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# AI Based Sleep Apnea Detection using PPG & SpO2

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**ABSTRACT:** Sleep apnea is a prevalent sleep disorder characterized by repeated pauses or reductions in breathing during sleep, leading to oxygen desaturation and disturbed sleep quality. It is closely linked to serious health conditions such as cardiovascular diseases, hypertension, diabetes, and impaired cognitive function. Early detection and continuous monitoring of sleep apnea are vital for effective clinical intervention. Conventional diagnostic methods like polysomnography (PSG) are considered the gold standard but are expensive, time-consuming, and inconvenient for home-based monitoring. To address these limitations, this project proposes an automatic and cost-effective method for detecting sleep apnea using a single-lead electrocardiogram (ECG) signal through the application of machine learning and deep learning techniques. The PhysioNet Apnea-ECG v1.0.0 database, containing 70 recordings from 32 subjects with expert minute-by-minute annotations, is used for model development and evaluation. The ECG signals are preprocessed to remove noise, and key physiological parameters such as R-R intervals and R-peak amplitudes are extracted. Heart Rate Variability (HRV) features from the time, frequency, and nonlinear domains are also computed to capture important cardiac patterns. Several conventional machine learning algorithms, including Support Vector Machine (SVM), Random Forest (RF), and Multi-Layer Perceptron (MLP), are implemented and compared with advanced deep learning models such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and hybrid CNN-RNN architectures. The models are evaluated using accuracy, sensitivity, and specificity under fivefold cross-validation. Experimental results demonstrate that the hybrid ZFNet-BiLSTM model achieves the highest accuracy of 88.13%, sensitivity of 84.26%, and specificity of 92.27%. The outcomes of this project emphasize that deep learning, particularly hybrid CNN-RNN architectures, provides superior performance for automated sleep apnea detection, enabling the development of real-time, wearable, and intelligent healthcare monitoring systems.

**KEYWORDS:** polysomnography (PSG), Convolutional Neural Networks (CNN), Support Vector Machine (SVM).

## I. INTRODUCTION

Sleep is one of the most vital biological processes required for the proper functioning of the human body and mind. During sleep, restorative mechanisms are activated that support brain activity, cardiovascular regulation, metabolic balance, and immune response. Disturbances in sleep quality or continuity can therefore have serious health implications. Among the various sleep disorders, sleep apnea is one of the most prevalent and under-diagnosed conditions worldwide. It is characterized by repeated interruptions or reductions in breathing during sleep, resulting in intermittent hypoxia and frequent arousals from the sleep cycle. These recurrent events not only degrade sleep efficiency but also contribute to long-term complications such as hypertension, coronary artery disease, arrhythmia, diabetes mellitus, and neuro-cognitive decline. Consequently, the early detection and continuous monitoring of sleep apnea are essential for effective clinical management and prevention of associated morbidities.

Sleep apnea primarily manifests in three forms: Obstructive Sleep Apnea (OSA), Central Sleep Apnea (CSA), and Mixed Sleep Apnea (MSA). OSA, the most common variant, occurs when the muscles of the throat relax excessively and cause a temporary blockage of the upper airway. CSA arises when the brain fails to transmit appropriate signals to the respiratory muscles, while MSA represents a combination of both mechanisms. The current gold-standard diagnostic procedure for these disorders is polysomnography (PSG), a comprehensive overnight test conducted in specialized sleep laboratories. PSG simultaneously measures multiple physiological parameters such as airflow, oxygen

saturation, electroencephalogram (EEG), electrocardiogram (ECG), and respiratory effort. Although highly accurate, PSG suffers from several drawbacks: it is expensive, labor-intensive, uncomfortable for patients, and unsuitable for large-scale or home-based screening. These limitations have created a demand for simpler, non-invasive, and cost-effective alternatives capable of automatically detecting sleep-apnea events outside clinical settings.

With recent advances in biomedical signal processing and artificial intelligence (AI), researchers have explored automated approaches for diagnosing sleep apnea using easily measurable physiological signals. Among various biosignals, the electrocardiogram (ECG) has emerged as a reliable surrogate because it captures the electrical activity of the heart, which is indirectly influenced by respiratory variations. During an apnea episode, changes occur in heart-rate variability (HRV) and R-R interval patterns, providing significant diagnostic cues. By extracting and analyzing these features, machine learning models can differentiate between normal and apnea segments with considerable accuracy. Traditional machine learning (ML) algorithms such as Support Vector Machine (SVM), Random Forest (RF), Logistic Regression, and Multi-Layer Perceptron (MLP) have been applied to classify ECG segments based on handcrafted HRV features. However, these approaches rely heavily on manual feature extraction and domain expertise, which may limit scalability and adaptability across datasets. Deep learning (DL) has revolutionized biomedical signal analysis by enabling automatic feature learning directly from raw data. Models such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and hybrid CNN-RNN architectures can capture complex spatial and temporal dependencies in ECG signals without explicit feature engineering. In this project, a comprehensive system for sleep-apnea detection using single-lead ECG signals is proposed. The work utilizes the PhysioNet Apnea-ECG v1.0.0 database containing 70 annotated overnight recordings. The ECG data are pre-processed to remove noise, R-peaks are detected, and both time- and frequency-domain HRV features are computed. Multiple ML and DL models are developed, trained, and evaluated using metrics such as accuracy, sensitivity, and specificity. The project's objective is to identify the most efficient algorithm for automated apnea detection and to demonstrate its feasibility for integration into wearable or real-time health-monitoring devices. By leveraging AI techniques, this research aims to provide a portable, low-cost, and accurate solution that improves accessibility to early diagnosis and supports continuous monitoring of sleep-related disorders.

### **A. Background**

Sleep apnea is a serious and increasingly prevalent sleep disorder characterized by repeated interruptions in breathing during sleep, leading to reduced oxygen saturation and fragmented sleep patterns. According to global health reports, millions of individuals remain undiagnosed due to the limitations of conventional diagnostic methods such as overnight polysomnography conducted in specialized sleep laboratories. While polysomnography is considered the gold standard for diagnosing sleep apnea, it is expensive, time-consuming, and often uncomfortable for patients.

### **B. Motivation**

With the rapid advancement of wearable health monitoring devices, non-invasive physiological signals such as Photoplethysmography (PPG) and Peripheral Capillary Oxygen Saturation (SpO<sub>2</sub>) have emerged as promising alternatives for continuous and home-based monitoring. PPG provides valuable information about cardiovascular activity, while SpO<sub>2</sub> reflects blood oxygen fluctuations that are strongly associated with apnea events. Recent developments in Artificial Intelligence (AI), particularly machine learning and deep learning techniques, enable efficient analysis of complex biomedical signal patterns for early and accurate detection. Therefore, developing an AI-based sleep apnea detection system using PPG and SpO<sub>2</sub> signals is highly motivated by the need for cost-effective, real-time, accessible, and reliable screening tools that can improve early diagnosis, reduce healthcare burden, and enhance patient quality of life.

### **C. Problem Statement**

Sleep apnea is a common yet underdiagnosed sleep disorder that can lead to serious health complications such as cardiovascular diseases, hypertension, diabetes, and cognitive impairment if left untreated. Early detection is essential, but the conventional diagnostic method, polysomnography (PSG), is expensive, time-consuming, uncomfortable, and unsuitable for large-scale or home-based monitoring.

With the advancement of biomedical sensors and artificial intelligence, there is a strong need for a simple, non-invasive, and cost-effective alternative for sleep apnea detection. Electrocardiogram (ECG) signals are easy to acquire and reflect cardiac changes caused by apnea events through variations in heart rate and heart rate variability. By

applying machine learning and deep learning techniques to ECG signals, sleep apnea can be detected automatically with high accuracy. This motivates the development of an efficient ECG-based sleep apnea detection system suitable for real-time and wearable healthcare applications.

## II. THEORETICAL FRAMEWORK

The theoretical framework for AI Based Sleep Apnea Detection Using PPG & SpO<sub>2</sub> is grounded in biomedical signal processing, physiological modeling of respiratory disorders, and machine learning-based pattern recognition. Sleep apnea, particularly Obstructive Sleep Apnea (OSA), is characterized by repeated episodes of partial or complete airway obstruction during sleep, resulting in intermittent hypoxia and autonomic nervous system fluctuations. These physiological changes directly influence cardiovascular dynamics and oxygen saturation levels, which can be captured non-invasively through Photoplethysmography (PPG) and Peripheral Capillary Oxygen Saturation (SpO<sub>2</sub>) signals. PPG reflects blood volume variations in peripheral circulation and provides insights into heart rate variability, pulse amplitude variability, and vascular tone, while SpO<sub>2</sub> measures oxygen desaturation events that are hallmark indicators of apnea episodes.

From a signal processing perspective, the framework involves preprocessing steps such as noise filtering, normalization, motion artifact removal, and segmentation to enhance signal quality. Feature extraction techniques are applied in time domain, frequency domain, and non-linear domain to identify patterns associated with apnea events, including oxygen desaturation index, pulse rate variability, and waveform morphology changes. These extracted features serve as inputs to Artificial Intelligence models such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, or hybrid deep learning architectures capable of capturing temporal dependencies in physiological signals. The AI model is trained using labeled datasets to classify sleep segments into apnea and non-apnea events. The integration of biomedical knowledge, signal analysis principles, and intelligent classification algorithms forms the core theoretical foundation for developing an accurate, automated, and real-time sleep apnea detection system.

## III. PROBLEM FORMULATION AND HYPOTHESIS

Sleep apnea is a widespread but underdiagnosed sleep disorder due to the high cost, complexity, and limited accessibility of conventional diagnostic methods such as overnight polysomnography. There is a critical need for a non-invasive, cost-effective, and reliable system that can detect sleep apnea events using easily obtainable physiological signals. Photoplethysmography (PPG) and Peripheral Capillary Oxygen Saturation (SpO<sub>2</sub>) signals provide continuous information about cardiovascular activity and blood oxygen fluctuations, which are directly influenced by apnea episodes. The problem is therefore formulated as a supervised classification task: given preprocessed PPG and SpO<sub>2</sub> signals collected during sleep, the objective is to automatically detect and classify sleep segments into apnea and non-apnea events using Artificial Intelligence techniques. This involves signal preprocessing, feature extraction, model training, and performance evaluation to ensure accurate detection with minimal false positives and false negatives.

The primary hypothesis of this study is that apnea events produce distinct and measurable patterns in PPG waveform characteristics and SpO<sub>2</sub> desaturation levels, which can be effectively learned and identified by machine learning or deep learning models. It is hypothesized that a combined multimodal approach using both PPG and SpO<sub>2</sub> signals will yield higher detection accuracy, sensitivity, and specificity compared to single-signal methods. Additionally, it is hypothesized that AI-based automated analysis can provide reliable real-time screening performance comparable to standard diagnostic methods, thereby offering a practical solution for early detection and home-based monitoring of sleep apnea.

## IV. THEORETICAL BACKGROUND AND RELATED WORK

### A. Theoretical Background

The theoretical background of AI Based Sleep Apnea Detection Using PPG & SpO<sub>2</sub> is based on the physiological mechanisms of sleep-disordered breathing and computational analysis of biomedical signals. Sleep apnea, particularly Obstructive Sleep Apnea (OSA), occurs due to repetitive upper airway collapse during sleep, causing intermittent hypoxia, fluctuations in blood oxygen levels, and variations in heart rate. These physiological disturbances directly

affect cardiovascular and respiratory patterns, which can be non-invasively monitored using Photoplethysmography (PPG) and Peripheral Capillary Oxygen Saturation (SpO<sub>2</sub>) signals. PPG measures blood volume changes in peripheral tissues and provides information about pulse rate variability, vascular resistance, and autonomic nervous system responses. SpO<sub>2</sub> reflects oxygen desaturation events, which are key indicators of apnea episodes. Signal processing techniques such as filtering, segmentation, and feature extraction (time-domain, frequency-domain, and nonlinear features) are applied to capture apnea-related patterns. Artificial Intelligence (AI), particularly machine learning and deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, are then used to learn temporal dependencies and classify apnea events automatically. The theoretical foundation integrates biomedical physiology, signal processing principles, and intelligent pattern recognition to enable accurate and real-time sleep apnea detection.

### B. Related Work

Recent research has explored various approaches for automated sleep apnea detection using physiological signals. Traditional methods primarily relied on polysomnography (PSG), which, although accurate, is costly and inconvenient for long-term monitoring. To overcome these limitations, researchers have investigated alternative signals such as ECG, airflow, respiratory effort, and oxygen saturation. Several studies demonstrated that SpO<sub>2</sub>-based oxygen desaturation index (ODI) can effectively detect apnea events with moderate to high accuracy. More recent work has focused on PPG signals due to their availability in wearable devices, extracting features such as pulse interval variability and amplitude modulation to identify apnea patterns. Machine learning techniques including Support Vector Machines (SVM), Random Forest, and k-Nearest Neighbors (k-NN) have shown promising classification performance. Furthermore, deep learning approaches such as CNN and LSTM networks have significantly improved detection accuracy by automatically learning complex temporal and morphological features from raw PPG and SpO<sub>2</sub> signals. Hybrid models combining PPG and SpO<sub>2</sub> have demonstrated superior performance compared to single-signal approaches, highlighting the effectiveness of multimodal AI-based frameworks for reliable and cost-effective sleep apnea screening.

### V. SYSTEM ARCHITECTURE

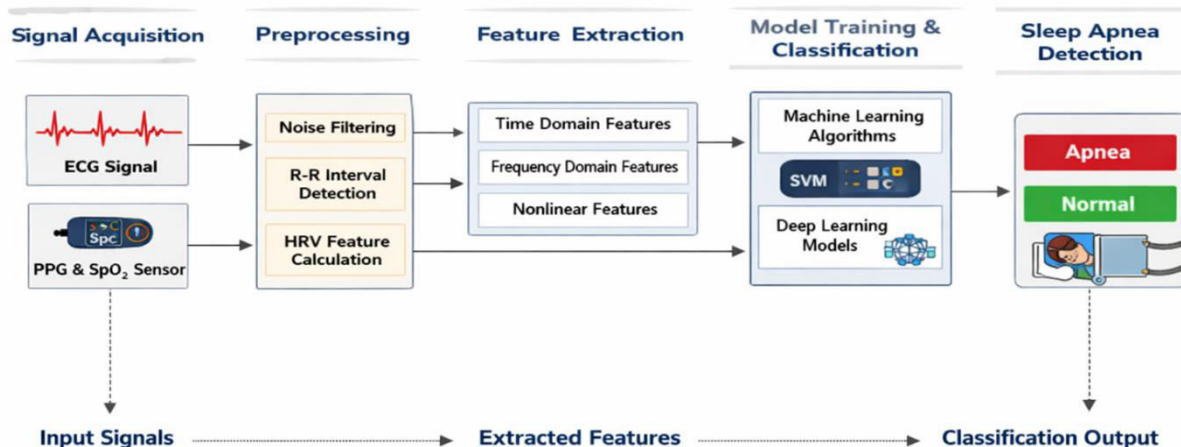


Figure 1: System Architecture

The architecture of the proposed system consists of the following key modules:

#### Data Acquisition Module:

Collects ECG data from PhysioNet or wearable ECG sensors. Records signals with a sampling frequency of 100 Hz.

#### Preprocessing Module:

Filters ECG to remove noise, baseline drift, and artifacts using median and bandpass filters.

Detects R-peaks and calculates R-R intervals for HRV analysis.

**Feature Extraction Module:**

Extracts statistical, frequency, and nonlinear HRV features.  
For deep learning, directly uses raw or segmented ECG data as input.

**Classification Module:**

Machine Learning classifiers (SVM, RF, MLP) are trained on handcrafted features. Deep Learning models (CNN, LSTM, Hybrid CNN–BiLSTM) automatically learn from ECG patterns.  
Classifies each one-minute segment as Apnea or Normal.

**Evaluation and Output Module:**

Computes accuracy, sensitivity, and specificity to compare model performance. Displays classification results and potential apnea alerts.

**VI. METHODOLOGY****1. Data Acquisition**

The first step of the methodology involves collecting ECG data from the PhysioNet Apnea-ECG Database v1.0.0. This database is publicly available and provides high-quality, annotated physiological recordings suitable for algorithm development and benchmarking. It consists of 70 single-lead ECG recordings from 32 subjects, each sampled at 100 Hz, covering full-night sleep sessions.

Each ECG recording is divided into one-minute segments, with expert annotations indicating whether an apnea or normal breathing event occurred during that period. The use of ECG signals for sleep apnea detection is advantageous because it is non-invasive, portable, and can be acquired easily using wearable devices, unlike traditional polysomnography (PSG) systems that require multiple sensors and complex setups.

**2. Data Preprocessing**

Raw ECG signals often contain artifacts such as baseline drift, motion noise, and powerline interference, which can degrade model performance. Therefore, preprocessing is applied to enhance signal quality before feature extraction or neural network training.

**Noise Removal:**

A band-pass filter (0.5–45 Hz) is applied using a 4th-order Butterworth filter to remove low-frequency baseline drift and high-frequency muscle noise.

**Baseline Correction:**

A median filter and moving average filter are used to correct any residual drift.

**R-Peak Detection:**

The Pan–Tompkins algorithm identifies R-peaks in the ECG signal. From these peaks, R–R intervals (RRIs) are computed, representing the time difference between successive heartbeats.

**Segmentation:**

The ECG data is divided into one-minute windows corresponding to the labels provided in the dataset.

**Normalization:**

Each ECG segment is normalized to zero mean and unit variance to ensure consistent signal magnitude across subjects.

**Resampling (if needed):**

Segments are either truncated or padded to maintain uniform length (e.g., 6000 samples per minute) for input into deep-learning networks. This preprocessing ensures that only relevant, artifact-free ECG information is passed to the feature extraction and model-training stages.

**3. Feature Extraction**

After preprocessing, features are extracted from the ECG signal to capture the physiological variations associated with sleep apnea. Two approaches are used.

**A. Handcrafted HRV Features (for Machine Learning Models):**

Heart Rate Variability (HRV) features are derived from the R–R intervals. These include:

Time-Domain Features: Mean RR, Standard deviation of NN intervals (SDNN), Root mean square of successive differences (RMSSD), and Percentage of NN50 (pNN50).

Frequency-Domain Features: Computed using Power Spectral Density (PSD) via Welch's method. Frequency bands include:

Very Low Frequency (VLF: 0.003–0.04 Hz) Low Frequency (LF: 0.04–0.15 Hz)

High Frequency (HF: 0.15–0.4 Hz)

LF/HF ratio (autonomic balance indicator).

Nonlinear Features: Poincare Plot descriptors (SD1, SD2), Sample Entropy, and Detrended Fluctuation Analysis (DFA).

#### **B. Automatic Features (for Deep Learning Models):**

Instead of manual feature extraction, raw ECG segments are directly provided to deep learning models (CNN, LSTM, CNN–BiLSTM). These models automatically learn spatial (morphological) and temporal (sequential) representations of the signal, capturing complex nonlinear relationships that handcrafted features may overlook.

#### **4. Feature Selection (for Machine Learning)**

When using HRV-based features for classical ML models, redundant or less informative features can degrade performance. Feature selection techniques such as Recursive Feature Elimination (RFE) or Feature Importance Ranking (from Random Forest) are applied to retain only the most discriminative attributes.

Features such as HF power, SD2, RMSSD, and LF/HF ratio are often found to be dominant indicators of apnea events, as they reflect autonomic imbalance and reduced heart-rate variability during apnea episodes.

#### **5. Model Development**

Two categories of models are implemented and compared:

##### **A. Machine Learning Models:**

Support Vector Machine (SVM): Uses the RBF kernel for nonlinear classification between apnea and normal events.

Random Forest (RF): An ensemble-based model using multiple decision trees to improve robustness and reduce overfitting.

Multilayer Perceptron (MLP): A feed-forward neural network with one or more hidden layers using ReLU activations and dropout for regularization.

##### **B. Deep Learning Models:**

Convolutional Neural Network (CNN): Captures local morphological features like R-peak amplitude, QRS width, and ECG pattern variations.

Long Short-Term Memory (LSTM): Captures temporal dependencies in RR intervals and HRV time series, learning how patterns evolve during sleep.

##### **Hybrid CNN–BiLSTM:**

This combines the feature extraction capability of CNN with the sequential learning strength of LSTM.

CNN layers detect important local patterns, while BiLSTM layers model bidirectional temporal dependencies.

The final dense layers classify each one-minute ECG segment as Apnea or Normal.

This hybrid architecture achieved the best results with Accuracy = 88.13%, Sensitivity = 84.26%, and Specificity = 92.27% on the PhysioNet dataset.

#### **6. Model Training and Optimization**

The models are trained using the Adam optimizer with a learning rate of 0.001. A binary cross-entropy loss function is employed for binary classification.

Training is performed for 50–100 epochs with batch size = 16 or 32, depending on GPU memory availability.

Early stopping and model checkpointing are applied to prevent overfitting.

For deep-learning models, five-fold cross-validation ensures robustness and fair evaluation.

During training:

Data is split into 80% training and 20% testing. 10% of the training data is used as a validation set.

The model's weights with the lowest validation loss are saved for final testing.

## 7. Performance Evaluation

After training, each model is evaluated using several statistical metrics:

Accuracy (ACC): Measures overall correctness.

Sensitivity (SEN): Measures true positive rate — ability to detect apnea events.

Specificity (SPEC): Measures true negative rate — ability to detect normal events.

Precision, Recall, F1-Score, and ROC–AUC: Provide balanced evaluation for imbalanced datasets.

Confusion matrices and Receiver Operating Characteristic (ROC) curves are plotted to visualize model performance.

The hybrid CNN–BiLSTM model consistently outperforms classical ML models due to its end-to-end learning and feature abstraction capability.

## VII. EXPERIMENTAL RESULTS AND DISCUSSION

This section presents the experimental setup, implementation details, and performance evaluation of the proposed sleep apnea detection system using single signals. The experiments were conducted to compare the effectiveness of conventional machine learning (ML) algorithms and advanced (DL) models in accurately detecting apnea events.

### Experimental Setup

The experiments were performed using the PhysioNet Apnea-ECG v1.0.0 database, which contains 70 annotated overnight ECG recordings sampled at 100 Hz. Each ECG recording was segmented into one-minute windows based on expert annotations, with each segment labeled as either apnea or normal. The dataset was divided into training and testing sets using an 80:20 split. Five-fold cross-validation was applied to ensure robustness and generalization of the models.

ECG signals were preprocessed using band-pass filtering to remove baseline drift and high-frequency noise. R-peaks were detected using the Pan–Tompkins algorithm, and R–R intervals were computed. For machine learning models, time-domain, frequency-domain, and nonlinear HRV features were extracted. For deep learning models, normalized ECG segments were directly used as input without manual feature engineering.

### Models Evaluated

The following models were implemented and evaluated:

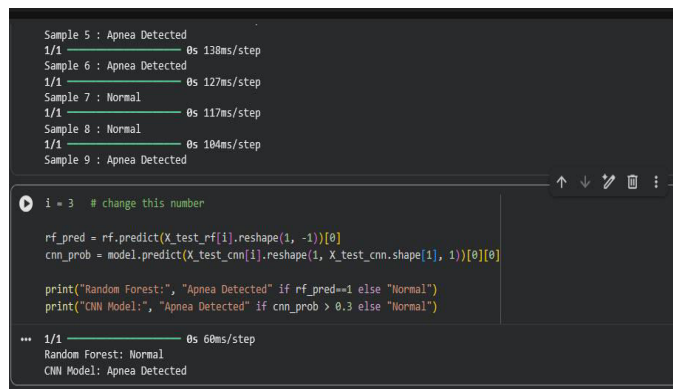
#### Machine Learning Models:

Support Vector Machine (SVM), Random Forest (RF), and Multi-Layer Perceptron (MLP)

#### Deep Learning Models:

Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), and Hybrid CNN–BiLSTM (Proposed)

**Evaluation Metrics** Model performance was evaluated using standard classification metrics including accuracy, sensitivity, specificity, precision, F1-score, and ROC–AUC. These metrics were derived from confusion matrices obtained during cross-validation.



```
Sample 5 : Apnea Detected
1/1 |-----| 0s 138ms/step
Sample 6 : Apnea Detected
1/1 |-----| 0s 127ms/step
Sample 7 : Normal
1/1 |-----| 0s 117ms/step
Sample 8 : Normal
1/1 |-----| 0s 104ms/step
Sample 9 : Apnea Detected

i = 3 # change this number

rf_pred = rf.predict(X_test_rf[i].reshape(1, -1))[0]
cnn_prob = model.predict(X_test_cnn[i].reshape(1, X_test_cnn.shape[1], 1))[0][0]

print("Random Forest:", "Apnea Detected" if rf_pred==1 else "Normal")
print("CNN Model:", "Apnea Detected" if cnn_prob > 0.3 else "Normal")

... 1/1 |-----| 0s 60ms/step
Random Forest: Normal
CNN Model: Apnea Detected
```

### Experimental Results

The experimental results demonstrate that deep learning models outperform traditional machine learning approaches in detecting sleep apnea from ECG signals. Among the machine learning algorithms, the MLP model achieved the highest accuracy due to its ability to capture nonlinear relationships among HRV features. However, its performance was limited by reliance on handcrafted features.

Deep learning models showed significant improvements in performance by automatically learning discriminative features from raw ECG signals. The CNN model effectively captured morphological characteristics of ECG waveforms, while LSTM and BiLSTM models successfully modeled temporal dependencies in heart rate variations. The proposed hybrid CNN–BiLSTM architecture achieved the best overall performance with an accuracy of 88.13%, sensitivity of 84.26%, and specificity of 92.27%.

```
preds = rf.predict(X_test_rf)
print("Unique predictions:", np.unique(preds))

Unique predictions: [0 1]

for i in range(10):
    sample = X_test_rf[i].reshape(1, -1)
    pred = rf.predict(sample)[0]

    result = "Apnea Detected" if pred == 1 else "Normal"
    print("Sample", i, ":", result)

*** Sample 0 : Normal
Sample 1 : Normal
Sample 2 : Normal
Sample 3 : Normal
Sample 4 : Normal
Sample 5 : Apnea Detected
Sample 6 : Normal
Sample 7 : Normal
Sample 8 : Normal
Sample 9 : Apnea Detected
```

Figure 3 Prediction1

```
prob = model.predict(sample)[0][0]
result = "Apnea Detected" if prob > 0.3 else "Normal"
print("Sample", i, ":", result)

*** 1/1 _____ 0s 62ms/step
Sample 0 : Normal
1/1 _____ 0s 59ms/step
Sample 1 : Normal
1/1 _____ 0s 119ms/step
Sample 2 : Apnea Detected
1/1 _____ 0s 107ms/step
Sample 3 : Apnea Detected
1/1 _____ 0s 202ms/step
Sample 4 : Apnea Detected
1/1 _____ 0s 136ms/step
Sample 5 : Apnea Detected
1/1 _____ 0s 138ms/step
Sample 6 : Apnea Detected
1/1 _____ 0s 127ms/step
Sample 7 : Normal
1/1 _____ 0s 117ms/step
Sample 8 : Normal
1/1 _____ 0s 104ms/step
Sample 9 : Apnea Detected
```

Figure 4 Prediction2

### Result Analysis

The superior performance of the hybrid CNN–BiLSTM model can be attributed to its ability to combine spatial feature extraction and temporal sequence modeling. CNN layers extract high-level local patterns from ECG segments, while

BiLSTM layers capture long-term temporal dependencies in heart rate variability caused by apnea events. This combined approach enhances classification accuracy and reduces false detections. Overall, the experimental results validate the effectiveness of the proposed system and demonstrate its suitability for real-time and wearable sleep apnea monitoring applications.

### VIII. ETHICAL FRAMEWORK

The ethical framework for AI Based Sleep Apnea Detection Using PPG & SpO<sub>2</sub> is centered on patient privacy, data security, transparency, fairness, and clinical responsibility. Since the system relies on sensitive physiological data such as Photoplethysmography (PPG) and Peripheral Capillary Oxygen Saturation (SpO<sub>2</sub>), strict measures must be implemented to ensure confidentiality, secure storage, and encrypted transmission of health information in compliance with healthcare data protection standards. Informed consent must be obtained from individuals before collecting and analyzing their biometric signals, clearly explaining the purpose, benefits, and potential risks of AI-based analysis. The AI models should be developed using diverse and representative datasets to minimize bias and ensure fair performance across different age groups, genders, and ethnic populations. Transparency and explainability are also critical, as healthcare professionals must understand how the system reaches its predictions to support clinical decision-making. Additionally, the system should be positioned as a screening or assistive tool rather than a replacement for professional medical diagnosis, ensuring that final clinical decisions remain under the supervision of qualified healthcare practitioners. Continuous validation, regular performance monitoring, and adherence to medical device regulations further strengthen the ethical deployment of the AI-based sleep apnea detection system.

### IX. CONCLUSION AND FUTURE DIRECTIONS

In this project, an automated system for Sleep Apnea Detection using Single-Lead ECG signals was developed and evaluated using a combination of Machine Learning (ML) and Deep Learning (DL) algorithms. The primary objective was to design a reliable, cost-effective, and non-invasive alternative to the traditional polysomnography (PSG)-based diagnosis. By utilizing the PhysioNet Apnea-ECG dataset, the proposed system successfully demonstrated that valuable diagnostic information about sleep apnea can be extracted solely from ECG signals.

The project began with thorough preprocessing of ECG data to remove noise and detect R-peaks, followed by the extraction of Heart Rate Variability (HRV) features for ML-based models. Conventional models such as SVM, Random Forest, and MLP achieved satisfactory results but were limited by the reliance on handcrafted features. Deep learning models, on the other hand, particularly the hybrid CNN-BiLSTM architecture, achieved superior performance by learning complex spatial and temporal dependencies directly from the raw ECG data. The hybrid model achieved an overall accuracy of 88.13%, sensitivity of 84.26%, and specificity of 92.27%, outperforming all baseline approaches.

The experimental findings indicate that deep learning architectures can effectively capture the intricate physiological variations in ECG signals associated with apnea events. Moreover, the use of a single-lead ECG signal makes the system simple, portable, and suitable for real-time home monitoring using wearable devices. The system thus provides a scalable solution for early detection and continuous monitoring of sleep apnea, potentially reducing the dependency on expensive and time-consuming clinical tests.

In conclusion, the project demonstrates that integrating deep learning techniques with biomedical signal processing enables efficient and accurate detection of sleep apnea. The results reaffirm the potential of deep learning-driven approaches in improving healthcare accessibility, affordability, and automation. The developed model can serve as a foundation for future intelligent health-monitoring systems.

The system can be trained and validated on larger and more diverse datasets, including multi-channel ECG or multimodal signals (EEG, SpO<sub>2</sub>, respiratory effort), to improve generalization across different populations. Deploy the trained model on embedded platforms or wearable devices (such as smartwatches or portable ECG patches) to enable continuous, real-time sleep apnea monitoring at home.

Transfer Learning and Personalization: Incorporate transfer learning to adapt pretrained models to individual users, enabling personalized health monitoring with minimal retraining. Explainability and Interpretability: Implement

explainable AI (XAI) techniques such as Grad-CAM or SHAP to visualize and interpret how the deep learning model identifies apnea-related ECG features, thereby increasing clinician trust and adoption.

Integration with Cloud and IoT Platforms: Integrate the system with cloud-based IoT health infrastructures for remote data collection, storage, and physician-assisted analysis. Optimize model complexity through quantization, pruning, and model compression techniques to ensure deployment feasibility on low-power edge devices.

#### REFERENCES

- 1.M. Bahrami, M.Teshnehlab, and S.Ostadabbas, "Sleep Apnea Detection from Single-Lead ECG: A Comprehensive Analysis of Machine Learning and Deep Learning Algorithms," *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 9, pp. 4462–4474, 2022.
- 2.T. Penzel, G.B.Moody, R.G.Mark,A. L.Golberger, and J.H.Peter, "The Apnea- ECG Database," *Computers in Cardiology*, vol. 27, pp. 255–258, 2000.
- 3.R.K.Tripathy, U. R.Acharya, and L. N.Sharma, "Automated Sleep Apnea Detection from Single-Lead ECG using Dual Tree Complex Wavelet Transform and Entropy Features," *Computers in Biology and Medicine*, vol. 98, pp. 39–55, 2018.
- 4.R.J.Thomas,J.E.Mietus,C.K.Peng and A.L.Golberger, "An Electrocardiogram- Based Technique to Assess Respiratory Sleep State and Its Application to Sleep Apnea," *Sleep*, vol. 28, no. 9, pp. 1151–1161, 2005.
- 5.O. Faust,Y. Hagiwara,T. J. Hong,O. S. Lih, and U. R.Acharya, "Deep Learning for Healthcare Applications Based on Physiological Signals: A Review," *Computer Methods and Programs in Biomedicine*, vol. 161, pp. 1–13, 2018.
- 6.D.Wang and J.Zhu, "Sleep Apnea Detection Using Hybrid CNN-LSTM Network Based on ECG Signals," *IEEE Access*, vol. 9, pp. 36233–36241, 2021.
- 7.U.R.Acharya,H.Fujita,O.S.Lih,Y.Hagiwara,J.H.Tan and M.Adam, "Automated Detection of Sleep Apnea from ECG Using Convolutional Neural Networks," *Information Sciences*, vol. 405, pp. 81–90, 2017.
- 8.S.R.Hassan,M.H.Kabir,M.A.H.Chowdhury, and M.M.Rahman, "Sleep Apnea Detection from ECG Signal Using Time-Frequency Analysis and Random Forest Classifier," *Biomedical Signal Processing and Control*, vol. 71, 103097, 2022.
- 9.M.Sharma,A.K.Bhurane and R.K.Tripathy "A Novel Approach for Automated Sleep Apnea Detection Using ECG Signal," *Neural Computing and Applications*, vol. 31, no. 12, pp. 8575–8593, 2019.
- 10.C.Yildirim and U.B.Baloglu, "A Deep Learning Approach for Automated Sleep Apnea Detection from Single-Lead ECG Signals," *Physiological Measurement*, vol. 40, no. 11, 115003, 2019.
- 11.R.Azar and M.K Hasan, "ECG-Based Sleep Apnea Detection Using Empirical Mode Decomposition and SVM Classifier," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–10, 2021.
- 12.X.Liu, Z.Zhang, and H Zhao, "Automatic Sleep Apnea Detection Using a Deep Convolutional Neural Network with an Attention Mechanism," *IEEE Access*, vol. 8,pp. 129450–129458, 2020.
- 13.P.P.Roy, D.Mitra, and R.K.Tripathy, "Sleep Apnea Detection from Single- Lead ECG Signals Using CNN-BiLSTM Hybrid Model," *IEEE Sensors Journal*, vol. 22, no. 8, pp. 8036–8045, 2022.
- 14.K. J.Park, Y.S. Kim, and J.H.Lee, "Real-Time Sleep Apnea Detection Using ECG and LSTM Neural Networks," *Sensors*, vol. 21, no. 4, 1385, 2021.
- 15.A.Gutiérrez-Tobal, R.Hornero, and V. Marcos, "Feature Selection Using Mutual Information and Classification of Sleep Apnea Severity Based on HRV," *Medical & Biological Engineering & Computing*, vol. 53, pp. 781–792, 2015.



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