Sleep Apnea Prediction Using Real Time ECG Data

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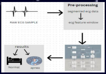
ABSTRACT

Breathing disturbances that persist more than ten seconds during sleep are the hallmark of the widespread disorder known as sleep apnea. These interruptions may manifest as a series of Apnea or Hypopnea events, each lasting for a brief duration. The AHI can be used to assess the severity of this disease. aditionally. the iagnosis of Sleep Apnea (SA) has relied on the costly and expert - intensive Polysomnography (PSG) technique, requiring continuous onitoring by medical professionals, given its high valence, there is a pressing need to identify and address Sleep Apnea at its early stages. To tackle this, an annotated dataset of ECG data has been mployed to detect the early onset of Sleep Apnea (SA). This data can be harnessed to classify individuals and assess their risk of developing Sleep Apnea, offering a more accessible and cost-effective approach to detection and intervention. This innovative approach not only provides a more cost-effective and scalable method for detecting Sleep Apnea but also reduces the burden on expert medical resources. Early identification and treatment can lower the health risks related to sleep apnea and greatly enhancequality of life.

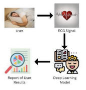
To address the challenges of diagnosis, a proposed study aims to build application assessing sleep apnea vulnerability. The study involves transforming heart rate signals into a file document , generating a risk report based on user data.



.The ECG signal data is extracted from the document . It determines whether the ECG signal's sample frequency is 100 Hz and raise an error if it deviates from this predicted value . It retrieves symbols related to the annotations and their corresponding sample numbers.

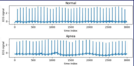
INTRODUCTION

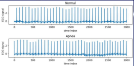
Sleep apnea, a prevalent but often ntreated sleep disorder, affects an timated 25 million people in the United States, with up to 80% of oderate-to-severe cases going untreated. Obesity, particularly in men, is a significant risk factor, with 70% of affected individuals being overweight or obese. The disorder is linked to higher risks of stroke, heart disease, and financial burdens due to medical costs and missed wages. Sleep apnea isn't exclusive to adults ; 1–4% of youngsters are affected. Its consequences extend beyond disrupting sleep, causing excessive daytime leepiness, mood swings, cognitive decline, and an increased risk of accidents.



PROPOSED SYSTEM

The proposed system integrates a web application and a deep learning model to assess an individual's risk of sleep apnea. Utilizing an ECG sensor (AD8262), the deep learning model , built with Flask and LSTM, processes the ECG signals. The AD8262 sensor , designed by Analog Devices, captures and processes heart activity, enabling the extraction of ECG signal data crucial for analysis. The web application, depicted in Figure 3, facilitates user eraction by allowing the upload of ECG signal files. Upon submission, the user provides details, triggering the generation of a report with the predicted output, as shown in the pop-up page (Figure 5). The dataset, comprising 70 records, aids in training and testing the model, with annotations generated based on human specialists' input. The deep learning model combines CNNs and LSTM layers for binary classification , achieving a total of 529,985 parameters. Training involves 20 epochs , resulting in a progressively improving accuracy , reaching 85.64% in the final epoch . The evaluation metrics , including precision , recall , and F1-score , contribute to assessing the model's performance, providing insights into its strengths and weaknesses.





CONCLUSIONS

As LSTMs can extract patterns and dependencies from temporal data, they are ideal for processing sequential data. Complex patterns may be present in sleep Apnea episodes, and LSTMs are useful for modeling such patterns. The method can be expanded by taking into account additional elements such as bdominal movements, saturated oxygen, and nasal airflow. It can also be expanded by automating the process so that the user can independently assess the risk on their own.

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