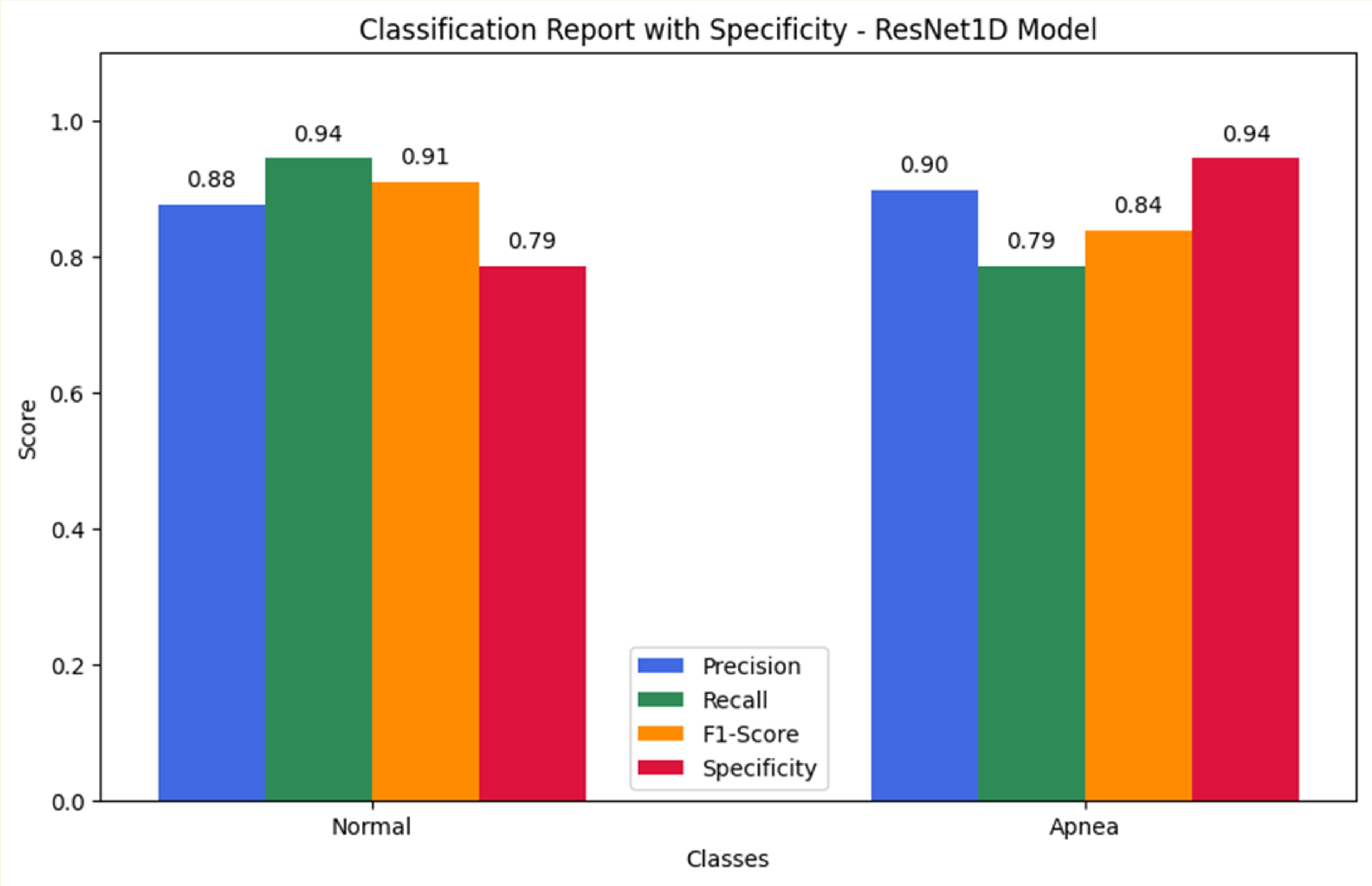


Fig 17. Classification Report of Sleep Apnea

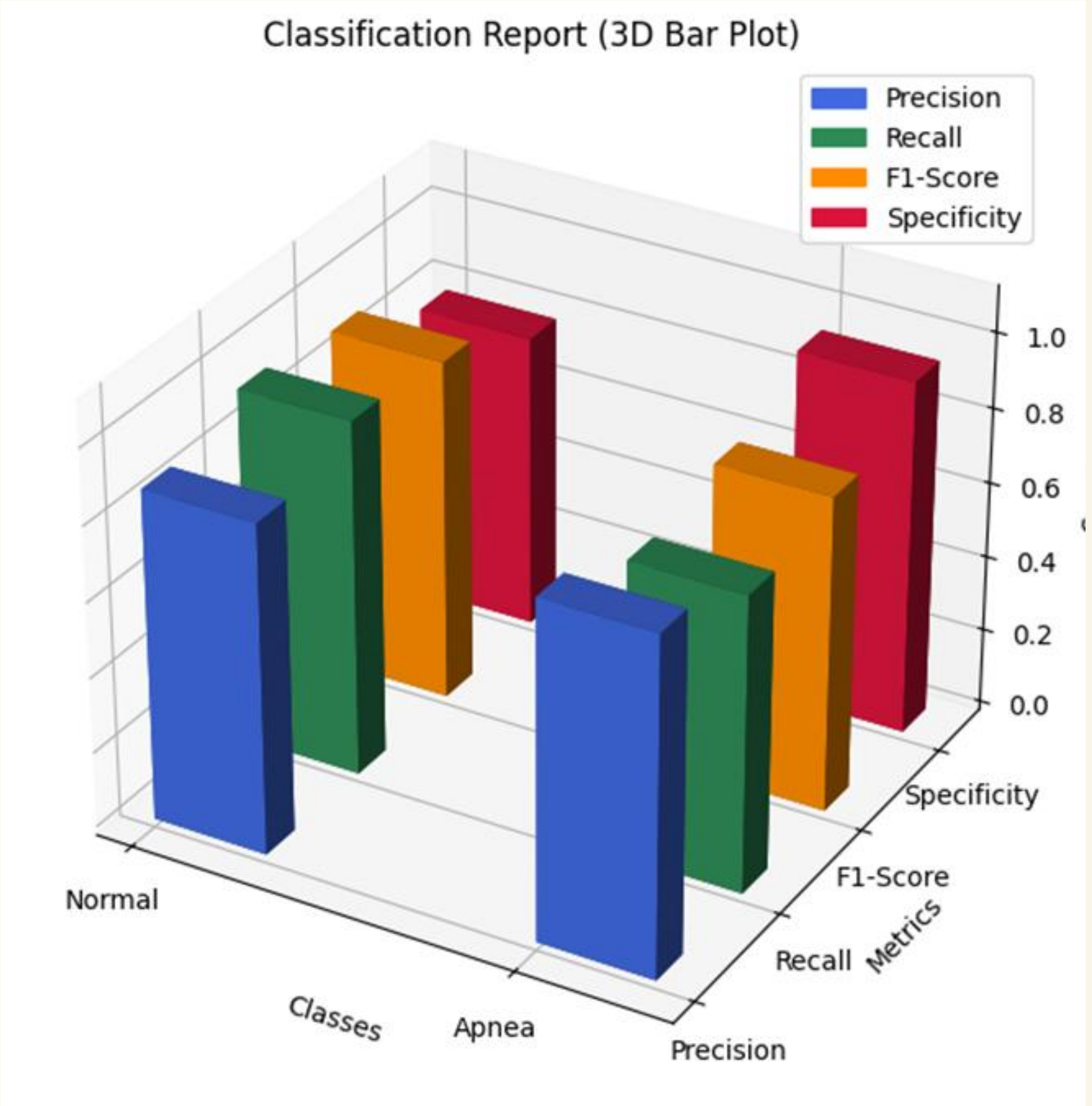


Fig 18. Classification Report of Sleep Apnea-3D plot

Conclusions:

- Developed CNN+BiLSTM and ResNet1D models using single-lead ECG from the Apnea-ECG dataset.
- Model Performance
  - ResNet1D: 96.10%
  - CNN+BiLSTM: 95.39%
  - CNN+BiLSTM was better at finding apnea events (higher recall and F1-score).
- ECG is simple and easy to use
  - great for home and wearable devices.
- Our models did better than many older methods.
- Advanced training: Custom Adam, learning rate scheduling, dropout

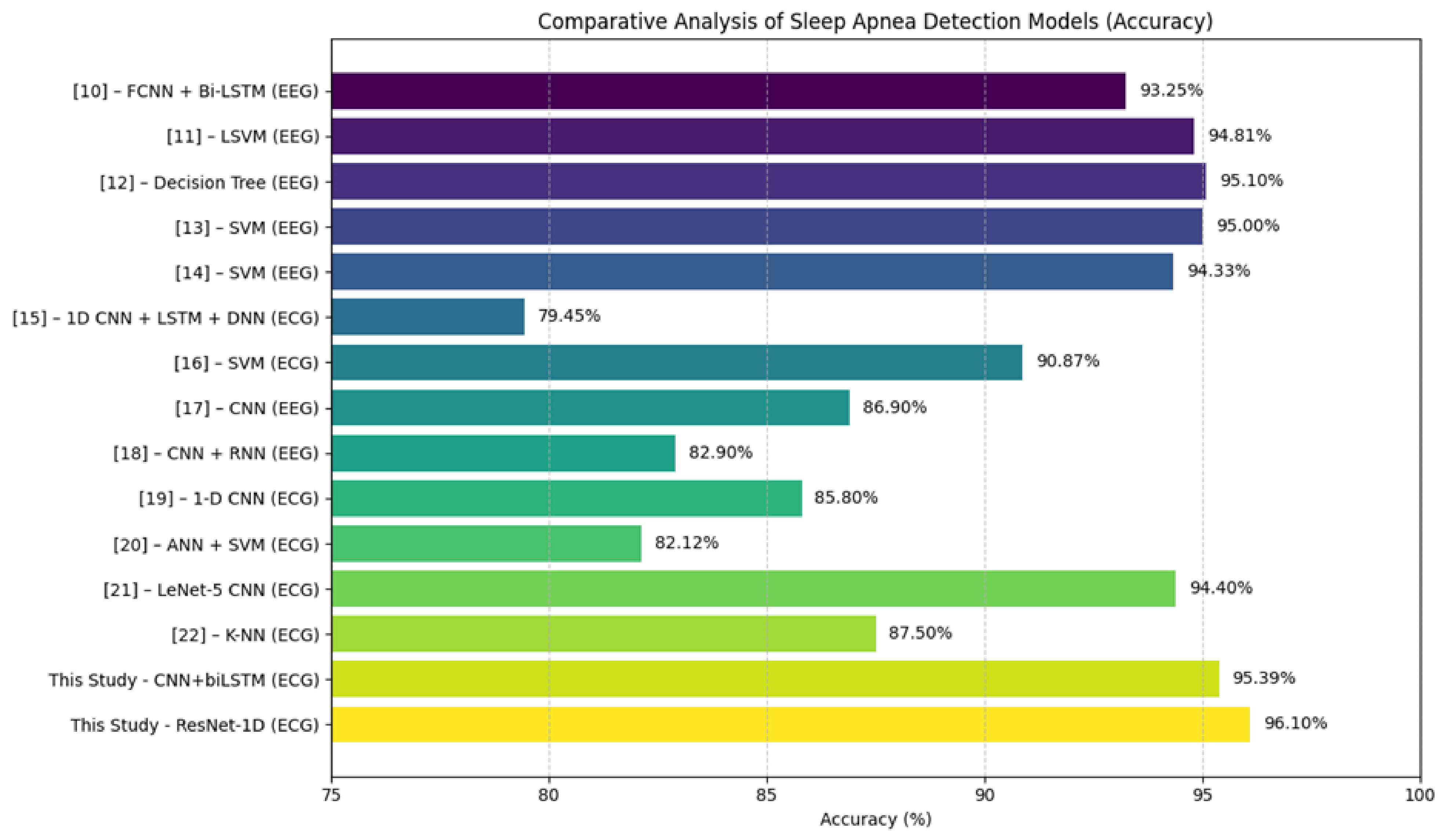


Fig 19. Comparative Analysis of Sleep Apnea Detection Models

Publication:

Submitted to the IJATEE Journals with the Title “Automated Sleep Apnea Prediction Using Deep Learning for Improved Health”

(Scopus indexed Journal)

Thank You