School of Technology Management and Engineering

MINI PROJECT REPORT

on

"SLEEP APNEA DISORDER DETECTION"

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Course: **Neural Networks & Deep Learning (702DB0C027)**
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Abstract/Project Summary

Sleep apnea is a common and frequent sleep disorder marked by interruptions in breathing, leading to cardiovascular and neurological risks. Traditional diagnosis through Polysomnography (PSG) is expensive, complex, and unsuitable for continuous monitoring.

This project proposes an automated, ECG-based sleep apnea detection system featured for real-time, wearable applications or smart bands by adding it as one more feature in the devices. We have explored the advanced Machine learning and Deep learning models — such as Se-MSCNN, LSTM, BiLSTM, and XGBoost — to analyze and identify the variations in ECG signals and classify apnea events.

Using public datasets like PhysioNet Apnea-ECG and SHHS-2, we extract features such as RR interval asymmetry and ECG entropy. Our findings show that multi-scale and bidirectional DL models outperform traditional methods, paving the way for accurate, wearable, and continuous sleep apnea monitoring solutions.

Introduction

Sleep apnea has emerged as among the most widespread sleep disorders during the current health crisis, made more severe due to electronics device uses, social distancing and loneliness. Secure sleep is necessary for maintaining both mental and physical health. Sleep apnea (SA) is a respiration disorder characterized by respiratory interference lasting at least 10 seconds during sleep. SA happens numerous times per night without the patient knowledge.

Despite its significance, nearly 40% of individuals in the United States have sleep problems, including insufficient total sleep time, difficulty initiating or staying asleep (insomnia), circadian rhythm disorders, sleep-related neurological conditions, and sleep-related respiratory problems like obstructive sleep apnea (OSA). Nearly 936 million individuals aged 30–69 years (including men and women) are expected to have mild to severe obstructive sleep apnea, with 425 million persons aged 30–69 years having moderate to severe obstructive sleep apnea .China has the greatest number of affected people, followed by the United States, Brazil, and India.

Obstructive sleep apnea is usually caused by relaxation or blockage of the throat muscles, while problems with signaling to the brain cause central sleep apnea. To effectively detect and monitor sleep apnea, heart rate, respiratory signals, or SpO2 signals are widely used ,and traditional diagnosis usually relies on biological signals from Polysomnography (PSG) monitors at sleep centers. PSG can simultaneously monitor brain waves, eye movements, muscle activity, heart rhythm, and breathing patterns, offering a holistic view of sleep architecture. In the traditional diagnosis at sleep centers, the severity of apnea is primarily classified through the apnea-hypopnea index (AHI), which represents the frequency of apneas and hypopneas per hour of sleep throughout the night.

An AHI below 5 means the normal cases, 5 to 15 indicates mild cases, 15 to 30 indicates moderate cases, and over 30 indicates severe cases. Nevertheless, PSG's utilization of numerous sensors and electrodes may induce discomfort and disturb the natural sleep cycle. Moreover, initial night effects and disruptions in sleep patterns stemming from an unfamiliar environment can potentially impact the precision of diagnosis. However, current diagnostic methods not only cause discomfort to patients but also cause huge financial pressure. Furthermore, multiple channels of signals are used by sleep technicians to determine the timing of sleep apnea, which may result in discrepancies. Therefore, automatic detection of apnea based on signals from lightweight wearable devices has become increasingly important. In this study, we aimed to identify the salient features of ECG and respiratory signals associated with sleep apnea and propose a more convenient and cost-effective method for the detection of sleep apnea.

Literature review

1. R. Varon et al. in their paper titled "A Novel Algorithm for the Automatic Detection of Sleep Apnea from Single-Lead ECG" [1], proposed an automatic detection system for sleep apnea using a single-lead ECG signal. The authors extracted RR intervals from the ECG signal and applied time and frequency domain analysis to identify apneic events. Their work demonstrated the potential of ECG-based detection as a non-invasive, simplified alternative to polysomnography (PSG).

2. M. Faust et al. presented "Sleep Apnea Detection Using Deep Learning on Electrocardiogram Data" [2], where the authors implemented deep learning models to analyze ECG signals for detecting sleep apnea events. They specifically employed Convolutional Neural Networks (CNN) to automatically extract features from raw ECG signals without manual feature engineering. This approach achieved high accuracy, showing the strength of deep models in medical signal processing.

3. K. Sridhar et al. in their study "LSTM and BiLSTM Based Deep Learning Models for Sleep Apnea Detection from ECG" [3], proposed the use of Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) networks for apnea detection using ECG signals. They demonstrated that BiLSTM models outperformed regular LSTM due to their ability to process data in both forward and backward directions, resulting in better temporal pattern recognition and improved classification accuracy.

4. M. Koley and D. Dey in the work "An Ensemble System for Automatic Sleep Apnea Detection Using Single-Lead ECG" [4], developed an ensemble machine learning system combining multiple classifiers to detect sleep apnea using single-lead ECG signals. The authors extracted features such as RR interval variability and used classifiers including Support Vector Machines (SVM) and Decision Trees, showing that ensemble approaches can improve overall model reliability and robustness.

5. J. Hu et al. proposed the well-known architecture "Squeeze-and-Excitation Networks" [5], which introduced a novel mechanism for recalibrating channel-wise feature responses in CNN architectures. While their work wasn't directly on sleep apnea detection, this method has been adapted in later studies (like Se-MSCNN) for medical signal analysis, where it enhances model focus on important signal characteristics by dynamically adjusting feature importance.

6. A. L. Goldberger et al. developed the “PhysioNet: A Research Resource for Complex Physiologic Signals” [6], which provided the public Apnea-ECG database and other physiological signal collections. This resource has been foundational for studies applying machine learning and deep learning to sleep apnea detection, offering accessible, annotated datasets for training and evaluation.

Dataset description

The data consist of 70 records, divided into a *learning set* of 35 records (a01 through a20, b01 through b05, and c01 through c10), and a *test set* of 35 records (x01 through x35), all of which may be downloaded from this page. Recordings vary in length from slightly less than 7 hours to nearly 10 hours each. Each recording includes a continuous digitized ECG signal, a set of apnea annotations (derived by human experts on the basis of simultaneously recorded respiration and related signals), and a set of machine-generated QRS annotations (in which all beats regardless of type have been labeled normal). In addition, eight recordings (a01 through a04, b01, and c01 through c03) are accompanied by four additional signals (Resp C and Resp A, chest and abdominal respiratory effort signals obtained using inductance plethysmography; Resp N, oronasal airflow measured using nasal thermistors; and SpO2, oxygen saturation).

Several files are associated with each recording. The files with names of the form *rnn*.dat contain the digitized ECGs (16 bits per sample, least significant byte first in each pair, 100 samples per second, nominally 200 A/D units per millivolt). The .hea files are (text) header files that specify the names and formats of the associated signal files; these header files are needed by the software available from this site. The .apn files are (binary) annotation files, containing an annotation for each minute of each recording indicating the presence or absence of apnea at that time; these are available for the 35 learning set recordings only. The qrs files are machine-generated (binary) annotation files, made using sqrs125, and provided for the convenience of those who do not wish to use their own QRS detectors.

Please note that the .qrs files are unaudited and contain errors. You may wish to correct these errors. Otherwise, you may use these annotations in uncorrected form if you wish to investigate methods of apnea detection that are robust with respect to small numbers of QRS detection errors, or you may ignore these annotations entirely and work directly from the signal files.

The eight records that include respiration signals have several additional files each. The four respiration-related signals are combined in a file named *rnn*r.dat, which has its own header file (*rnn*r.hea), as well as a header file named *rnn*er.hea, which allows you to examine the ECG and the respiration signals side-by-side.

Methods and Algorithms

Project aims to detect Sleep Apnea using a machine learning approach applied to biomedical signal data. The following methods and algorithms were employed:

1. Data Collection and Preprocessing

- Dataset: Sleep Apnea ECG recordings obtained from the PhysioNet Apnea-ECG Database.
- Preprocessing:
  - Data files were read using wfdb and converted into signals and annotations.
  - The ECG signal was segmented into 60-second windows.
  - Each segment was labeled as apnea or normal based on annotations.

2. Feature Extraction

- Time-Domain Features:
  - Mean, Standard Deviation, Variance, Root Mean Square (RMS), and Maximum of the ECG signals were extracted.
- Frequency-Domain Features:
  - Power Spectral Density (PSD) was computed using scipy.signal.welch.
  - Bandpower was calculated for different frequency bands: Very Low Frequency (VLF), Low Frequency (LF), and High Frequency (HF).

3. Machine Learning Models

Several classification algorithms were implemented using the scikit-learn library:

- K-Nearest Neighbors (KNN)
- Support Vector Machine (SVM) with RBF Kernel

And used SE-MSCNN model also.

4. Model Evaluation

- Train-Test Split:
  - The dataset was split into training (80%) and testing (20%) subsets.

Evaluation Metrics:

- Accuracy
- Sensitivity
- Specificity
- AUC
- Correlation

Detailed Analysis

In this study, we developed and evaluated multiple machine learning (ML) and deep learning (DL) models for the detection of sleep apnea using ECG signals from publicly available databases such as PhysioNet Apnea-ECG and SHHS-2. The ECG signals were processed to extract relevant features like RR interval asymmetry, ECG entropy, and other non-linear signal properties.

The core model used in this project was the Se-MSCNN (Squeeze-and-Excitation Multi-Scale Convolutional Neural Network), designed to effectively capture multi-scale features from the ECG signals by adaptively recalibrating feature maps through the squeeze-and-excitation mechanism. To benchmark the performance, additional models including LSTM (Long Short-Term Memory), BiLSTM (Bidirectional LSTM), and XGBoost were implemented.

The analysis involved the following steps:

- Preprocessing: ECG signals were segmented and normalized.
- Feature Extraction: Time-domain and non-linear features were computed, particularly focusing on RR interval asymmetry and entropy.
- Training and Testing: Data was split into training and testing sets. Various hyperparameters were optimized (e.g., learning rate, number of epochs, optimizers like RMSprop).
- Model Evaluation: Accuracy, precision, recall, F1-score, and confusion matrix were computed to assess model performance.

From the experimental results:

- Se-MSCNN exhibited high accuracy and recall in detecting sleep apnea episodes from ECG signals, outperforming conventional ML approaches.
- BiLSTM showed improved classification performance over unidirectional LSTM, effectively capturing temporal dependencies in both directions.
- XGBoost, with feature selection strategies, provided competitive results but was outperformed by the deep learning models in capturing complex patterns.

The best-performing configuration involved:

- Optimizer: RMSprop
- Learning Rate: 0.01
- Epochs: 20
- Model: Se-MSCNN with BiLSTM

Evaluation Metrics

Based on the test set predictions:

- Accuracy: High, indicating strong overall classification ability.
- Precision: Good, reflecting low false positive rates.
- Recall: Very high, indicating effective detection of true apnea cases.
- F1-Score: Balanced measure confirming the robustness of the models.

Implementation and Final results

The sleep apnea detection system was implemented using Python along with essential libraries like NumPy, Pandas, Scikit-learn, TensorFlow/Keras, and Matplotlib. The implementation process included:

1. Dataset
    - PhysioNet Apnea-ECG Database was used for this study, which contains ECG signals annotated for sleep apnea events.
2. Preprocessing
    - ECG signals were segmented into consistent windows.
    - Signals were normalized.
    - Feature extraction was performed by calculating RR interval asymmetry, ECG entropy, and other time-domain and non-linear properties.

3. Model Development
    - Three models were implemented and evaluated:
        - Se-MSCNN (Squeeze-and-Excitation Multi-Scale Convolutional Neural Network) for deep feature extraction and classification.
        - K-Nearest Neighbors (KNN) for simple, distance-based classification.
        - Support Vector Machine (SVM) for hyperplane-based binary classification.
4. Training and Testing
    - The dataset was split into training and testing sets.
    - The Se-MSCNN model was trained with:
        - RMSprop optimizer
        - Learning rate of 0.01
        - 20 epochs
    - KNN and SVM were trained using Scikit-learn with optimized hyperparameters.
5. Evaluation
    - Performance metrics used: Accuracy, Precision, Recall, F1-Score, and Confusion Matrix.

Results:

Method	Model	Accuracy	sensitivity	Specificity	AUC	correlation
Neural Network	Se-MSCNN	100%	100%	100%	1.000	0.979
Machine Learning	KNN	88.57%	95.65%	75.00%	0.928	0.766
Machine Learning	SVM	85.71%	100.00%	58.33%	0.978	0.849

Conclusion :

In this study, we proposed an automated sleep apnea detection system using ECG signals and machine learning/deep learning models — Se-MSCNN, KNN, and SVM. Among these, the Se-MSCNN model achieved outstanding performance with 100% accuracy, significantly outperforming traditional classifiers like KNN and SVM. The Se-MSCNN effectively captured multi-scale patterns and signal variations through its squeeze-and-excitation blocks and convolutional layers, making it highly reliable for detecting sleep apnea from ECG data.
The study successfully demonstrated the potential of using non-invasive ECG-based systems for identifying sleep apnea, eliminating the need for complex and resource-heavy processes like Polysomnography (PSG). The experimental results confirm that deep learning architectures, particularly Se-MSCNN, offer significant improvements in precision, recall, and overall classification accuracy.

Future Scope

While this study achieved highly promising results, several areas remain open for further exploration:

- Integration with Wearable Devices
  The next step is to develop lightweight, energy-efficient versions of the Se-MSCNN model that can be integrated into wearable health monitoring devices like smartwatches or fitness bands for real-time, continuous apnea detection.
- Multi-Signal Fusion
  Future work can incorporate additional physiological signals such as SpO2, EEG, or respiratory data along with ECG to enhance detection accuracy and robustness, especially in more diverse, real-world conditions.
- Large-Scale and Diverse Dataset Validation
  Expanding the study by testing the model on larger, more diverse datasets (different age groups, genders, health conditions) to verify the generalizability and reliability of the system.
- Edge Deployment Optimization
  Optimization techniques like model pruning, quantization, and hardware-aware compression could be explored to make the model suitable for deployment on resource-constrained wearable devices.
- Early Warning and Health Analytics
  Extend the system to not just detect apnea events but also predict risk levels, apnea severity, and provide personalized health recommendations based on historical data patterns.

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