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Sleep Apnea Detection from Single-Lead ECG: A Comprehensive Analysis of Machine Learning and Deep Learning Algorithms

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Abstract*: Sleep apnea, a prevalent sleep breathing disorder, poses significant health risks, necessitating accurate detection for appropriate treatment. This study comprehensively analyzes machine learning and deep learning algorithms using the PhysioNet ECG Sleep Apnea v1.0.0 dataset. Electrocardiogram signals underwent preprocessing and segmentation before applying various algorithms for sleep apnea detection. Conventional machine learning methods such as linear and quadratic discriminate analyses, logistic regression, support-vector machines, and decision trees, along with deep learning techniques including convolutional and recurrent networks, were implemented and modified to suit biosignal processing tasks. The dataset was divided into training, validation, and test sets, with a fivefold cross-validation scheme ensuring robust evaluation. Hybrid deep models demonstrated superior performance, achieving an accuracy of 88.13%, sensitivity of 84.26%, and specificity of 92.27%. This study offers valuable insights into the efficacy of different machine learning and deep learningalgorithms for sleep apnea detection, with potential extensions to other sleep-related events. The developed algorithms are publicly available on GitHub.*

Keywords: Deep learning, detection, electrocardiogram (ECG), machine learning, sleep apnea

I. INTRODUCTION

Sleep, a significant aspect of human life, is divided into rapid eye movement (REM) and non-REM (NREM) stages. These stages affect our physiology differently, with REM sleep associated with increased sympathetic activity and cardiovascular instability, while NREM sleep sees decreased heart rate and blood pressure. Sleep disorders, including obstructive sleep apnea (OSA) and central sleep apnea (CSA), are on the rise, with around 70 million adults in the US affected. These disorders can lead to serious health issues and increased morbidity and mortality rates. Detecting sleep apnea accurately is crucial for preventing associated health complications.

Researchers have focused on developing algorithms, particularly using electrocardiogram (ECG) signals, for sleep apnea detection. ECG-based methods offer convenience and precision. While conventional machine learning algorithms were initially used, recent advancements in deep learning have shown promise due to their automatic feature extraction capabilities.

This study compares conventional machine learning and deep learning algorithms for sleep apnea detection using single-lead ECG data. Experiments were conducted on the same dataset under consistent conditions to ensure fair comparison. Unlike previous studies that often tuned hyperparameters on the same data used for evaluation, this study employed separate training, validation, and test sets for thorough evaluation. The research significantly extends previous analyses by examining 14 conventional machine learning and deep learning methods, along with feature importance analysis.

II. LITERATURE SURVEY

The literature survey explores the rising prevalence of sleep disorders, emphasizing obstructive sleep apnea (OSA) and central sleep apnea (CSA), affecting millions worldwide. Researchers focus on developing accurate, portable

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technologies, with electrocardiogram (ECG) signals showing promise for detection. Traditional machine learning algorithms initially used are now being surpassed by deep learning methods for automatic feature extraction. This survey reviews studies comparing machine learning and deep learning approaches for sleep apnea detection, highlighting the importance of fair evaluation practices and the significance of identifying effective features from ECG signals

III. PROPOSED SYSTEM

Accurate detection of sleep apnea is vital for managing its side effects. Current methods include questionnaires, medical image analysis, signal processing, and polysomnography (PSG), but these are often impractical outside specialized settings. Wearable sleep technologies are needed for unobtrusive monitoring. Physiological signals, particularly electrocardiogram (ECG), show promise for wearable monitors.

Machine learning (ML) and deep learning (DL) are key approaches for sleep apnea monitoring. ML relies on expert-defined features, while DL automates feature extraction. ML methods like support vector machines (SVM) and artificial neural networks (ANN) have shown promise in previous studies. DL models, such as convolutional neural networks (CNN) and recurrent neural networks (RNN), offer automatic feature extraction. Studies have demonstrated the effectiveness of DL in improving accuracy, particularly in real-time detection from single-lead ECG signals.

Proposed methods include real-time detection using motion detection with microwave Doppler radar and wearable devices based on single-lead ECG for home monitoring enhancement. Future research should focus on evaluating different artificial intelligence models under standardized settings to understand their capabilities and limitations, aiding in the selection of appropriate algorithms for smart wearables, thus improving sleep apnea management and overall healthcare systems

Fig. 1: System Architecture

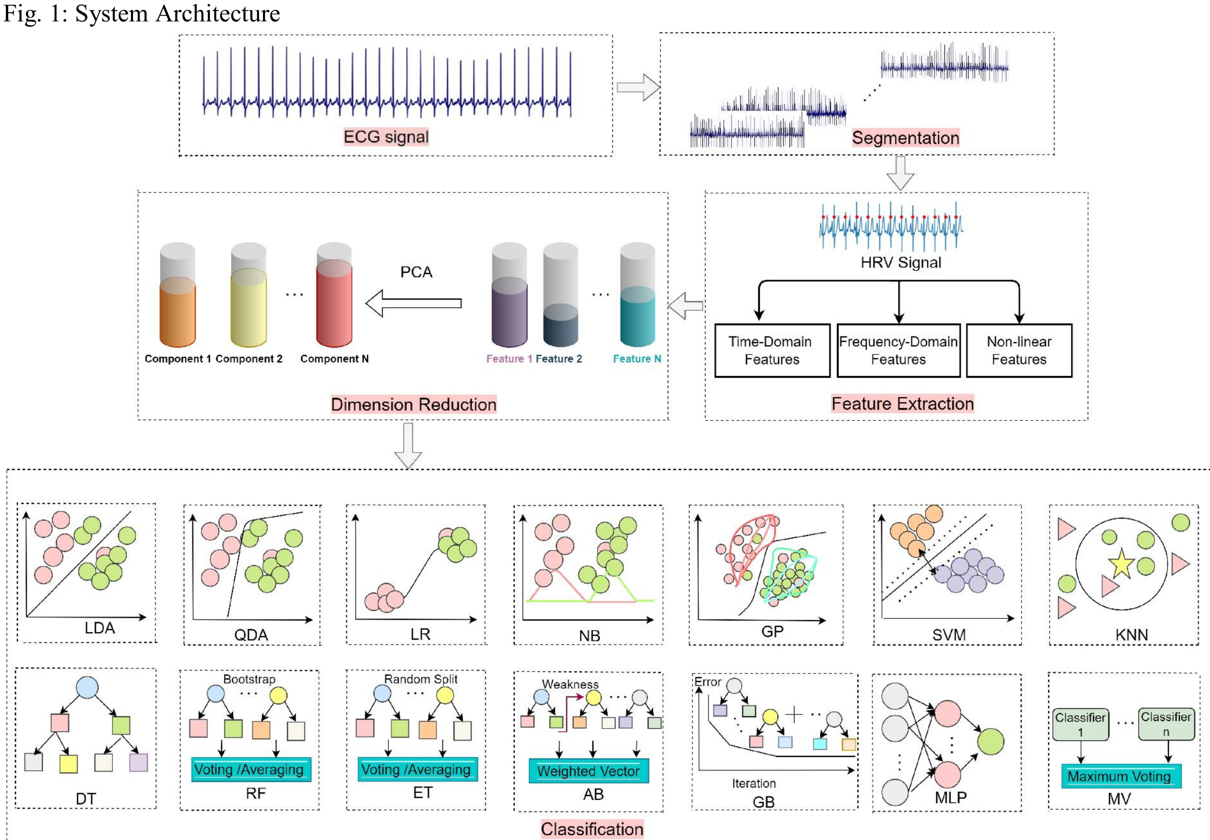

Fig. 1: Fig. 1. Flowchart representation of our developed framework for the evaluation of conventional machine learning algorithms in the detection of sleep apneafrom single-lead ECG

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Dataset:

In this study, we utilized the PhysioNet Apnea-ECG Database to construct and evaluate our models. The database comprises 70 recordings obtained from 32 individuals, with a demographic distribution including seven females, with an average age of 44 years (±11). The dataset exhibits variability in the apnea-hypopnea index (AHI), with an average AHI of 24 (±25). Participants' physical characteristics include an average height of 175 cm (±6) and weight of 86 kg (±22). The dataset is categorized into four groups: A, B, C, and X. Thirteen individuals exhibit an AHI of ≤5 and are classified as normal, while 13 individuals have an AHI > 30, categorized as severe sleep apnea cases. Additionally, six individuals have an AHI ranging from 5 to 30, classifying them under the mild and moderate apnea category. Each of the 70 recordings has an average duration of 8.2 hours (±0.52), with ECG signals sampled at 100 Hz. Sleep apnea annotations are provided by a sleep expert at 1-minute intervals throughout the recordings.

Preprocessing:

The ECG signals were divided into 1-minute segments. We used the Hamilton R-peak detection method, based on publicly available code, to identify R-peaks. A median filter recommended by Chen et al. helped remove unreliable points. We then extracted R-R Intervals and R-peak amplitudes from these peaks, preprocessing them for machine learning algorithms discussed in Section IV. Additionally, we applied cubic interpolation at 3 Hz to ensure uniform sampling of R-R intervals and R-peak amplitudes. These interpolated data were then fed into the deep learning models. To capture temporal patterns effectively, we segmented the input data into smaller segments of 60/n seconds and designed n-cell Deep Recurrent Neural Networks (DRNNs) to analyze them (with n set to 2).

Model:

The project focuses on utilizing deep learning models, specifically Convolutional Neural Networks (CNNs) and Deep Recurrent Neural Networks (DRNNs), for the detection of sleep apnea from single-lead Electrocardiogram (ECG) data. Various CNN architectures such as VGG16, VGG19, ZF-Net, and Alex-Net are adapted and optimized for this purpose. The models are designed to extract important frequency-domain features and analyze statistical and nonlinear characteristics of Heart Rate Variability (HRV) to identify patterns indicative of sleep apnea.

In addition to CNNs, the project incorporates DRNNs, including Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), and Gated Recurrent Unit (GRU), to capture temporal dependencies in the ECG data. These DRNNs are structured as multi-layered cells that receive 2-D input structures and output dimensions tailored for effective feature extraction and classification.

The hybrid CNN-DRNN architectures demonstrate promising results, showcasing the ability of deep learning models to outperform traditional machine learning algorithms in sleep apnea detection tasks. The models are trained and evaluated using the PhysioNet Apnea-ECG Database, which contains recordings from individuals with varying apnea-hypopnea indexes

Overall, the project highlights the significance of deep learning techniques, particularly CNNs and DRNNs, in accurately detecting sleep apnea from single-lead ECG signals. By leveraging the power of neural networks and advanced architectures, the models exhibit superior performance and pave the way for further research and advancements in the field of sleep disorder detection and healthcare monitoring.

Predict:

Smart wearables enable vital sleep and health monitoring, relying on precise real-time algorithms. This study compared machine learning and deep learning for single-lead ECG sleep apnea detection. Deep learning surpassed conventional methods, with CNN-based models excelling over DRNNs in processing short ECG segments. Hybrid CNN-DRNN architectures, notably ZFNet-BiLSTM for accuracy and specificity and ZFNet-GRU for sensitivity, delivered superior performance. Thus, employing hybrid deep neural networks is advocated for effective sleep apnea detection from ECG signals.

IV RESULT

The study conducted a comprehensive analysis of sleep apnea detection utilizing the PhysioNet Apnea-ECG Database v1.0.0. By employing a stratified cross-validation approach, the study addressed the dataset's inherent imbalance and ensured reliable model evaluation. Through extensive experimentation with both conventional machine learning and deep learning algorithms, the research revealed the superiority of deep learning models, particularly hybrid architectures like ZFNet-BiLSTM, in accurately detecting sleep apnea from single-lead ECG signals. Notably, the study highlighted the significance of HRV features, especially frequency-domain features, and emphasized the effectiveness of utilizing both R-R intervals and R-peak amplitudes for enhanced detection performance. Furthermore, the study showcased the potential for future research in real-time apnea event prediction and emphasized the importance of addressing noise and motion artifacts for improved reliability. Despite the advancements achieved, the study acknowledged the limitations of the dataset and called for future efforts to collect more diverse and extensive data, particularly considering different types of apneas. Overall, the study underscores the promising role of machine learning and deep learning algorithms in advancing sleep apnea detection systems towards more accurate and practical clinical applications

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