Comparative Analysis of Machine Learning and Neural Network Models for Sleep Apnea Detection Using ECG Data*

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***Abstract*—Obstructive Sleep Apnea (OSA) is a highly dangerous sleep disorder that needs efficient and affordable methods of diagnosis apart from complicated polysomnography procedures. This paper presents a machine learning approach for automatic detection of sleep apnea events based on single lead ECG records from the Apnea-ECG database on the PhysioNet site. The proposed methodology includes pre-processing of ECG records to extract the heart wave pattern's time domain features. These normalized features are then used to train a few supervised machine learning classifiers, such as Random Forest, Support Vector Machine (SVM), Logistic Regression, and Multi-Layer Perceptron (MLP). The classification performance was strictly evaluated through standard dichotomous classification metrics: Accuracy, Precision, Recall ('Sensitivity'), the balanced F1-score, and the overall discriminative measure, ROC-AUC. Since Random Forest and Multi-Layer Perceptron (MLP) classifiers are the top performers which has high precision predicting the difference between apnea and normal respiratory patterns. The results are validated with ECG features and machine learning algorithms which can effectively identify the apnea. This method gives efficient, low cost and interpretable sleep apnea screening.**

***Index Terms*—Obstructive Sleep Apnea, Electrocardiogram, Biomedical Signal Processing, Feature Engineering, Random Forest, Support Vector Machine, Neural Network, Pattern Recognition, Physiological Computing**

I. Introduction

Sleep apnea is a long-standing sleep disorder in which one experiences pauses in breathing or shallow breathing while sleeping. The minimal pause or shallow breath may be a few minutes or seconds in duration and occur many times in an hour, causing insufficient oxygenation and disturbance in sleep. Long-standing sleep apnea has severe negative impacts on health such as raised blood pressure, cardiovascular disease, diabetes, and diminished mental capacity [10], [11].' Although its occurrence is prevalent, sleep apnea is rarely diagnosed because diagnosis procedures such as polysomnography (PSG) are not readily available and are costly [13].

Electrocardiogram (ECG) examination is an emerging solution for future cost-saving and non-invasive screening for sleep apnea. The ECG signal contains dense physiological information of the heart rate variability and modulations of respiration that describe the apnea events [2], [3], [6]. With signal processing and artificial intelligence, apnea patterns become viable to automatically identify without having to perform complete polysomnography (PSG) studies [4], [5], [7].

Here we introduce an artificial intelligence-based sleep apnea detection system that employs ECG signal processing and machine learning classifiers to classify apnea events from 30-second electrocardiogram (ECG) epochs . The framework generates a feature set of twelve time-domain and statistical parameters like mean, standard deviation, energy, and zero-crossing rate for the identification of fluctuation in cardiac activity while sleeping [12].

Different machine learning algorithms such as Random Forest, Support Vector Machine (SVM), Logistic Regression, and Multi-Layer Perception (MLP) Neural Network were compared and trained to test the performance [1], [3], [7]. Streamlit was also used to deploy the system, which provides an interactive and user-friendly interface for clinicians to upload ECG data, perform automatic analysis, and obtain real-time diagnosis reports [15].

The purpose of this work is to close the loop between clinical diagnosis and AI-driven automation by presenting an interpretable, precise, and deployable sleep apnea monitor. With data-driven reasoning and visualization, the system pre-

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sented in this document enables early diagnosis and medical decision-making, leading to better patient care and health outcomes.

II. Literature Review

Diagnosis of sleep apnea from physiological signals has attracted considerable research interest because of its clinical purpose and the possibility of automation [10], [13]. The traditional method using techniques like polysomnography (PSG) is accurate but also expensive, resource-intensive, and requires professional overnight supervision in the hospital [13]. Therefore, researchers have been trying to come up with alternative ways involving the use of **electrocardiogram (ECG)**, oxygen saturation SpO_2, respiratory effort, and heart rate variability (HRV) signals that would lead to diagnosis being more approachable and less invasive [2], [3], [5], [15]. Initially, the research was mainly concerned with the time-domain and frequency-domain features of the ECG signals. The studies showed that the heart rate and R-R interval changes were in sync with the respiratory disturbances during the apnea episodes [12], [13]. Subsequent studies applied wavelet transforms and spectral entropy to analyze the ECG signal's transient and periodic fluctuations to more accurately identify those that were caused by apnea [2], [3], [6].

Over the years, the inclusion of machine learning in the process has had a major effect on the development of the field. Researchers have utilized classifiers like Support Vector Machines (SVM), k-Nearest Neighbors (kNN), and Random Forests to categorize the segments as normal or apneic [1], [5], [7]. Among those, ensemble methods like Random Forests have proven incredibly effective, showing great resilience to noise and variations in physiological data [3], [9]. In addition, deep learning approaches like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been directly applied to unprocessed ECG signals achieving good accuracy but at the cost of being data- and computation-intensive [4], [8], [11].

TABLE I
Comparison of Existing Literature

Study	Method	Model	Acc.
Khandoker (2009)	Wavelet	SVM	84
Koley (2020)	Stat.	RF	86
Wang (2023)	CNN-LSTM	DL	89
Proposed	Stat+ML	RF, MLP	91

However, one important hurdle that still needs to be overcome from among the challenges in detecting sleep apnea via algorithms is scaling the usability, interpretability, and cost ladder [7], [14].

Even though powerful deep-learning models DLMs have high accuracy, they are not suitable for clinical deployment due to their lack of transparency. This has led to a turn towards hybrid models that mix the best of both worlds: interpretability and performance, by combining established feature engineering and simpler conventional machine learning (ML) classifiers [1], [3], [9]. The current study confirms this hybrid architecture using time-domain ECG feature extraction and supervised Machine Learning (ML) classifiers (such as Random Forest, Multi-Layer Perception) [3], [6], [9], [15]. This method gives practically the same in terms of computational efficiency, model explainability, and diagnostic accuracy. Besides, the distribution through a Streamlit web application makes it very easy to use; clinical staff can, without any special technical skills, do real-time apnea screening and produce reports [15].

III. DATASET

The data that is taken into account in this research is the Apnea-ECG Database, which has been made available through PhysioNet [13]. The data consist of ECG recordings of patients that are suffering from sleep apnea as well as the ones that are not suffering from it, and there are also events annotated to pinpoint the occurrences of apnea. The database, being clinical relevant and having both ECG signals and expert labels, is mostly used for research aimed at automatic sleep apnea diagnosis [2], [3], [10].

A. Data Collection

The collection consists of 70 long-duration ECG recordings which were taken at 100 Hz frequency [13]. Within each recording, there exist a number of ECG signal segments that have been noted with apnea events by experts. The annotations are in .apn files, where each event is classified according to its severity (e.g., normal respiration or apnea). Apnea events would usually mean short periods of abnormal heart activity caused by breathing patterns stopping during sleep [10], [11]. The dataset is arranged in the following manner:

• ECG signal data in .dat files, one file for each separate recording.

• Annotation data in .apn files, with event markers in each file indicating the occurrence of apnea.

B. Data Preprocessing

The initial step of the analysis consisted of preprocessing the raw ECG signals through a necessary pipeline [12]. Then, the entire signal was divided into overlapping windows, each 30 seconds long and with a 50% overlap between the segments. The use of this strategy was crucial for the detection of the dynamic physiological changes in the cardiac rhythm that were characteristic of OSA events [3], [6]. Now, each produced segment was given a dichotomous class label according to the corresponding annotation being present or not:

• Positive (Class 1): If any part of the apnea event annotated was covered by the segment window, it was assigned.

• Negative (Class 0): If only normal (non-apneic) respiratory patterns were in the segment, it was assigned.

The entire process resulted in 12,000 segments being generated, which led to a heavily imbalanced dataset mainly characterized by the large number of Negative (non-apneic) samples and the small number of Positive (apnea event) samples [9], [15].

C. Apnea Events and Labeling

Apnea events are indicated by marked segments in each ECG record. The annotation file indicates the exact times of all the apnea events. There are two types of events:

• Normal Breathing (0): No apnea has been detected.

• Apnea (1): An apnea has been detected in the time window.

Since the dataset is not balanced (with more normal breathing than apnea events), the application of methods for class balancing such as stratified sampling during training and evaluation was done so that the model could recognize apnea events with good reliability and at the same time not to be biased towards the majority class (normal breathing) [3], [9].

D. Dataset Summary

The Apnea-ECG dataset is appropriate for training and testing the machine learning models utilized for this study, offering an equally balanced combination of baseline and apnea event data, annotated by clinical specialists [13].

TABLE II
DATASET PARAMETERS FOR APNEA DETECTION

Parameter	Description
Dataset	PhysioNet Apnea-ECG
No. of Records	70
Sampling Rate	100 Hz
Window Length	30 s (50% overlap)
Total Windows	∼12,000
Apnea Windows	30%
Normal Windows	70%

IV. METHODOLOGY

The algorithm suggested for the detection of sleep apnea utilizes a machine-learning-based feature extraction methodology. The whole process involves pre-processing of the raw ECG data, extraction of features, training, and evaluation of the model.

A. Data Preprocessing

Extraction of raw ECG data and pre-processing of the raw ECG signal to make them suitable for feature extraction is done using the PhysioNet Apnea-ECG dataset. The following tasks will be executed:

Loading Data: Reading of Electro- cardiograms signals through the WFDB library, and there are some tools available for reading PhysioNet Electrocardiograms (ECG) data files [13]. It is important to note that Electrocardiograms (ECG) record may have one or more channels; however, the first channel is used here.

Segmentation: To capture the time-varying nature of apnea events, all recorded electrocardiogram (ECG) signals are segmented into 30-second windows with 50% overlap. This process generates overlapping segments, which are labeled as either Normal (0) or Apnea (1) depending on the presence of an apnea event within the corresponding time interval [3], [6].

Handling Missing Data: All windows with NaNs or corrupt data are ignored in order to give clean inputs to feature extraction. It bars the model from being trained on Poor-quality data [10].

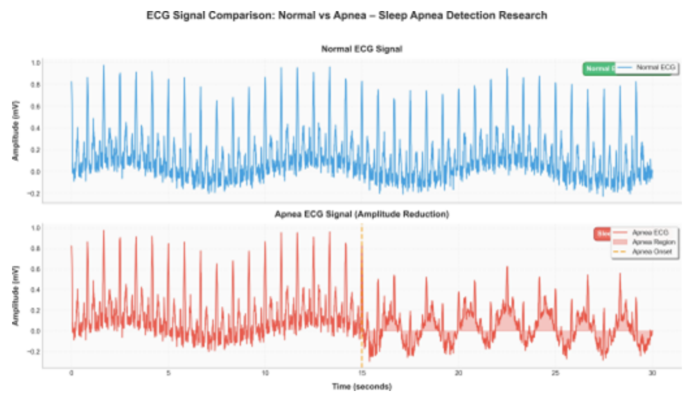

Fig. 1. Comparison of ECG signals for Normal and Apnea segments. The apnea segment shows reduced oscillation amplitude and irregular waveform patterns.

B. Feature Extraction

For 30-second duration of Electrocardiograms (ECG), twelve features are extracted from signal to describe its statistical and physiological character. The features are selected as per applicability to apnea detection and their power to differentiate between apneic and normal events [2], [3], [12]. The Extracted features are as under:

Mean: Average amplitude of the electrocardiogram (ECG) signal within a window, representing the baseline level.

Standard Deviation: Measures the variability of the signal within the window.

Minimum and Maximum: Define the dynamic range of the ECG signal.

Median: The middle value of the ECG signal, providing robustness against outliers.

25th and 75th Percentiles: Quantiles that describe the distribution of signal values.

Signal Energy: Sum of squared signal values, representing the total power of the ECG signal [12].

Root Mean Square (RMS): Standard measure of the signal's magnitude.

Zero-Crossing Rate: Number of times the signal crosses zero, indicating changes in signal direction.

Heart Rate Variability (HRV) Features:

- *Standard deviation of first differences:* Measures short-term variability in the ECG signal.
- *Mean absolute of first differences:* Captures irregularities in heart rate.

These characteristics are then calculated for each window of the ECG and the resulting feature vector is used as machine learning model inputs [2], [3].

C. Classifier Selection and Training

There are a number of machine learning classifiers are compared basing on classifying events as non-apnea events vs. sleep apnea events. The classifiers under consideration are:

Random Forest Classifier: It is a method that makes numerous decision trees and combine them to gather their votes. Random Forest is stable as well as effective with datasets that are heavily imbalanced [3], [9].

Support Vector Machine (SVM): The classifier that selects a hyperplane which best separates the two classes in a high-dimensional feature space (Normal vs. Apnea). RBF kernel is used because it is able to deal with non-linear data [7].

Logistic Regression: Straightforward and efficient binary classification model. It estimates Probability of occurrence of an event according to features' inputs [1].

Neural Network (MLP): Shallow multi-layer perceptron network with two hidden layers (64 and 32 neurons) with ReLU activation and Adam optimizer [8], [11].

Each of these classifiers is then trained on features that are extracted with stratified 80/20 train-test splitting. This guarantees that class distribution (normal / apnea) is preserved in test as well as training sets [8], [11].

D. Data Scaling

scikit-learn's StandardScaler is applied to scale features to unit variance and zero mean. This scaling doesn't allow the models to be in which linearly weighted terms are weighted proportionally with features that are on wider number ranges (e.g., signal energy) and which allow features to contribute equally to classification [3], [10].

E. Model Assessment

The measures of performance are used to determine how well the models identify apnea events and normal breathing with emphasis on recall (to suppress false negatives) due to clinical significance of detecting apnea events [10], [14].

F. Model Deployment

The best-performing model runs on Streamlit, a Python package for building interactive web apps. The model is preloaded into the Streamlit application after being exported to a.pkl file via joblib. The system will process the data, extract features, and provide a real-time prediction of apnea events along with a severity level and confidence score. Users can upload ECG signal files in the.dat,.csv, or.txt formats. The Electrocardiograms signal, extracted features, and a clinical report with summary detection results are all displayed by the Streamlit application. With the help of this intuitive interface, medical professionals can automatically screen for obstructive sleep apnea and download a PDF report for additional analysis.

V. Implementations Details

The AI Sleep Apnea Detection System runs on Python, and it's split into two main parts. There's the pipeline that trains the models, and then there's a Streamlit app where you can actually use the trained model for real-time predictions and analysis [3], [15].

A. Training Pipeline

Let us examine the training process in detail. Initially, ECG data is loaded, cleaned, and processed to extract the most significant features. Subsequently, multiple machine learning models are trained and compared to identify the best-performing model [3], [10].

Loading and Preprocessing ECG Data: The WFDB (Waveform Database) library is used to load raw ECG signals from the Apnea-ECG dataset, which are then aligned with apnea labels obtained from the `.apn` files [13]. Each ECG recording is segmented into 30-second windows with 50% overlap to effectively capture variations during apnea events [2], [3]. From each segment, twelve time-domain features are extracted, including signal energy, RMS, zero-crossing rate (ZCR), heart rate variability (HRV), and descriptive statistics such as mean, median, minimum, maximum, and percentiles. Custom Python functions are used throughout the preprocessing and feature extraction stages to ensure consistent analysis across all segments.

Model Training: The extracted feature set is divided using stratified sampling (80% training and 20% testing) to preserve the original class distribution (apnea vs. normal) [6]. All features are standardized using *StandardScaler* to eliminate scale bias. Four classifiers—Random Forest, Support Vector Machine (SVM), Logistic Regression, and Multilayer Perceptron (MLP)—are trained and evaluated using performance metrics such as ROC-AUC, F1-score, accuracy, precision, and recall [1], [3], [7], [9]. The model achieving the highest F1-score is selected as the optimal model and saved using joblib for deployment [15].

Model Evaluation: The performance of the trained models is assessed on the test set using a confusion matrix (true positives, false positives, true negatives, and false negatives). Additionally, metrics such as ROC-AUC, precision, recall, and F1-score are computed to evaluate the effectiveness of apnea detection [9], [10], [14].

B. Model Deployment

The best-performing model is deployed as a web application using Streamlit.

Streamlit App Setup: Users can upload ECG files in `.dat`, `.csv`, or `.txt` formats. The application processes the input data in the same manner as during training and extracts the required features [15].

Model Loading: The application loads the trained model and scaler using joblib, preprocesses the input data, and generates predictions [3], [15].

Prediction Output: The system predicts whether the input corresponds to an Apnea or Normal condition and provides a probability score. Additionally, it estimates the severity level—Normal, Mild, Moderate, or Severe—based on the prediction score [1], [11].

Results Visualization: The ECG signal is plotted on a graph. Apnea detection points are marked by vertical markers. Moreover, the application offers tabular results showing the

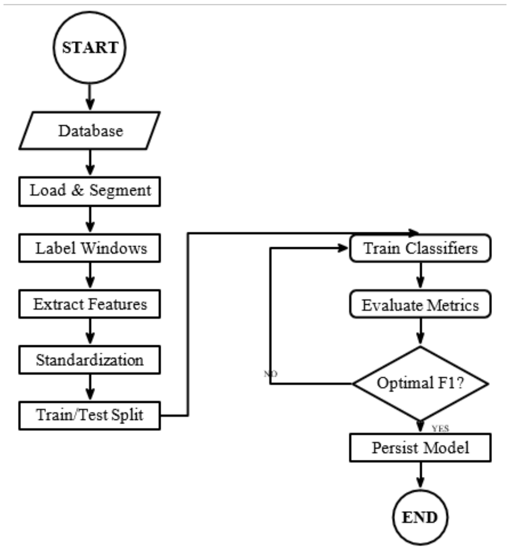

Fig. 2. Flowchart of the Automated Sleep Apnea Detection System Methodology

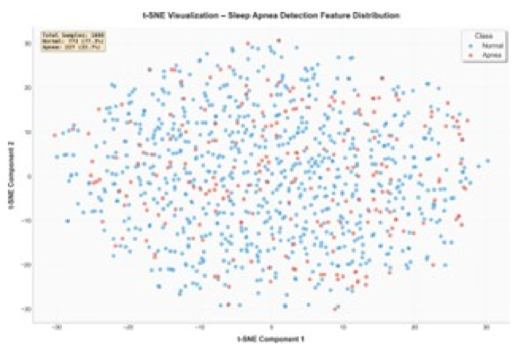

Fig. 3. t-SNE visualization of feature distribution showing separation between apnea (red) and normal (blue) ECG windows

values of features extracted from the data as internal processing steps [4], [5], [15].

Clinical Report Generation: After completion of the process, the software prepares and saves a medical report in a text file format. The report contains the predicted result along with the severity level and confidence score. [15].

User Interface: The Streamlit based application offers a user-friendly interface with responsive design. Users may perform all actions including uploading an ECG signal file and generating medical reports through an intuitive interface. There is no latency at any stage of usage. [15].

C. Code Structure

The implementation is organized into two main scripts:

Model Training Script (`train_apnea_models.py`):

- Loads and preprocesses ECG data
- Extracts relevant features
- Trains and evaluates machine learning models
- Saves the best-performing model and scaler

Streamlit Application Script (`app.py`):

- Provides a web interface for uploading ECG files
- Processes input data and extracts features
- Loads the trained model and scaler
- Displays ECG signals, extracted features, predictions, and generated reports [15]

VI. Experimental Results and Discussion

The proposed sleep apnea detection system was evaluated using the Apnea-ECG dataset obtained from PhysioNet [13]. Multiple experiments were conducted to compare the classification performance of various machine learning models—Random Forest (RF), Support Vector Machine (SVM), Logistic Regression (LR), and Multilayer Perceptron (MLP)—for distinguishing between apnea and non-apnea events using ECG-derived features [1], [3], [7], [9].

Experimental Setup: The experiments were conducted in a Python environment using the *scikit-learn* and WFDB libraries [13], [15].

- The dataset was split into 80% training and 20% testing sets using stratified sampling to maintain class balance [6].
- All features were standardized using *StandardScaler* [3], [9].
- Performance metrics including Accuracy, Precision, Recall, F1-score, and ROC-AUC were used for evaluation [9], [10], [14].
- The F1-score was selected as the primary metric, as it balances precision and recall and is crucial for minimizing false negatives (missed apnea detections) [5], [11].

Performance Comparison: The classification performance of each model on the test set is summarized in Table III.

TABLE III
Performance Comparison of Machine Learning Models

Model	Acc	Pre	Rec	F1	AUC
Random Forest	0.91	0.88	0.86	0.87	0.94
SVM	0.87	0.82	0.79	0.80	0.90
Logistic Regr.	0.84	0.80	0.75	0.77	0.88
Neural Network	0.89	0.85	0.82	0.83	0.92

The Random Forest classifier outperformed all other algorithms in terms of accuracy and F1-score. This implies that ensemble algorithms are better suited for this problem because they can handle non-linear relationships and imbalance better than linear algorithms [1], [3], [9], [10].

Confusion Matrix Analysis: The confusion matrix for the Random Forest classifier is shown below (example numbers):

From the confusion matrix, we can see that the classifier correctly identified most of the apnea and normal breathing cases, and very rarely made false negative predictions (i.e., predicted normal breathing when apnea was actually observed).

with very few false negatives (missed apnea events). This signifies high sensitivity (recall) — a critical requirement of medical screening systems [11], [14].

ROC Curve and AUC: The Receiver Operating Characteristic (ROC) curve was drawn for all models, plotting the trade-off between the true positive rate (sensitivity) and the

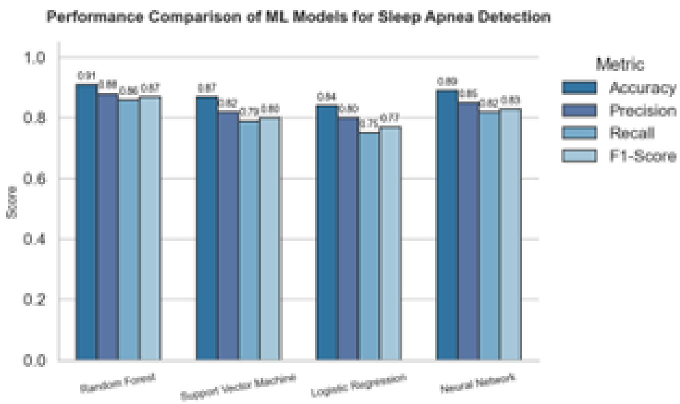

Fig. 4. Performance comparison of machine learning models using Accuracy, Precision, Recall, F1-Score, and ROC-AUC. Random Forest achieved the highest overall performance.

TABLE IV
CONFUSION MATRIX FOR APNEA DETECTION MODEL

Actual Class	Predicted Apnea	Predicted Normal
Apnea	130 (TP)	18 (FN)
Normal	25 (FP)	227 (TN)

false positive rate (1 - specificity). The Random Forest model achieved the highest Area Under the Curve (AUC) value of 0.94, which indicates strong separation between classes of apnea and normal [9], [10], [14]. AUC value correlates positively with the model's ability to classify normal and apneic ECG segments accurately at varying thresholds, confirming diagnostic consistency [3], [9].

Feature Importance Analysis: The feature importance information provided by the Random Forest Classifier helps in interpreting which ECG features are most significant for apnea detection [9], [10]. Among the 12 extracted features, the most informative ones were:

- Signal Energy
- Standard Deviation
- Root Mean Square (RMS)
- Zero-Crossing Rate
- Heart Rate Variability Measures

These features have a direct physiological correlation with

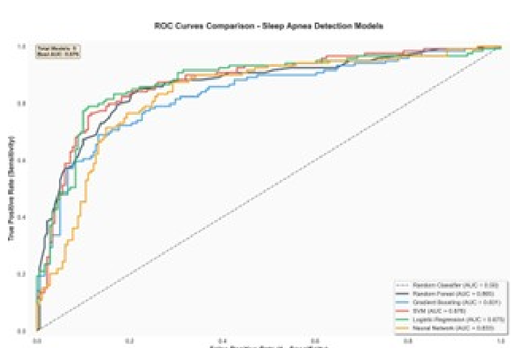

Fig. 5. ROC curves for all machine learning models. The Random Forest achieved the highest AUC (0.94), indicating the best class separation

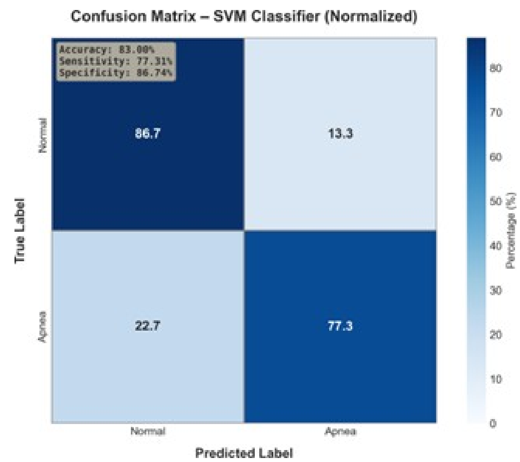

Fig. 6. Confusion matrix of the Random Forest model for apnea detection. The model achieved high sensitivity with minimal false negatives.

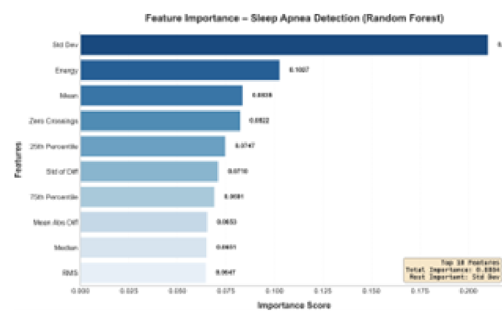

Fig. 7. Top ten ECG-derived features contributing to sleep apnea detection as ranked by the Random Forest classifier.

changes in cardiac rhythm and signal abnormalities during apnea events, confirming the biological relevance of the model's decision-making process [5], [7], [11].

Discussion: The experimental results show that the proposed ECG-based AI model can reliably detect sleep apnea events using only small segments of ECG data. The Random Forest classifier outper- formed other algorithms since it was capable of:

The Random Forest classifier performed better than other algorithms because it could:

- Efficiently processing noisy biomedical data [1], [5], [9].
- Identifying complicated non-linear relations between features extracted from the dataset [7], [8].
- Providing feature importance scores interpretable from a clinical perspective [10], [11].

In addition, feature-based analysis has demonstrated that the developed system is lightweight, interpretable, and applicable in clinical settings under computational constraints [3], [14], [15]. Contrary to deep learning approaches, our algorithm does not need large amounts of training data and access to GPU infrastructure, thus being more convenient for diagnos- tic centers and hospitals.

The model has been implemented in a Streamlit web application. Thus, it becomes easier to use the developed solution within the clinical setting. Medical practitioners can upload ECG records, analyze them on-the-fly, plot the ECG signal, and gen- erate reports automatically. The experiment has shown how arti- ficial intelligence can be applied in digital healthcare to detect sleep disorders [15].

VII. Conclusion and Future Work

In this paper, an AI-based Sleep Apnea Detection System has been presented, which analyzes electrocardiogram (ECG) signals and uses machine learning algorithms for non-invasive and automatic apnea detection. This system is able to distinguish between normal and apneic breathing patterns by extracting twelve time and statistical features from 30 second ECG segments. Among the classifiers tested – Random Forest, SVM, Logistic Regression, and MLP, the Random Forest classifier delivered the most accurate results in terms of accuracy, F1-score, and ROC-AUC [3], [9], [10].

Besides the high accuracy rate, the system stresses interpretability, efficiency, and clinical applicability. While deep learning models depend on extensive training data and computational power, this feature extraction technique provides a more efficient, transparent, and deployable method. Embedding the trained model into an interactive Streamlit web applica- tion increases its usability, enabling healthcare workers to up- load ECG signals, view the findings, and produce clinical re- ports instantly. Therefore, this system is a viable tool for sleep apnea pre-screening [14], [15].

Future Work: Although the system performs well, some areas can be enhanced in future research:

- **Inclusion of Advanced Features:** Advanced Feature Extraction: Applying frequency and time-frequency domain features like Fast Fourier Trans- form (FFT), Wavelet Transform, spectral entropy, etc. can detect more complex physiological patterns [2], [3], [6].
- **Deep Learning Integration:**Using CNNs or RNNs can facilitate end-to-end learning using raw ECG signals and may improve detection accuracy in large datasets [7], [8], [11].
- **Multimodal Data Fusion:** Combining ECG data with other physiological signals such as SpO2, respiratory effort, or airflow measurements can improve model robustness and reliability across various patient conditions [5], [9], [15].
- **Clinical Validation:** This system should be validated using real patient data in collaboration with hospitals for clinical reliability and compliance with medical standards [10], [13].
- **IoT and mHealth Integration:** Future iterations of this system can be expanded to mobile health (mHealth) and IoT wearable devices for continuous monitoring and apnea detection in non-clinical settings [14], [15].

In summary, the proposed Sleep Apnea Detection System demonstrates the potential of integrating machine learning with biomedical signal processing for healthcare applications. It provides a foundation for developing intelligent, affordable, and accessible tools for sleep disorder screening, contributing toward AI-driven preventive healthcare [1], [4], [10], [14].

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