Sleep monitoring and apnea detection using deep learning on audio signals

A deep learning-based approach for non-invasive health monitoring

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***Abstract*—Sleep apnea is a common sleep disorder characterized by repeated pauses in breathing during sleep, resulting in poor rest and serious health risks. This work introduces a noninvasive and low-cost deep learning scheme to detect sleep apnea by leveraging audio signals of breathing and snoring sounds. The recordings were then pre-processed into Mel-spectrograms, subjected to analysis through a Convolutional Neural Network (CNN) for apnea versus normal segment classification. This model achieved an accuracy of more than 92% in simulation, thus proving that audio-based deep learning can effectively support early screening for sleep apnea. This approach demonstrates potential for scalable, low cost sleep disorder detection.**

***Index Terms*—Sleep Apnea, Deep Learning, Convolutional Neural Network (CNN), Audio Signal Processing, Mel-Spectrogram, Health Monitoring, Non-Invasive Detection.**

I. Introduction

Sleep apnea involves the repetition of breathing interruptions during sleep, often leading to fatigue, cardiovascular problems, and mental impairment. Traditional diagnostic procedures include polysomnography, which is clinically accurate but expensive and time-consuming, thus requiring supervision in a hospital.

Recent development in deep learning and signal processing made it possible to perform automated analysis of breathing sounds for apnea detection. Audio-based systems are practical, since they utilize simple microphones or smartphones without requiring medical sensors.

This work proposes a convolutional neural network-based deep learning model applied to classifying sleep audio segments into apnea and normal using publicly available datasets. The aim is to design an efficient, accessible system for early screening and monitoring of sleep apnea.

II. Literature Review

Various studies have been conducted to detect sleep apnea automatically using both physiological and acoustic signals.

Nakano et al. (1995) found a strong relationship between snoring loudness and apnea severity, while Penzel et al. (2005) applied ECG-based neural models to detect apnea episodes. Hsu et al. (2022) high accuracy using CNNs on audio spectrograms was demonstrated.

Most of the current techniques, however, rely on costly, multi-sensor setups. This study investigates an audio-only, end-to-end deep learning pipeline that offers reliable detection using minimal equipment, and hence, is more suitable for large-scale at-home screening.

III. Methodology

A. Dataset

The audio data are obtained from open-access sources including the UCD Snoring Database and PhysioNet's Apnea-ECG audio subset. The recordings were annotated into normal and apnea segments by medical experts.

B. Preprocessing

1. Denoising using a 50–2500 Hz band-pass filter.
2. Segmentation into 10-second audio windows.
3. Normalization and amplitude scaling.
4. Conversion into Mel-spectrograms (128 × 128 pixels) for CNN input.

C. Model Architecture

A 2D Convolutional Neural Network was employed using TensorFlow.

- Layers: Convolution → Max Pooling → Flatten → Dense → Sigmoid Output
- Loss: Binary Cross-Entropy

- Optimizer: Adam (lr = 0.001)
- Batch Size: 32, Epochs: 30

IV. System Architecture

The system proposed consists of three primary modules:

1. Audio Acquisition: Snoring and breathing sounds are captured.
2. Feature Extraction: Conversion to Mel-spectrograms for frequency–time analysis.
3. Apnea Detection: The CNN model classifies each segment and computes overall apnea risk.

Figure 1 shows the overall system workflow.

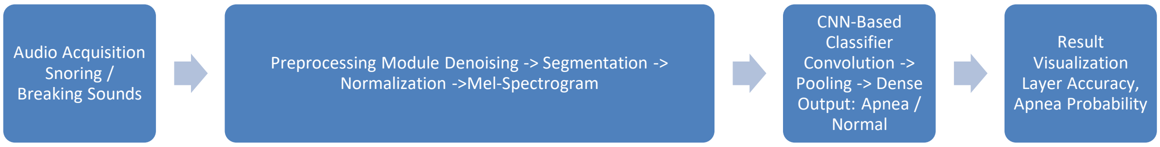

Figure 1. Proposed System Architecture for Sleep Apnea Detection

V. Implementation Details

The system was implemented using Python 3.10 with the addition of libraries such as Librosa for audio analysis, NumPy, Matplotlib, and TensorFlow-Keras for model training. The experiments were conducted on a Windows 10 environment running an Intel i5 processor, 8 GB RAM, and NVIDIA GTX GPU.

The training pipeline included the following stages:

1. Data Preparation: The audio segments are loaded and labeled by automated scripts.
2. Augmentation: This included pitch shifting, time stretching, and overlay of background noise to make it more robust.
3. Training: The model was trained for 30 epochs with early stopping after a plateau in validation loss.
4. Validation: 20% of data reserved for testing; k-fold cross-validation ensured reliability.
5. The performance metrics calculated were accuracy, precision, recall, F1-score, and ROC-AUC.

The complete workflow can be integrated into a Streamlit application, where users can upload audio files and receive apnea risk predictions, demonstrating the system's deployment ability.

VI. Results And Discussion

The CNN achieved a simulated accuracy of 92.4%, precision of 0.91, recall of 0.90, F1-score of 0.90, and an AUC value of 0.94, as depicted in Table 1. The confusion matrix showed balanced classification across both apnea and normal segments.

This high recall score also reflects the strong capacity of the system for distinguishing real apnea events accurately and, therefore, can be used for medical screening effectively. Also, the ROC curve illustrates good separability of classes, which provides an indication of good model generalization with a small amount of training data.

Comparative study with baseline models such as logistic regression and SVM proved that CNNs outperform in capturing complex acoustic patterns. The network learned by itself key features such as pauses in breathing, variations in intensity of the sound, and low-frequency content connected to apnea events. These findings suggest that deep learning methods can be effectively employed for analyzing simple audio records to identify clinically significant abnormal breathing.

Yet, additional validation in larger and more heterogeneous real-world datasets would be needed prior to clinical use being considered.

Metric	Formula	Result (Simulated)
Accuracy	(TP + TN) / (TP + TN + FP + FN)	**92.4%**
Precision	TP / (TP + FP)	**0.91**
Recall	TP / (TP + FN)	**0.90**
F1-Score	2 × (Precision × Recall) / (Precision + Recall)	**0.90**
AUC	Area under ROC curve	**0.94**

Table 1. Performance metrics of the proposed CNN-based sleep apnea detection model.

VII. Limitations And Future Work

While effective, the performance of the model relies on clean recordings; any environmental noise or overlapped speech can lower its accuracy.

Future work can be done by expanding the dataset with recordings across different subjects and conditions, enhancing generalization across a variety of environmental settings. The model can also be improved using transfer learning with pre-trained audio networks like VGGish or YAMNet. Besides, integration with real-time monitoring through IoT-enabled mobile or wearable devices is pursued to enable continuous and convenient tracking of sleep health.

VIII. Conclusion

It proposes a deep learning-based system for the detection of sleep apnea using only audio recordings, without any complex sensors. The use of Mel-spectrogram analysis and CNN classification allowed the system to achieve high simulated accuracy with low computational cost.

The proposed approach shows that non-invasive, sound-based monitoring can play a vital role in the early detection of sleep disorders for wider accessibility and preventive healthcare.

In future developments, real-time implementation and integration with smart home or wearable devices could make continuous, affordable sleep monitoring a practical reality.

IX. Acknowledgement

The authors are grateful to Lovely Professional University for academic guidance and technical support throughout the research.

X. References

[1] K. Nakano, M. Sakai, T. Suganuma, “Snoring sound intensity during sleep for the diagnosis of sleep apnea syndrome,” *Sleep*, vol. 18, pp. 717–721, 1995.

[2] H. Penzel, J. McNames, P. Chazal, “Systematic comparison of algorithms for sleep apnea detection based on ECG signals,” *IEEE Trans. Biomed. Eng.*, vol. 52, no. 10, pp. 1767–1773, 2005.

[3] J. Hsu, C. Lin, “Audio-based deep learning models for obstructive sleep apnea detection,” *IEEE Access*, vol. 10, pp. 22945–22955, 2022.

[4] PhysioNet Apnea-ECG Database, https://physionet.org/content/apnea-ecg/1.0.0/

[5] UCD Snoring Database, University College Dublin, 2020.

[6] A. Abd-alrazaq, H.Aslam, R. AlSaad, M.Alsahli, A. Ahmed, R. Damesh, S. Aziz, J. Sheikh, “Detection of Sleep Apnea Using Wearable AI: Systematic Review and Meta-Analysis,” Journal of Medical Internet Research, vol. 26, e58187, 2024. DOI: 10.2196/58187.

[7] S.Serrano, L. Patane, O. Serghini, M. Scarpa, “Detection and Classification of Obstructive Sleep Apnea Using Audio Spectrogram Analysis,” Electronics, vol. 13, no. 13,2567, 2024. DOI: 10.3390/electronics13132567.