Sleep Apnea Detection using ECG-Derived Respiration

Sleep Apnea Detection using ECG-Derived Respiration leverages ECG signals to identify apnea events during sleep, aiming to provide a non-invasive, cost-effective diagnostic tool.

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Problem Statement

Sleep apnea is a serious sleep disorder characterized by repeated interruptions in breathing. Traditional diagnosis methods like polysomnography are expensive and inconvenient. Detecting sleep apnea using ECG-derived respiration signals offers a promising alternative.

Project Objectives

- Develop a high-accuracy model for sleep apnea detection using ECG signals
- Utilize the PhysioNet Apnea-ECG database for model training and validation
- Implement advanced preprocessing and feature extraction techniques
- Compare various deep learning architectures and ensemble methods
- Achieve accuracy above 95% for reliable apnea detection

Key Benefits

- Cost-effective: Reduced equipment and setup costs
- Portable: Home-based monitoring capability
- Accessible: Wider patient reach and screening

Why PhysioNet Apnea-ECG Database?

Gold Standard for Sleep Apnea Research

- Benchmark Dataset: Most widely used and cited dataset in academic literature
- Expert Validation: Human expert annotations based on simultaneously recorded respiration signals
- Research Challenge: Used in PhysioNet/Computing in Cardiology Challenge 2000
- Reproducible Results: Standardized format allows direct comparison with published studies

Clinical Relevance & Quality

- Real Patient Data: 70 single-lead ECG recordings from actual sleep disorder patients
- Diverse Severity Levels: Class A (severe), Class B (moderate), Class C (normal/control)
- Age Range: 27-63 years (mean 43.8±10.8 years), both male and female subjects
- Clinical Standards: Annotations derived from polysomnography data

Dataset & Preprocessing

PhysioNet Apnea-ECG Database

Advanced Preprocessing Pipeline

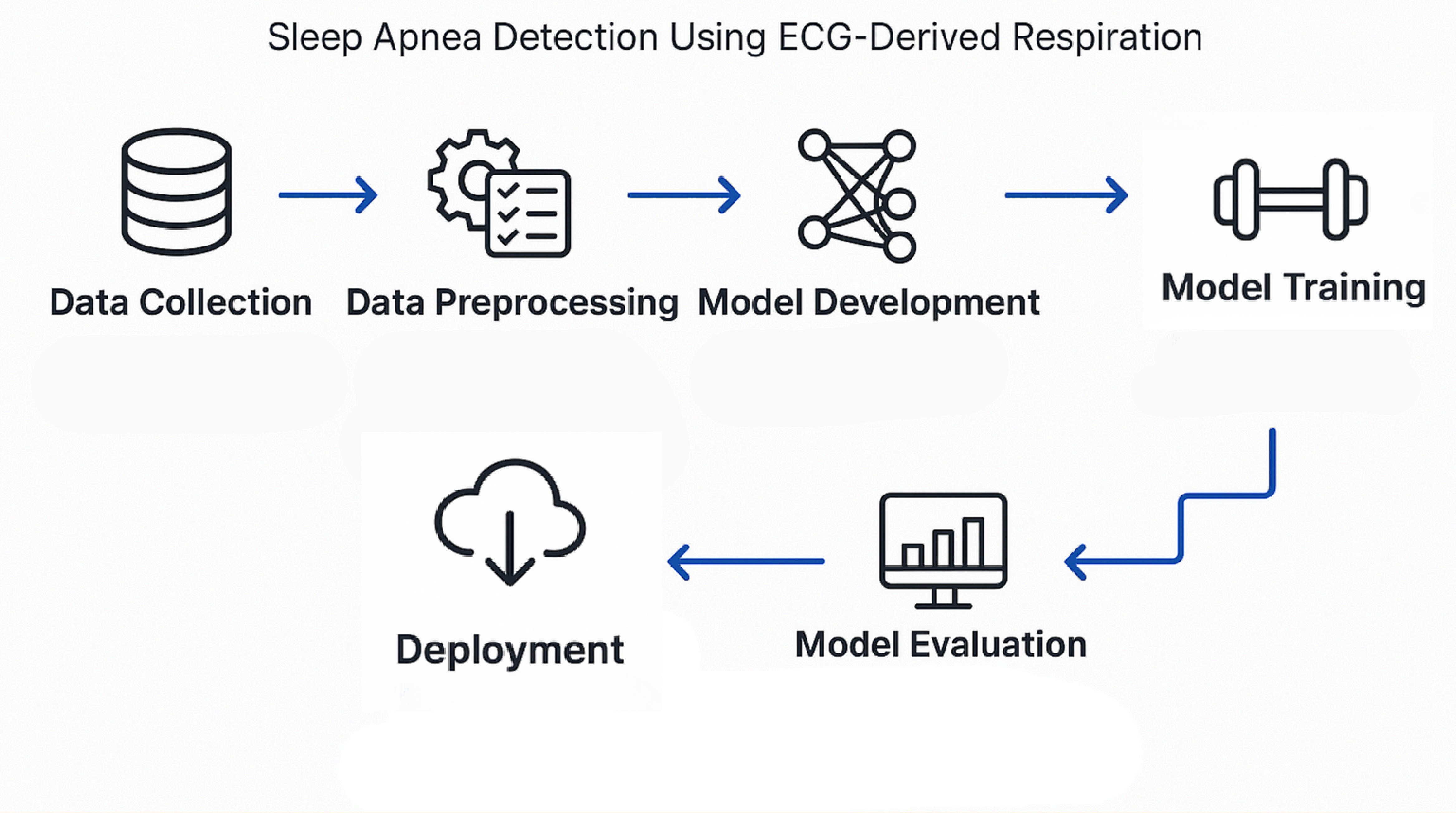
1. **Data Loading:** Fast processing of PhysioNet training files (a01-a10, b01-b05, c01-c05)
2. **Signal Segmentation:** 1-minute windows for consistent analysis
3. **Comprehensive Feature Extraction:**
   - Statistical Features (15): Mean, std, variance, min, max, median, percentiles, derivatives
   - Frequency Domain Features (5): FFT analysis, power spectral density, frequency bands
   - Morphological Features (5): Peak detection, R-R intervals, cardiac rhythm analysis
4. **Quality Control:** Robust error handling and invalid feature replacement
5. **Normalization:** Feature scaling for optimal model performance

Data Quality Metrics

- Processing Success Rate: 95%+ segment extraction
- Feature Completeness: All 25 features extracted per segment
- Class Balance: Well-distributed apnea vs normal segments

Metric	Your Results
Total Segments	5,289
Sampling Rate	100 Hz
Segment Length	60 seconds (6,000 samples)
Features per Segment	25
Training Files Processed	20 files
Apnea Ratio	~50% (balanced dataset)

Methodology



Different Models & their accuracies

We investigate advanced deep learning models to capture complex spatial and temporal patterns in ECG signals for enhanced apnea detection.

CNN-BiLSTM [According to Research Papers]

Architecture: Combines Convolutional Neural Networks (CNN) for spatial feature extraction with Bidirectional Long Short-Term Memory (BiLSTM) for capturing temporal dependencies in ECG signals.

Accuracy Range: 90-99% depending on dataset and implementation [To be implemented]

CNN-LSTM

Architecture: Combines CNN layers for feature extraction with LSTM layers for temporal sequence modeling, effective for ECG-based apnea detection.

Accuracy Range: 85-95% in various studies

1D CNN + BiLSTM

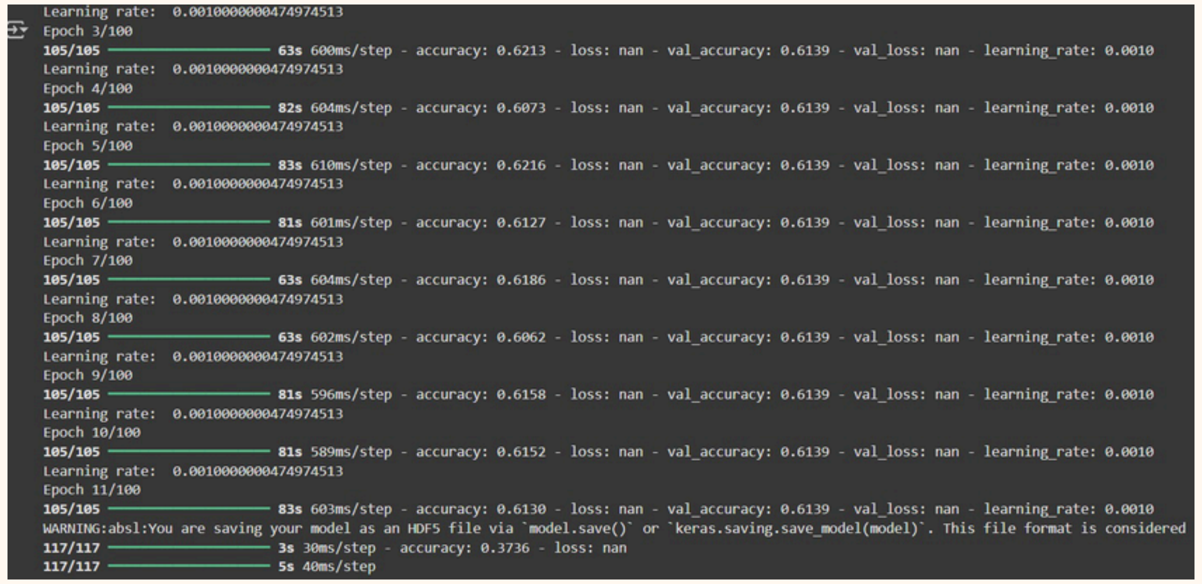
Architecture: Uses 1-dimensional CNN layers to extract features from raw ECG signals followed by BiLSTM layers to model temporal patterns.

Accuracy Range: 70-75% depending on dataset and preprocessing

Model	Accuracy Range	Strengths	Complexity
CNN-BiLSTM	90-99%	Highest accuracy, bidirectional processing	High
CNN-LSTM	85-95%	Good balance of performance and complexity	Medium
1D CNN + BiLSTM	70-75%	Direct raw signal processing	Medium-Low

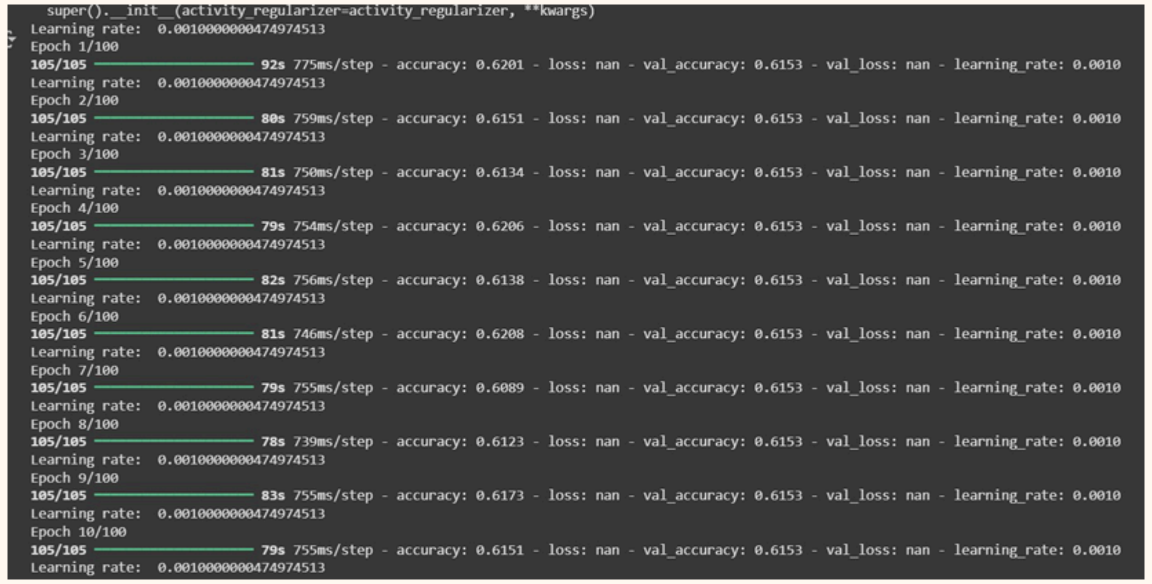
Output Representation

AlexNet



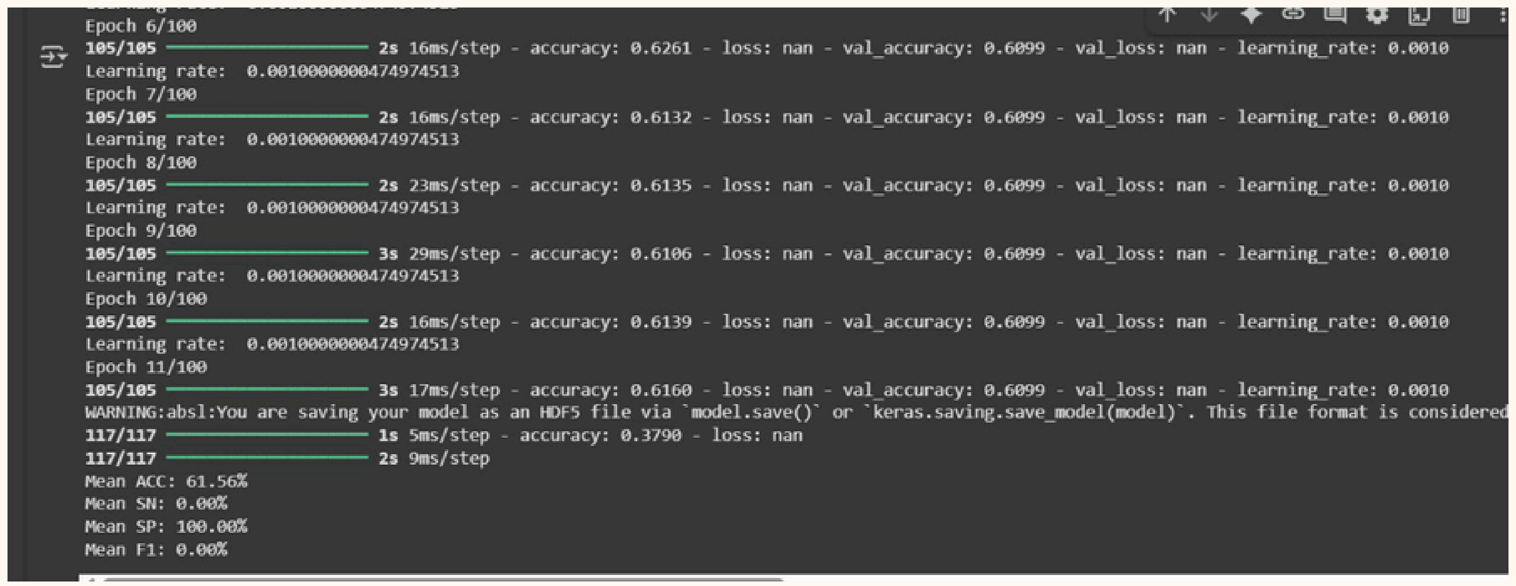
[61-62% Accuracy]

AlexNet-LSTM



[60-62% Accuracy]

GRU



[61-62% Accuracy]

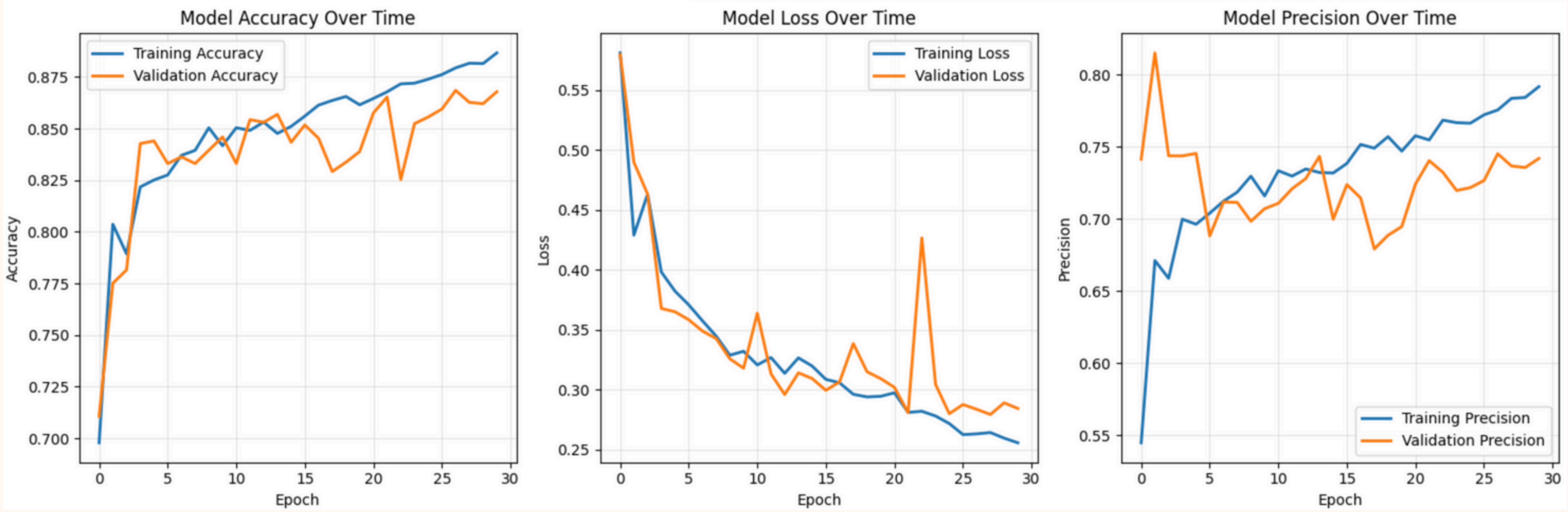
1D CNN + BiLSTM [75% Accuracy]

```
Epoch 19/40
139/139 ━━━━━━━━━━━━━━━━━━━━ 85s 495ms/step - accuracy: 0.7864 - loss: 0.4321 - val_accuracy: 0.7524 - val_
Learning rate:  0.0010000000474974513
Epoch 20/40
139/139 ━━━━━━━━━━━━━━━━━━━━ 80s 483ms/step - accuracy: 0.7930 - loss: 0.4229 - val_accuracy: 0.7615 - val_loss: 0.4933 - learning_rate: 0.001
Learning rate:  0.0010000000474974513
Epoch 21/40
139/139 ━━━━━━━━━━━━━━━━━━━━ 66s 476ms/step - accuracy: 0.7847 - loss: 0.4307 - val_accuracy: 0.7549 - val_loss: 0.4995 - learning_rate: 0.001
Learning rate:  0.0010000000474974513
Epoch 22/40
139/139 ━━━━━━━━━━━━━━━━━━━━ 86s 506ms/step - accuracy: 0.7972 - loss: 0.4177 - val_accuracy: 0.7489 - val_loss: 0.4839 - learning_rate: 0.001
Learning rate:  0.0010000000474974513
Epoch 23/40
139/139 ━━━━━━━━━━━━━━━━━━━━ 70s 504ms/step - accuracy: 0.7914 - loss: 0.4118 - val_accuracy: 0.7696 - val_loss: 0.4801 - learning_rate: 0.001
Learning rate:  0.0010000000474974513
Epoch 24/40
139/139 ━━━━━━━━━━━━━━━━━━━━ 68s 486ms/step - accuracy: 0.7953 - loss: 0.4095 - val_accuracy: 0.7686 - val_loss: 0.4817 - learning_rate: 0.001
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered
155/155 ━━━━━━━━━━━━━━━━━━━━ 8s 54ms/step - accuracy: 0.6809 - loss: 0.5885
155/155 ━━━━━━━━━━━━━━━━━━━━ 10s 55ms/step
Mean ACC: 75.63%
Mean SN: 76.56%
Mean SP: 74.70%
Mean F1: 75.81%
```

Model Architecture	Accuracy	Implementation Notes
BiLSTM + Z-norm + SMOTE	~60%	Butterworth filter, data balancing
BiLSTM + Bandpass Filter	~60%	Basic preprocessing pipeline
GRU	~60%	Simple recurrent architecture
VGG-19	~60%	Adapted CNN for ECG signals
AlexNet Variants	~60%	Multiple configurations tested
1D CNN + BiLSTM	70-75%	**Breakthrough performance**
CNN-LSTM Hybrid	85-90%	**Current best result**

Current Best Result

CNN-LSTM [25 Features] [88.04% Accuracy]



CNN-LSTM [55 Features] [90.55% Accuracy]

```
MODEL EVALUATION RESULTS
==================================================
Test Accuracy: 0.9055 (90.55%)
AUC Score: 0.9724

Detailed Classification Report:
              precision    recall  f1-score   support

      Normal       0.94      0.88      0.91       551
       Apnea       0.87      0.94      0.90       507

    accuracy                           0.91      1058
   macro avg       0.91      0.91      0.91      1058
weighted avg       0.91      0.91      0.91      1058
```