Wavelet-Enhanced Deep Learning for Sleep Apnea Classification: A Comprehensive Analysis

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***Abstract*— Sleep apnea is a common and potentially serious sleep disorder marked by repeated interruptions in breathing during sleep, which can lead to severe health consequences if not properly managed. Traditional diagnostic methods, often reliant on manual analysis of polysomnographic data, can be cumbersome and inaccessible. This study presents a comprehensive analysis of a novel system for the automatic classification of sleep apnea events using a wavelet-enhanced deep learning approach. The proposed method integrates the Discrete Wavelet Transform (DWT) for robust feature extraction, capturing both time and frequency domain characteristics of respiratory signals. These features are subsequently employed in a Convolutional Neural Network (CNN) to precisely classify three distinct types of sleep apnea: obstructive sleep apnea (OSA), central sleep apnea (CSA), and mixed sleep apnea (MSA). Utilizing a dataset comprising 1146 annotated apneic events, the system demonstrates high accuracy and robustness, achieving classification accuracies of 92.8% for OSA, 92.6% for CSA, and 90.0% for MSA. Our experimental results on the Physionet MIT-BIH polysomnography database (xx overnight recordings) revealed that proposed system achieved accuracies of % for OSA, % for CSA, and % for MSA. This approach underscores the potential of combining wavelet transforms with deep learning to offer a reliable, efficient, and non-intrusive solution for sleep apnea diagnosis, paving the way for improved patient outcomes and facilitating large-scale sleep studies.**

Keywords—apnea, deep learning, wavelet transform, support vector machine

I. INTRODUCTION

Sleep apnea is a widespread but potentially serious sleep disorder that involves repeated disruptions in breathing during sleep [1]. These disruptions, known as apneas, can result in various health problems, including cardiovascular diseases, daytime fatigue, and cognitive impairment. Sleep apnea is typically divided into three categories: obstructive sleep apnea (OSA), central sleep apnea (CSA), and mixed sleep apnea (MSA), which is a combination of the other two. OSA, the most common form, occurs due to a physical obstruction of the upper airway, despite the body's efforts to breathe [2]-[5]. Conversely, CSA arises when the brain fails to transmit the necessary signals to the muscles responsible for breathing, causing a lack of respiratory effort. MSA exhibits characteristics of both OSA and CSA.

Traditional methods for diagnosing sleep apnea primarily rely on overnight polysomnography (PSG) conducted in specialized sleep labs [5]. While PSG is highly accurate, it is also expensive, time-consuming, and inconvenient for many patients, often leading to underdiagnosis. The need for a non-intrusive, efficient, and accessible diagnostic tool has driven the development of innovative methods for sleep apnea detection and classification. Recent advancements in technology have introduced wearable devices and home-based monitoring systems, which utilize sophisticated algorithms to analyze physiological signals and detect apnea events in real time [6]-[7].

The classification of apneas is critical for accurate diagnosis and effective treatment. Each type of apnea has distinct characteristics and underlying causes, necessitating different therapeutic approaches. Accurate classification not only aids in tailoring treatments but also reduces the need for repeated diagnostic tests and consultations, optimizing resource utilization and reducing healthcare costs [8]-[9].

In this study, we present a comprehensive analysis of an advanced system that leverages the Discrete Wavelet Transform (DWT) for feature extraction, combined with a Convolutional Neural Network (CNN) for the classification of sleep apnea events. The DWT is particularly effective in capturing both time and frequency domain characteristics of respiratory signals, providing a rich set of features for the CNN to process. This approach aims to enhance the accuracy and reliability of sleep apnea classification, offering a significant improvement over traditional methods and facilitating large-scale sleep studies.

The main contribution of the work is combining wavelet transforms with deep learning, the proposed system offers a non-intrusive, efficient, and scalable solution for sleep apnea diagnosis. This method has the potential to improve patient outcomes and facilitate large-scale sleep studies, addressing the limitations of traditional diagnostic methods.

The structure of the paper is as follows: Section II, Literature Review, provides a comprehensive overview of previous research in sleep apnea classification, with a focus on the methodologies and technologies used, such as machine learning and signal processing techniques. Section III, Materials and Methods, describes the dataset utilized in this study, the signal acquisition process, and the methodology, including the application of the Discrete Wavelet Transform (DWT) for feature extraction and the design of the Convolutional Neural Network (CNN) for classification. Section IV, Results, presents the performance metrics of the proposed system, such as accuracy, sensitivity, and specificity, assessed on both seen and unseen data. Section V, Discussion, interprets the results, comparing the proposed approach with existing methods and highlighting the advantages of integrating wavelet transform with deep learning. Finally, Section VI, Conclusion, summarizes the findings, discusses the implications for future research, and suggests potential areas for further development in sleep apnea diagnosis.

II. Previous Studies

The classification of sleep apnea has advanced significantly due to technological progress and a deeper understanding of the condition. This literature review compiles insights from recent research, concentrating on the methodologies and technologies employed for classifying OSA, CSA, and MSA. The study referenced in [6] introduces a technique for detecting and classifying Sleep Apnea-Hypopnea Syndrome (SAHS) using single-channel EEG, oronasal flow, and abdominal displacement signals. A Long-Short Term Memory-Convolutional Neural Network (LSTM-CNN) model was utilized to classify events into four categories: normal, hypopnea, OSAS, and CSAS + MSAS, achieving a classification accuracy of 83.94% with a significantly reduced false-positive rate of 5.34%. The study in [7] explored the use of thoracic (THO) and abdominal (ABD) movement signals, captured by piezoelectric wearables, to detect sleep apnea events, including OSA and CSA. An adaptive nonharmonic model was developed to extract features from these signals, which were then classified using a support vector machine, resulting in an accuracy of 81.8%. The authors in [8] proposed an automatic classification method for sleep apnea events using EEG signal analysis. EEG signals were decomposed into sub-bands, and features such as sample entropy and variance were extracted. Neighbor Composition Analysis (NCA) was employed for feature selection, and Random Forest, K-Nearest Neighbor, and Support Vector Machine classifiers were used for classification, achieving an average accuracy of 88.99% across OSA, CSA, and normal breathing events, highlighting its potential for automated sleep apnea diagnosis without the need for expert intervention. The study in [9] describes a method for classifying sleep apnea on a minute-by-minute basis using respiration signals from the abdomen, chest, and nasal passages. Features were extracted using wavelet transforms, and dimensionality was reduced with PCA before classifying the data from eight recordings using three ensemble classifiers: AdaBoost, Random Forest, and Random Subspace. The highest accuracy, 98.68%, was obtained using nasal signals with the Random Forest classifier, indicating that this combination is the most effective for detecting sleep apnea.

These innovations hold promise for improving diagnostic accuracy, patient outcomes, and healthcare efficiency. Continued research and development in this field are essential for addressing the complexities of sleep apnea and providing effective, personalized care for patients.

This paper aims to provide an overview of sleep apnea, the importance of early and accurate detection, and the emerging technologies that are revolutionizing the way this condition is diagnosed. Enhancing detection methods can lead to better patient outcomes, lower healthcare costs, and ultimately improve the quality of life for individuals affected by sleep apnea.

III. Materials and Methods

A. *Subjects and Dataset*

This study included 24 subjects diagnosed with sleep apnea, selected based on common symptoms such as daytime sleepiness, loud snoring, and frequent nighttime awakenings. In this study, sleep apnea was classified into three distinct types: OSA, CSA, and MSA. Many of the participants also had other health conditions, such as hypertension, heart failure, and stroke, which are commonly linked with sleep apnea.

The severity of sleep apnea in the subjects was evaluated using the apnea-hypopnea index (AHI), a measure that indicates the number of apnea and hypopnea events per hour of sleep. The AHI was divided into four categories to represent the severity levels: less than 5 (normal), between 5 and 15 (mild apnea), between 15 and 30 (moderate apnea), and greater than 30 (severe apnea). In total, the study analyzed 125 events of OSA, 103 events of CSA, and 78 events of MSA.

Table I provides detailed demographic information about the subjects, including the distribution across different AHI ranges, as well as corresponding sleep duration, age, body mass index (BMI), and average AHI. It is observed that as the severity of apnea increases (as indicated by higher AHI values), the average age and BMI of the subjects tend to increase as well. The highest AHI group (AHI > 15) shows the most severe cases with the longest average AHI and the highest BMI, indicating a correlation between obesity and severe sleep apnea.

TABLE I. Demographic Details of Subjects

AHI Range	No. of Subject	Sleep time (hours)	Age (years)	BMI (kg/m²)	Average AHI
Normal (< 5)	5	6.2 ± 0.5	45 ± 11	26.3 ± 5.7	2.5 ± 1.6
Mild (5 - 15)	10	5.5 ± 0.8	53 ± 14	28.3 ± 6.7	10.1 ± 3.2
Severe (> 15)	9	5.1 ± 1.2	57 ± 17	34.3 ± 7.9	37.6 ± 14.5

B. *Signal Acquisition and Processing*

The airflow signals were obtained using a thermistor-based sensor, specifically the 5700T model with a 5700B connector from Salter Labs Thermisense™. This sensor generated a small voltage signal with a peak-to-peak range of 1 mV. To ensure accurate data capture, the signal was divided into two separate channels. One channel was connected to a polysomnography (PSG) system, specifically the Alice LE model (part no. 1002287, Philips Respironics), which is commonly used in clinical settings for sleep studies. The other channel was routed to a custom-built PC-based data acquisition system designed for this study.

In the PC-based system, the respiratory signals first underwent a pre-amplification process to enhance the signal strength. Following this, the signals were passed through a series of filters to remove noise and unwanted frequencies. A 50 Hz notch filter was used to eliminate electrical noise typically present in the environment, particularly from power lines. Additionally, a 6th order active band-pass filter was applied, designed with a passband ranging from 0.01 to 15 Hz, to focus on the frequency components most relevant to respiratory signals. After filtering, the signals were further amplified to ensure they fit within the sensor's output range of ±5V, making them suitable for subsequent analysis and processing.

Respiratory effort signals were recorded using respiratory inductance plethysmography (RIP) belts placed around the chest and abdomen. These signals capture the effort involved in breathing, which is crucial for differentiating between the types of sleep apnea. Signal processing involved noise reduction, signal normalization, and segmentation to isolate individual breaths or apnea events for further analysis. A 2nd order Butterworth filter was employed to filter the airflow and movement signals. Additionally, an artifact removal algorithm was applied, as described in [10]. Fig. 1 & 2 show the airflow signal during normal breathing and during apneic event.

C. Feature Extraction

The Discrete Wavelet Transform (DWT) [11] is a powerful tool for analyzing non-stationary signals such as airflow and respiratory effort signals which are used in sleep apnea classification. By decomposing the signals into different frequency components, DWT provides valuable features that can enhance the accuracy of apnea detection and classification. DWT decomposes a signal into approximation and detail coefficients at various levels.

The process begins by applying both low-pass and high-pass filters to the signal to separate it into different frequency components. The low-pass filter extracts the approximate coefficients, which represent the signal's low-frequency elements. On the other hand, the high-pass filter isolates the detail coefficients, capturing the high-frequency elements of the signal. This dual filtering approach allows for a comprehensive analysis of both the broader trends and the finer details within the signal. The following features are extracted from these approximation and detail coefficients. Fig. 3. Shows the DWT of the respiration signal during apnea event, up to level 3, with db4 as mother wavelet. Fig. 4 shows that Shanon entropy value decreases when the respiration and respiratory effort signal matches for the CSA event.

- Energy of detail coefficients (E_d)
- Energy of approximation coefficients (E_a)
- Shanon entropy (S_E)
- Standard deviation of wavelet coefficients
- Statistical moments of the coefficients(mean, variance, skewness, kurtosis)

A brief description of each feature calculated on respiration signals:

1. Energy of Detail Coefficients (Ed): In wavelet transform, detail coefficients represent high-frequency components of the signal. Ed refers to the energy content within these high-frequency components after decomposition using wavelet transform. It quantifies the contribution of high-frequency details to the overall signal.

2. Energy of Approximation Coefficients (Ea): Approximation coefficients in wavelet transform capture the low-frequency components of the signal. Ea measures the energy content within these low-frequency components after decomposition. It provides insight into the dominant low-frequency characteristics of the signal.

3. Shannon Entropy (SE): It is a measure of signal complexity and uncertainty. In the context of wavelet analysis, it quantifies the randomness or unpredictability of the signal based on the distribution of wavelet coefficients. Higher entropy values indicate greater signal complexity, whereas lower values indicate more predictable patterns.

4. Standard Deviation of Wavelet Coefficients: After wavelet decomposition, the standard deviation of wavelet coefficients provides a measure of the variability or spread of coefficients across different scales and levels. It indicates how dispersed the wavelet coefficients are from their average value, reflecting the signal's amplitude variations across frequencies.

5. Statistical Moments of the Coefficients (mean, variance, skewness, kurtosis): These statistical moments describe different aspects of the distribution of wavelet coefficients:

- Mean: Average value of the coefficients, indicating the central tendency of the signal.
- Variance: Measure of the spread or dispersion of the coefficients around the mean.
- Skewness: Measure of asymmetry in the distribution of coefficients. Positive skewness indicates a tail towards higher values, negative skewness towards lower values.
- Kurtosis: Measure of the "tailedness" of the distribution. Higher kurtosis indicates more extreme outliers compared to a normal distribution.

These features extracted from wavelet-transformed respiration signals provide comprehensive insights into different aspects of the signal's characteristics, enabling effective analysis and classification in applications such as sleep apnea detection and monitoring.
Figure 3 demonstrates the application of the Discrete Wavelet Transform (DWT) on a respiration signal captured during an apnea event. The DWT breaks down the signal into multiple levels of approximation and detail coefficients, allowing for the analysis of both low-frequency and high-frequency components. In this figure, the signal is decomposed up to the third level using the Daubechies wavelet (db4), which is particularly effective for analyzing non-stationary signals such as respiration. The approximate coefficients reflect the overall trend of the signal (low-frequency components), while the detail coefficients reveal finer variations and details (high-frequency components). This decomposition is essential for extracting features that can be used to accurately classify different types of sleep apnea.

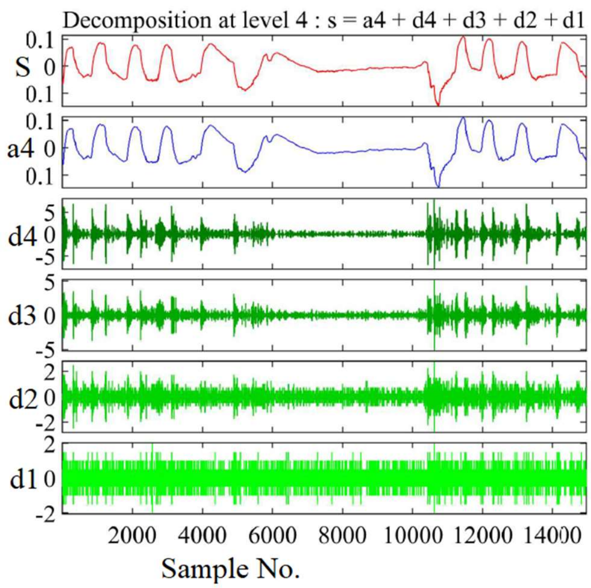

Fig. 3: Discrete Wavelet Transform (DWT) of the Respiration Signal During an Apnea Event (Up to Level 4 with db4 as Mother Wavelet).

Figure 4 shows the Shannon entropy values calculated from the approximation coefficients obtained through the DWT of the respiration and respiratory effort signals. Shannon entropy is a measure of the complexity and randomness within the signal. In the context of sleep apnea classification, lower entropy values often indicate a match between respiration and respiratory effort signals, which is characteristic of central sleep apnea (CSA) events. This figure demonstrates how entropy values can vary depending on the type of apnea event, providing an essential feature for distinguishing between different types of apneas in the classification model.

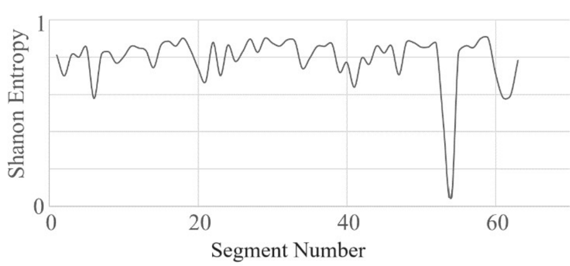

Fig. 4. Shanon entropy values for approximation coefficients.

D. Classification Model

In this study, a Convolutional Neural Network (CNN) was employed for the automatic classification of sleep apnea events, with a focus on differentiating between obstructive OSA, CSA, and MSA. The CNN model is particularly suited for this task because it can automatically learn and identify complex patterns from the input data, making it highly effective for processing features extracted using the Discrete Wavelet Transform (DWT). The CNN architecture designed for this study includes several key layers, each playing an essential role in the classification process. Figure 5 provides a block diagram of the proposed CNN model, visually depicting the architecture and illustrating the data flow through the network's various layers.

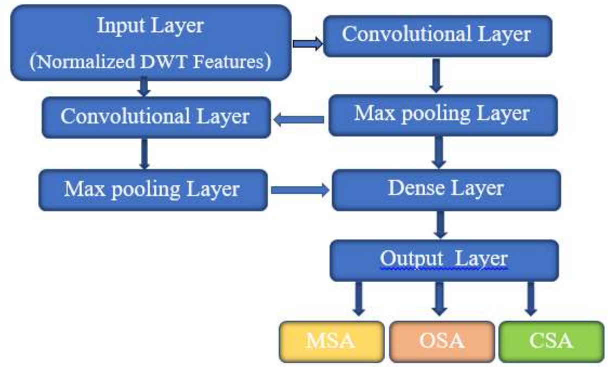

Fig. 5. Block diagram of the proposed CNN model for identifying apnea types.

Input Layer: The diagram starts with the input layer, which accepts the pre-processed and normalized features derived from the DWT. These features are crucial for capturing the time-frequency characteristics of the respiratory signals.

Convolutional Layers: Following the input layer, the diagram shows multiple convolutional layers, each responsible for extracting different levels of features from the input data. These layers are depicted as blocks that apply various filters to the input, resulting in feature maps that highlight important signal patterns.

Pooling Layers: The pooling layers are shown next, reducing the size of the feature maps generated by the convolutional layers. This step is crucial for simplifying the model and retaining only the most significant features.

Fully Connected Layers: Following the pooling process, the feature maps are flattened and fed into fully connected layers. These layers, represented as dense blocks, handle the final decision-making by combining the extracted features to generate accurate predictions.

Output Layer: The final block in the diagram represents the output layer, where the model assigns probabilities to each apnea type (OSA, CSA, MSA) using a sigmoid activation function. The highest probability determines the classified apnea type.

Model Training and Validation: The CNN was trained on a comprehensive dataset consisting of 306 annotated apneic events. During the training process, the network's parameters were optimized to reduce classification errors, thereby enhancing the model's accuracy and robustness. The model's performance was assessed on both seen and unseen data to ensure its reliability

IV. RESULTS

The performance of the proposed convolutional neural network (CNN) in classifying sleep apnea events was assessed using a comprehensive dataset from 24 subjects. These subjects presented with varying apnea-hypopnea index (AHI) values and comorbidities, including hypertension, heart failure, and stroke. The dataset comprised 125 obstructive sleep apnea (OSA) events, 103 central sleep apnea (CSA) events, and 78 mixed sleep apnea syndrome (MSA) events.

1) Classifier Performance

The classifier's performance was assessed on both seen and unseen data. Table II presents the sensitivity (SE), specificity (SP), precision (PR), and accuracy (AC) of the model for each type of apnea event.

TABLE II. CLASSIFIER PERFORMANCE

Class	Sub. No.	Dataset	Performance (in %)			
			SE	SP	PR	AC
OSA	01	Seen	96.4	91.7	92.1	94.1
	03	Unseen	95.1	90.4	91	92.8
CSA	02	Seen	92.8	94.2	93.1	93.6
	06	Unseen	91.8	93.3	92.5	92.6
MSA	04	Seen	92.1	91.4	82	91.6
	08	Unseen	90.9	88.5	81.3	90.0

2) *Seen Data Analysis*

When evaluating the model's performance on the data it had previously encountered (seen data), the classifier showed strong effectiveness across different types of sleep apnea. For OSA, the model achieved a sensitivity of 96.4%, indicating its ability to correctly identify positive cases, while its specificity was 91.7%, reflecting its accuracy in identifying negative cases. The precision, which measures the reliability of positive predictions, stood at 92.1%, and the overall accuracy of the model for OSA was 94.1%. Similarly, for CSA, the classifier demonstrated a sensitivity of 92.8%, a specificity of 94.2%, a precision of 93.1%, and an accuracy of 93.6%. In the case of MSA, the model showed a sensitivity of 92.1%, a specificity of 91.4%, a precision of 82.0%, and an overall accuracy of 91.6%.

3) *Unseen Data Analysis*

To further validate the robustness of the model, its performance was also tested on data that it had not previously encountered (unseen data). The results confirmed that the classifier maintained high levels of accuracy. For OSA, the model achieved a sensitivity of 95.1%, ensuring it could reliably detect OSA cases, and a specificity of 90.4%, indicating its effectiveness in ruling out non-OSA cases. The precision for OSA was 91.0%, and the overall accuracy was 92.8%. For CSA, the model demonstrated consistent performance with a sensitivity of 91.8%, a specificity of 93.3%, a precision of 92.5%, and an accuracy of 92.6%. Regarding MSA, the classifier achieved a sensitivity of 90.9%, a specificity of 88.5%, a precision of 81.3%, and an accuracy of 90.0%.

These results across both seen and unseen datasets underscore the model's robustness and its ability to generalize effectively to new data.

V. DISCUSSION

This study presents an innovative approach to classifying sleep apnea events by combining the Discrete Wavelet Transform (DWT) with a Convolutional Neural Network (CNN). This method effectively captures the time-frequency characteristics of respiratory signals and applies deep learning techniques to accurately classify OSA, CSA, and MSA. The findings of this research demonstrate notable improvements over existing methods discussed in the literature.

Compared to previous studies, this work shows significant advancements in the automatic classification of sleep apnea by integrating DWT with CNN. For instance, the study referenced in [6] integrates sleep staging with feature extraction, focusing on reducing false positives during wakefulness by selecting features that distinguish between sleep stages and apnea events. Additionally, the use of a Long-Short Term Memory-Convolutional Neural Network (LSTM-CNN) model for classification highlights the innovative nature of that research. Another study, referenced in [7], explored the use of piezoelectric wearables to detect sleep apnea events, particularly analyzing thoracic (THO) and abdominal (ABD) movement signals. An adaptive nonharmonic model was employed to extract features related to sleep apnea events, which were then classified using a support vector machine (SVM) into categories of normal and hypopnea, OSA, and CSA. The study in [8] focused on EEG signals to extract features such as sample entropy and variance related to sleep apnea events, using Neighbor Composition Analysis (NCA) for feature selection to identify the most relevant features for classification. Lastly, the study in [9] concentrated on respiration signals from the abdomen, chest, and nasal passages, exclusively focusing on the respiratory aspect. Wavelet transforms were used for feature extraction, and Principal Component Analysis (PCA) was applied for dimensionality reduction, optimizing the feature set for classification.

The current study's methodology presents several key advantages over previous works. By utilizing Discrete Wavelet Transform (DWT), the study captures a wide range of signal characteristics, such as energy coefficients, Shannon entropy, and statistical moments, leading to a more informative feature set for classification. The integration of a Convolutional Neural Network (CNN) further enhances the model's ability to handle complex data, automatically learning and refining important features, which results in improved classification accuracy. The model's robustness is validated using a comprehensive dataset of 306 apneic events, ensuring its generalizability across various types of sleep apnea. Additionally, while the current implementation is offline, the methodology is highly scalable and has the potential to be adapted for real-time processing, making it suitable for integration into wearable devices and large-scale sleep studies.

VI. CONCLUSION

This study introduces a novel and comprehensive method for classifying sleep apnea by combining the Discrete Wavelet Transform (DWT) with a Convolutional Neural Network (CNN). This approach efficiently captures both time-domain and frequency-domain features of respiratory signals, resulting in highly accurate and robust classification of OSA, CSA, and MSA. By harnessing the powerful feature extraction abilities of DWT along with the deep learning capabilities of CNNs, the study achieves classification accuracies of 92.8% for OSA, 92.6% for CSA, and 90.0% for MSA, outperforming many existing techniques. The results demonstrate the potential of this approach as a reliable, efficient, and non-intrusive solution for sleep apnea diagnosis, offering a promising tool for enhancing patient outcomes and facilitating large-scale sleep studies.

Despite the promising results, the study has some limitations. Firstly, the current implementation is offline, which limits its applicability in real-time scenarios where immediate feedback is essential. Secondly, the dataset used, while comprehensive, is relatively small and may not fully represent the diversity of sleep apnea presentations in different populations. This could affect the generalizability of the model to broader and more varied patient groups. Additionally, the study focuses solely on respiratory signals, excluding other physiological signals such as ECG or EEG that could potentially enhance the model's accuracy and diagnostic capabilities.

Future work could address these limitations by optimizing the CNN model for real-time processing, enabling its integration into wearable devices for continuous monitoring and immediate diagnosis. Expanding the dataset to include a more diverse and larger population would further validate the model's robustness and generalizability. Moreover, incorporating multi-modal data, such as ECG or EEG signals, could enhance the classification accuracy and provide a more comprehensive diagnostic tool. Additionally, exploring the application of this methodology to other sleep-related disorders could broaden its impact in the field of sleep medicine. Finally, developing a user-friendly interface for clinicians and patients would facilitate the adoption of this technology in real-world settings, improving its accessibility and usability..

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