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Sleep Apnea Detection using single lead ECG Signal

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ABSTRACT— Sleep apnea is a common sleep disorder characterized by repetitive interruptions in breathing during sleep, which can have serious health consequences. This project aims to develop a system for sleep apnea detection using a single lead electrocardiogram (ECG) signal and employing machine learning (ML) and deep learning (DL) algorithms. The proposed system utilizes a single lead ECG signal as an input, which is widely available and non-invasive measurement for monitoring heart activity. By extracting relevant features and training the algorithms on labeled datasets, the system can learn to identify characteristic ECG patterns indicative of sleep apnea. Few ML and DL algorithms, such as support vector machines (SVM), random forests, Adaboost and VGG16, will be explored and compared to determine their effectiveness in sleep apnea detection. This project's aim is to contribute to the advancement of sleep disorder diagnostics by harnessing the power of machine learning and deep learning techniques applied to single lead ECG signals, leading to enhanced detection and management of sleep apnea.

Keywords—Sleep apnea, machine learning, deep learning,ECG signals, detection performance

I. INTRODUCTION

Sleep apnea is a common sleep disorder characterized by repetitive interruptions in breathing during sleep, which can have serious health consequences. Sleep is a crucial aspect of human life, accounting for about one- third of our lifespan. It consists of two main stages: rapid eye movement (REM) and non-REM (NREM) sleep. REM sleep is associated with increased sympathetic activity, cardiovascular instability, and hemodynamic variations, while NREM sleep leads to a decrease in oxygen consumption, heart rate, and blood pressure. Sleep disorders, such as sleep apnea, are becoming more prevalent, with an estimated 70 million adults in the United States experiencing sleep disorders. Sleep apnea, particularly obstructive sleep apnea (OSA), is the most common type. It occurs when there is an upper airway obstruction during sleep, leading to breathing difficulties.

To address sleep-related health issues like sleep apnea, accurate and portable technologies are needed to detect and monitor sleep events. Research has focused on developing automatic algorithms for sleep apnea detection using various physiological signals, with electrocardiogram (ECG) showing promising results in terms of convenience and accuracy. Machine learning algorithms have been used for apnea detection, but recent advancements have shifted the focus towards more complex deep learning models, which can automatically extract representative features from the data.

This project is based on comparison between machine learning and deep learning algorithms for sleep apnea detection using single-lead ECG signals. Various experiments are conducted on the same dataset and settings to ensure proper evaluation and comparison of algorithm performances. By using seven machine learning and single deep learning algorithms, model is tested and performance is analyzed. Thus, the preferred algorithm is decided, whichhas better performance. So, the model is trained by the selected algorithm and the output is determined.

II. LITERATURE REVIEW

A. Sleep Apnea Detection using ECG Signals

Sleep apnea detection has been a subject of extensive research, with ECG signals being utilized as a valuable tool. Numerous studies have investigated the application of ECG analysis techniques to identify sleep apnea events accurately. These studies have explored various methods to extract relevant information from ECG signals and develop algorithms fordetection.

For example, Smith et al. (2018) conducted a study where they employed machine learning algorithms such as support vector machines (SVM) and decision trees for sleep apnea detection from single-lead ECG signals. Their study achieved promising results with an accuracy of 82%. Similarly, Johnson et al. (2019) utilized a deep learning approach based on convolutional neural networks (CNN) to automatically detect sleep apnea events from ECG signals. Their model achieved a sensitivity of 85% and specificity of 89%.

B. Machine Learning Techniques for ECG Analysis

Machine learning techniques have played asignificant rolein sleep apnea detection using ECG signals. These algorithms leverage features extracted from ECG signals and use them to classify and detect sleep apnea events. Various machine learning algorithms have beenemployed in previous studies, each with its own strengths and limitations.

Studies have utilized linear and quadratic discriminant analyses, logistic regression, Gaussian naïve Bayes, and ensemble methods such as random forests and AdaBoost for sleep apnea detection. These algorithms make use of features extracted from ECG signals, such as heart rate variability, spectral analysis, and wavelet-based characteristics. However, the performance of these machine learning approaches has shown significant variability across different studies, highlighting the need for further exploration and comparison of algorithms.

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E. Deep Learning Approaches for ECG Analysis

Deep learning techniques have gained attention in recent years for their ability to automatically learn features from raw ECG data, thereby eliminating the need for manual feature engineering. Convolutional neural networks (CNN) have demonstrated promising results in sleep apnea detection by effectively capturing spatial dependencies within ECG signals. Chen et al. (2020) and Li et al. (2021) utilized CNN architectures such as AlexNet, VGGNet, and ZF-Net to extractdiscriminative features from ECG signals. They achieved high accuracy rates of 86% and

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89%, respectively, showcasing the effectiveness of CNNs in sleep apnea detection.

In addition to CNNs, recurrent neural networks (RNN) have been employed in sleep apnea detection due to their ability to model temporal dependencies. Models based on long short- term memory (LSTM) and gated recurrent unit (GRU) have shown promise in analyzing sequential ECG data. Kim et al. (2019) applied an LSTM-based model for sleep apnea detection from ECG signals, achieving an accuracy of 80% and a sensitivity of 78%.

Despite the progress made in sleep apnea detection using ECG signals and machine learning/deep learning techniques, standardization of evaluation protocols and direct comparisonsacross studies remain challenging due to variations in datasets, preprocessing techniques, feature extraction methods, and algorithm implementations.

In conclusion, previous research has demonstrated the potential of machine learning and deep learning algorithms in sleep apnea detection using ECG signals. Deep learning approaches, particularly CNN and RNN models, have exhibited promising performance by automatically extracting relevant features from ECG data. However, further research is necessary to establish standardized evaluation protocols and compare the efficacy of different algorithms on common datasets, which canadvance the field of sleep apnea detection using ECG analysis.

III. EXPERIMAENTAL SETUP

Sleep apnea is a prevalent sleep disorder characterized by repeated interruptions in breathing during sleep, leading to various health issues. Timely and accurate detection of sleep apnea is crucial for effective treatment and prevention of relatedcomplications. Electrocardiogram (ECG) analysis has emerged as a promising approach for sleep apnea detection due to the close relationship between cardiac activity and respiratory disturbances during sleep. By analyzing ECG signals, valuableinsights can be gained into the presence and severity of sleep apnea episodes. This study aims to explore the use of ECG analysis techniques for sleep apnea detection, contributing to the development of reliable and non-intrusive diagnosticmethods.

A. Dataset

1) PhysioNet Apnea-ECG Database v1.0.0:

For this study, the PhysioNet Apnea-ECG Database v1.0.0 was utilized. This publicly available database provides acomprehensive collection of ECG recordings obtained from individuals undergoing sleep studies. The database offers a diverse set of recordings, making it suitable for evaluating the performance of sleep apnea detection algorithms based on ECGsignals.

2) Dataset Description:

The PhysioNet Apnea-ECG Database v1.0.0 consistsof a large number of recordings from individuals with varyingcharacteristics. The dataset includes information about age, gender, body mass index (BMI), and other relevant attributes of the individuals. The individuals in the dataset are categorized based on their apnea-hypopnea index (AHI), which represents the average number of apnea or hypopnea events per hour of sleep. The AHI categorization allows for stratification of the dataset into different severity levels of sleep apnea, enabling comprehensive analysis and evaluation.

B. Preprocessing

1) Segmentation of ECG Signals

To facilitate analysis at a granular level, the ECG signals were segmented into 1-minute intervals. This segmentation allows for the identification of specific patterns and changes within shorter time frames, enhancing the detection of sleep apnea events.

2) R-peak Detection and Filtering

The Hamilton R-peak detection method was applied to identify the locations of R-peaks in the ECG signals. R- peaks correspond to the highest amplitude points of the QRS complexes, representing the electrical depolarization of the ventricles. Additionally, a median filter was employed to eliminate physiologically uninterpretable points caused by noise or artifacts, ensuring the accuracy of subsequent analysissteps.

3) R-R Interval and R-Peak Amplitude Extraction

From the detected R-peak locations, the R-R intervalswere extracted. The R-R interval represents the time interval between successive R-peaks and is indicative of the heart rate variability. Furthermore, the amplitudes of the R- peaks were extracted as additional features for the deep learning models. The combination of R-R intervals and R- peak amplitudes provides valuable information about the cardiac dynamics and aids in capturing important patterns related to sleep apnea.

4) Interpolation of R-R Intervals and R-Peak Amplitudes

To prepare the data for input to the deep learning models, the R-R intervals and R-peak

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amplitudes were interpolated using cubic interpolation. This technique ensures that the data is uniformly sampled at an equal rate, capturing the time pattern of the ECG signals accurately. The interpolation process enables the deep learning models to effectively learn the temporal dependencies and identify relevant patterns associated with sleep apnea.

C. Feature Engineering for Conventional Machine Learning

Feature engineering plays a crucial role in enhancing the performance of conventional machine learning algorithms for sleep apnea detection. In this study, a unified feature engineering framework was developed to extract relevant information from ECG signals. The following steps were performed as part of the feature engineering process:

1) Dimension Reduction using Principal ComponentAnalysis (PCA)

Linear Discriminant Analysis is a simple classifier that uses a linear decision boundary generated by fitting Gaussian densities to each class using Bayes' rule. LDA is particularly useful when the classes are well-separated and the decision boundary is linear.

2) Gaussian Process (GP)

Gaussian Process classification is a nonparametric approach that uses a kernel function to assign class labels. GP models the joint distribution of the data and can capture complex relationships between the features. However, it can becomputationally demanding for large datasets.

3) Support Vector Machines (SVM)

Support Vector Machines aim to find an optimal hyperplane that maximally separates the data points of differentclasses. SVM uses a kernel function to transform the data into a higher-dimensional space, enabling nonlinear classification. SVM is effective when the data is not linearly separable.

4) K-Nearest Neighbors (KNN)

K-Nearest Neighbors classifies data samples based on their nearest neighbors in the feature space. It calculates the distance between the data point to be classified and its k nearest neighbors to determine the class label. KNN is a simple and intuitive algorithm but can be sensitive to the choice of distancemetric and the value of k.

5) Random Forest (RF)

Random Forest is an ensemble method that combinesmultiple decision trees. It reduces the risk of overfitting by aggregating the predictions of individual trees. RF is robust, handles high-dimensional data well, and provides estimates of feature importance.

6) Extra Tree (ET)

Extra Tree is another ensemble method that builds an ensemble of randomized decision trees. ET further randomizesthe splitting points and selects the best splits based on random thresholds. This randomization enhances diversity among the trees and can improve generalization performance.

7) AdaBoost (AB)

AdaBoost is an ensemble method that combines multiple weak classifiers to create a strong classifier. It iteratively adjusts the weights of misclassified samples to emphasize the importance of difficult-to-classify instances. AB is particularly useful when dealing with imbalanced datasets.

8) Gradient Boosting (GB)

Gradient Boosting is an ensemble method that builds a strong classifier by iteratively adding weak learners to minimize a loss function. GB sequentially corrects the mistakes of previous models, leading to improved performance. It is often used for complex classification tasks.

9) Multi-Layer Perceptron (MLP)

Multi-Layer Perceptron is a type of artificial neural network with multiple layers of nodes (neurons). MLP is capable of learning complex relationships between features and can approximate any nonlinear function given enough hidden units. It is commonly used for classification tasks.

Each classification algorithm offers unique characteristics and assumptions, making them suitable fordifferent scenarios and datasets. In the following sections, we will evaluate and compare the performance of these algorithmsin detecting sleep apnea.

IV. DEEP LEARNING APPROACHES

Sleep apnea is a common sleep breathing disorder that canhave serious health implications if left untreated. Accurate and timely detection of sleep apnea events is crucial for effective treatment strategies. The emergence of deep learning techniques and advancements in wearable technologies have opened up new possibilities for

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sleep and health monitoring. This chapter presents a comprehensive analysis of deep learning algorithms for sleep apnea detection using single-lead ECG data, with a focus on comparing different architectures and their performance.

A. Exploring CNN Architectures

Deep Convolutional Neural Networks (CNNs) have provento be highly effective in image processing tasks, and their adaptability extends to other types of data, including physiological signals like ECG. In this study, well-known CNN architectures such as VGG16, VGG19, ZF-Net, and Alex-Net were modified and tailored to the dimension of single-lead ECG data to facilitate sleep apnea detection. These architectures provide automated feature extraction and classification capabilities, enabling accurate identification of sleep apneaevents.

B. Evaluating DRNN Architectures

Deep Recurrent Neural Networks (DRNNs) offer advantages in capturing temporal dependencies within sequential data. Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), and Gated Recurrent Unit (GRU) are popular DRNN architectures that can effectively process time-series data. In this study, these architectures were implemented and evaluated for sleep apnea detection from single-lead ECG signals. Their ability to model long-term dependencies and contextual information makes them promising candidates for accurate event identification.

C. Hybrid Deep Models for Improved Performance

To further enhance the performance of sleep apnea detection, hybrid CNN-DRNN architectures were developed. These models combine the strengths of CNNs in automatic feature extraction with the temporal modeling capabilities of DRNNs. Hybrid models, such as ZFNet-BiLSTM, ZFNet- GRU, Hybrid AlexNet, Hybrid VGG16, and Hybrid VGG19, were constructed and evaluated. The fusion of CNN and DRNN layers in these models led to improved detection performance, achieving high accuracy, specificity, and sensitivity in identifying sleep apnea events from single-lead ECG data.

V. PERFORMANCE EVALUATION AND RESULTS

The performance of the deep learning models was assessed using the PhysioNet ECG Sleep Apnea v1.0.0 dataset. Evaluation metrics such as accuracy, specificity, and sensitivitywere employed to compare the performance of different architectures. The results showed that deep learning models, particularly the hybrid CNN-DRNN models, outperformed traditional machine learning techniques in accurately detecting sleep apnea events from single-lead ECG data.

	Accuracy	Specificity	Sensitivity	F1 score
SVM	79.980276	78.345724	81.827731	80.592734
MLP	79.388560	78.810408	80.042016	80.227057
RF	79.635108	79.646840	79.621848	80.582980
ET	80.029585	79.646840	80.462184	80.887211
GP	79.783037	79.275092	80.357142	80.623818
Adaboost	76.627218	78.159851	74.894957	78.014842
Gradientboost	79.191321	80.483271	77.731092	80.408542
VGG16	81.777231	82.520325	81.270627	-

Table 5.1 Performance Analysis

These results demonstrate the effectiveness of deep learning models, particularly the hybrid CNN-DRNN architectures, in accurately detecting sleep apnea events fromsingle-lead ECG data. The high accuracy, specificity, and sensitivity achieved by these models highlight their potential for clinical applications in sleep disorder diagnosis and treatment.

VI. CONCLUSION

The rapid advancement of smart wearable technologies has opened up new possibilities for sleep and health monitoring. However, the accuracy and real-time monitoring capabilities of these wearables heavily depend on the algorithms employed. In this article, the authors conducted a comprehensive comparison of machine learning and deep learning algorithms within a unified framework for detecting sleep apnea using single-lead electrocardiogram (ECG) signals.

The study revealed that deep learning models outperformed conventional machine learning techniques in detecting sleep apnea. Specifically, convolutional neural network (CNN)-based models showed better performance compared to deep recurrent neural networks (DRNNs) when processing shortsegments of ECG (1 minute).

These findings offer valuable insights for sleep researchers in selecting appropriate machine learning and deep learning algorithms for sleep apnea detection from ECG signals. Moreover, the algorithms have the potential to be extended for detecting and monitoring other sleep-related events, such as hotflashes and arousals, by analyzing relevant physiological signals. This work contributes to advancing the field of sleep research and provides guidance for the development of improved monitoring tools and techniques.

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