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AI-Based Snoring Detection and Early Sleep Apnea Prediction Using Deep Learning: Review

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Abstract

Obstructive sleep apnea (OSA) is largely underdiagnosed due to the reference test, overnight polysomnography (PSG) requiring a sleep laboratory and trained staff. Because loud, habitual snoring is among the first outward signs of OSA, a number of recent studies ask whether deep learning can turn snoring audio and low-cost physiological signals into an early warning outside the clinic. This paper reviews seven recent studies and several supporting works for that question, including CNN, attention-based CNN–BiLSTM, ResNet with audio spectrogram transformers, and end-to-end PSG models.. We compare them by method, reported findings and stated limitations, outline the common processing pipeline and discuss privacy and ethical concerns. Deep models show promise for screening, but practical use is limited by small datasets, class imbalance, heavy computation, weak explainability and little validation in home settings. In summary, we summarize the design requirements for a lightweight, explainable apnea risk system deployable in the home.

Keyword : obstructive sleep apnea, snoring detection, deep learning, polysomnography, spectrogram, explainable AI, wearable sensing

I.I. INTRODUCTION

Snoring is the vibration of the soft tissues of the upper airway when air passes through a narrowed passage during sleep. Occasional snoring is normal and typically not harmful. Obstructive sleep apnea (OSA) is characterized by repeated episodes of airway collapse, cessation of breathing, drops in blood oxygen, and fragmented sleep . However, OSA is often accompanied by loud, frequent snoring . The majority of the several hundred million adults worldwide with OSA are undiagnosed [1]. Untreated it is associated with daytime sleepiness, hypertension and other cardiovascular and metabolic problems [2The gold standard for diagnosis is the overnight polysomnography (PSG) recording brain activity, airflow, respiratory effort,

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oxygen saturation and heart signals in a sleep laboratory. PSG is accurate but expensive, uncomfortable and only available in larger centers. Waiting lists are long and many patients are never tested. So there is a real need of a screening method that people can use at home.

Because deep learning is extremely powerful, it can easily take this role. Ordinary sound recordings collected by smartphones can be analyzed with the help of advanced patterns recognition algorithms. In the recent years, many studies on the applicability of deep-learning technologies in this area of research have been published, avoiding serious contribution to common knowledge. This paper makes attempts to gather all major findings in this area to present: (i) the structured summary of the most recent relevant studies on snoring and apnea detection; (ii) the description of the commonly used snoring and apnea detectors; and (iii) ethical and privacy implications of the problem discussed..

There is a structure to the remainder of the paper. It is as follows. In Section II, there is given the medical background and acoustic background. Section III describes the issue and objectives. In Section IV, the significance of the topic today is explained. Section V contains a literature review. Sections VI to VIII involve datasets, the processing plan, model families, and the evaluation process. The remaining Sections, IX to XI, tension some difficulties, gaps in the research, and future perspectives of the subject of thespeech. Lastly, the paper ends with Section XII..

II. BACKGROUND

A. Sleep Apnea and Its Severity

Apnea refers to a cessation of breathing during sleep, which lasts for at least 10 seconds. Hypopnea, on the other hand, corresponds to partial lowering of airflow, which results in reduction in oxygen saturation and awakening. The frequency of these events is expressed as apnea-hypopnea index (AHI), which indicates how many events happen per hour of sleep. People with AHI of 5–15 experience mild sleep apnea, while those with AHI of 15–30 have moderate sleep apnea, and those whose AHI exceeds 30 suffer from severe sleep apnea.B. Acoustic Characteristics of Snoring

Snoring is caused by the vibrations of various tissues such as the soft palate, tongue base, and epiglottis, and hence the area and extent of narrowing determines the resulting sound spectrum. Therefore one can deduce at which location the obstruction occurs from the snoring recordings. Among the snoring types associated with apnea we typically see a periodic pattern characterized by a loud snoring sound, followed by silence, and a gasp when breathing continues. A model capable of processing say individual frames doesn’t capture this pattern, which is one of the reasons why researchers prefer using temporal models and attention mechanisms.

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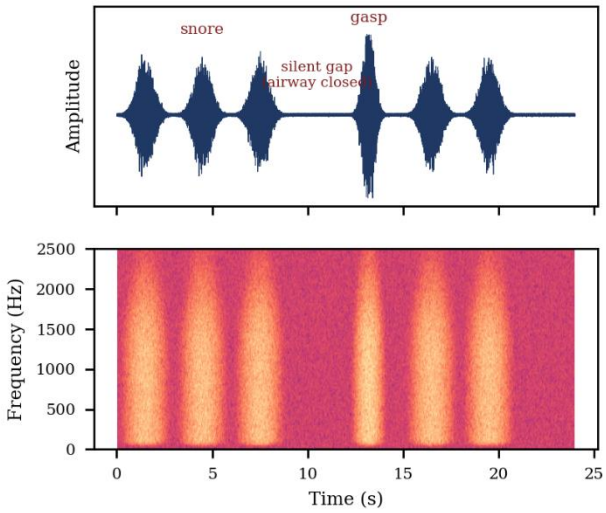


Fig. 1. Illustrative synthetic signal (not patient data): waveform and spectrogram showing repeated snores, a silent gap, and a gasp.

III. PROBLEM STATEMENT AND OBJECTIVES

A. Problem Statement

The questions that this study addresses are whether an automated system can identify snoring and use it with other inexpensive signals to predict the onset of sleep apnea early. Three problems arise here. On the one hand, snoring is an early symptom of OSA, but the common test to identify it is rather expensive and time-consuming. On the other hand, the existing automated solutions are either not accurate or fast enough for constant use and not usable by most people. In addition, it is not known what methods can be trusted outside their original datasets. Thus, the aim is to create a system that is accurate, affordable, and easy to use, and this review assesses the progress made so far.

B. Objectives

1) To study current AI and deep learning techniques for snoring detection and early apnea prediction.

2) To examine the datasets, feature-extraction methods, and models (CNN, LSTM, Transformer) used in published work.

3) To compare existing approaches on data, reported performance, advantages, and limitations.

4) To assess reliability, ethical and privacy concerns, and real-world applicability.

5) To identify research gaps and suggest directions for accurate, early apnea prediction.

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IV. RELEVANCE TO CURRENT TECHNOLOGY TRENDS

In view of the multiple technological tendencies, this topic holds utmost relevance. Deep learning enables identifying patterns in the audio signal with greater precision thanhandcrafted techniques. By means of wearable devices, users can track their health for the entire night, and mobile networks and cloud computing contribute to processing and analyzing data in an effective manner. Telemedicine and digital health services enable rapid notification of the medical community about the potential threats as well. For instance, in India, people living in remote places might face problems in accessing sleep laboratories and costly PSG (polysomnography). The introduction of an AI snore detection system based on the use of the smartphone or the affordable wearable device can help find those people who are vulnerable to obstructive sleep apnea (OSA) and urge them to get examined in a timely manner. These innovations mark a considerable shift from dealing with problems when symptoms worsen to data-driven screening and prevention of apnea in advance.

V. LITERATURE SURVEY

Research on artificial intelligence-based snoring diagnosis indicates that convolution neural networks (CNNs) processes spectrogram images with capabilities to enable the diagnosis of obstructive sleep apnea OSA without any physical contact and can detect the places where the air passage is blocked [3]. Tartaglia and collaborators reviewed 42 articles and described the performance of the methods with classification and OSA detection accuracy of up to 98.6%. However, the performance of different approaches varied fundamentally and a lack of independent verification makes the method applicable only in laboratory conditions [3]. The authors proposed a hybrid model that combines attention-based CNN and BiLSTM models and thus achieves the synergy of spatial extraction and temporal studies to increase the performance of apnea diagnosis with minimum application of polysomnography-based methods [4]. In this study, two public datasets are used, namely, the UCD Sleep Apnea Database with 25 subjects and OSASUD with 30 patients. It has been proven that the hybrid model has achieved 91.43% on UCD with all features employed and 95.36% on OSASUD with ANOVA features only. In particular, the model achieved 84% recall for UCD and the researchers report the OSA event sensitivity around 82-89% for different types of apnea and hypopnea. Despite the excellent results achieved, the small sample sizes

In their work, Lu et al. report the use of speech recognition transformers in conjunction with ResNet for the purpose of assessing snoring, however, they claim that their results are only preliminary and need to be validated in clinical contexts [5]. Kjaer et al., on the other hand, implement a different strategy and create systems that can automatically detect apneas while training them on PSG data directly, although at the costs of large amount of relevant data and some expensive hardware [6].

With their systematic reviews, authors provide a larger perspective. For instance, Haghighat et al. state that AI technology has high enough sensitivity and specificity concerning the assessment of OSA when compared to classic methodologies, although it has to be noted that the majority of studies analyzed were small, biased, and did not undergo prospective validation [7]. Moreover, Peng et al. analyze various

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modalities such as ECG, EEG, SpO2, snoring, and air flow and conclude that the synchronization of two or more modalities performs better than the other three, but again pay attention to limited amount of available data, contrasting distribution of data, and low level of multicenter validity [8]. In addition to that, Abd-alrazaq et al. conduct a review of AI controlled, laboratory-grade data, whereas the studies closest to home use are the least validated. Fourth, authors report different metrics on different datasets, so numbers from separate papers cannot be compared directly. For this reason Table I compares methods and limitations rather than ranking them by accuracy.

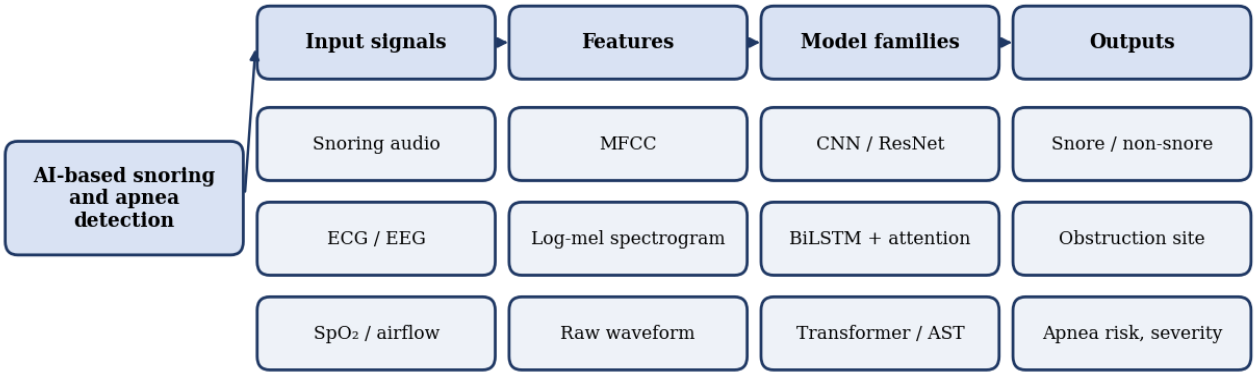


Fig. 2. Overview of inputs, features, models, and outputs in AI-based snoring and apnea detection.

TABLE I. SUMMARY OF REVIEWED STUDIES ON AI-BASED SNORING AND APNEA DETECTION

Study	Method	Key finding	Limitation
Tartaglia et al., 2026 [3]	Review of AI snoring analysis with CNNs	Non-invasive OSA screening; can classify obstruction site	Small dataset; some obstruction types hard to detect
Rathore et al., 2026 [4]	Attention-based CNN + BiLSTM	Better apnea detection; less dependence on PSG	High computational cost; needs large labelled data
Lu et al., 2026 [5]	ResNet + audio spectrogram transformer	Effective snoring classification for apnea-related patterns	Early-stage; needs real-world validation
Kjaer et al., 2026 [6]	End-to-end deep learning on PSG	Accurate apnea-event detection across datasets	High data and computation needs; costly setup

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Study	Method	Key finding	Limitation
Haghighat et al., 2025 [7]	Systematic review of AI accuracy for OSA	High sensitivity and specificity versus conventional methods	Small samples, bias risk, few prospective studies
Peng et al., 2025 [8]	Review of ML/DL on ECG, EEG, SpO_2, airflow, snoring	Multimodal signals outperform single signals	Few public datasets; class imbalance; poor generalization
Abd-alrazaq et al., 2024 [9]	Meta-analysis of wearable AI systems	Low-cost, home-based screening is feasible	Heterogeneous data; inconsistent metrics; little clinical validation

VI. DATASETS AND SIGNAL MODALITIES

The studies published cover only a limited number of datasets. The Munich-Passau Snore Sound Corpus (MPSSC) includes recorded snoring sounds that are labeled based on the body area producing the sound (velum, oropharynx, tongue base, or epiglottis). It has turned into a common standard in snoring type classification. The PSG-Audio dataset is characterized by matching audio recordings with full polysomnographic data, which allows linking snoring with apnea episodes. SimuSOE offers synthesized snoring recordings. Apart from audio, the studies utilize ECG, EEG, SpO_2, and airflow data. Audio recording has the advantage of being collected using a cell phone, while the physiological channels provide richer information but require specialization of equipment.

It is important to note that there is a regular issue with the small size of datasets used, their recording under controlled conditions, and the fact that major part of the recordings belongs to non-apneal episodes. When models developed on these datasets perform well during testing, they may fail when other microphone, room, and population are used.or non-snore, and a second stage aggregates the results over the night into an apnea-risk estimate. Performance is normally reported as accuracy, sensitivity, specificity, F1-score, and area under the ROC curve. For screening, sensitivity matters most, because a missed case costs more than a false alarm that leads to a clinical check.

B. Model Families

Convolutional neural networks acquire location-based frequencies and time characteristics stemming from the use of spectrograms, thus being number one choice for most of the research [15]. On the other hand, recurrent algorithms such as LSTM and BiLSTM are able to describe sound propagation through time [16], making them a good choice when apnea is not registered as a sound but rather as snoring, silence and gasping. Nevertheless, hybrid CNN and LSTM models combine both abilities, while attention layers allow the model to concentrate on more important signals. Unlike other types of neural nets, transformers are entirely based on attention [17], and audio spectrogram transformers transfer this idea into sound [18].

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These models are proven to be very efficient although most of the time they are not as trustworthy. The comparison table is provided below.

C. Training Practices

Since there is a limited amount of labeled snoring data available, the authors make use of certain common techniques. For example, data augmentation by adding background noise, shifting the recordings in time, or masking parts of the spectrogram helps create a larger dataset and makes the models less sensitive to recording conditions. Resampling or weighting the loss may solve the issue of class imbalance so that apnea-associated sounds are not ignored. Another common technique which helps to avoid using much labeled data is transfer learning, which involves fine-tuning a neural network thus trained on general sounds or images on the snoring data. All these techniques have an impact on the performance results and, therefore, for making fair comparisons between the results obtained by different studies, it is crucial to know how the techniques were used.

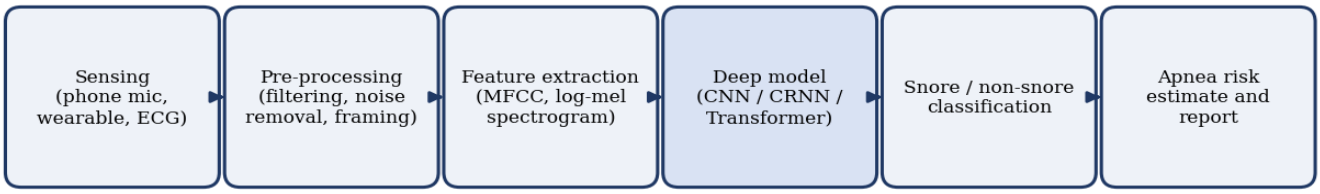


Fig. 3. Typical processing pipeline for snoring detection and apnea-risk estimation.

TABLE II. QUALITATIVE COMPARISON OF MODEL FAMILIES USED IN THE REVIEWED WORK

Model family	Typical input	Strengths	Weaknesses
CNN / ResNet	Mel spectrogram image	Strong local pattern learning; mature and fast to train	Limited long-range temporal context
LSTM / BiLSTM	Feature sequence (MFCC)	Models temporal evolution of events	Slower training; harder to parallelize
CNN + BiLSTM + attention	Spectrogram segments	Combines local and temporal cues; focuses on key segments	Higher complexity; needs more labelled data
Transformer / AST	Spectrogram patches	Global context; strong accuracy when data is sufficient	Data- and compute-hungry; hard to run on phones
End-to-end on PSG	Multichannel physiological signals	Highest information content; accurate event detection	Needs lab-grade recordings; costly setup

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VIII. EVALUATION PRACTICE

The conventional classification rates are disclosed by most studies. Using TP, TN, FP, and FN for true positives, true negatives, false positives, and false negatives, sensitivity can be defined as TP / (TP + FN), specificity as TN / (TN + FP), precision as TP / (TP + FP), and the value of F1 score is to be 2PR / (P + R), with P being precision and R recall (or sensitivity). Relying on accuracy alone could lay one into deception in cases where non-apnea segments prevail since a model that always predicts (‘normal’) can still obtain a reasonably high score.

The manner in which data are split is equally important as that of metric usage. In cases when recordings made by one individual are allotted in both sets (training and testing), the model can learn the person’s voice and breathing instead of the disorder resulting in artificial rising of accuracy. Subject-wise splits or leave-one-subject-out cross validation can help avoid that. The type of the ground truth can also distinguish papers: some give event-based testing, while others night-based with the help of AHI exceeding limits

.IX. ETHICAL, PRIVACY AND PRACTICAL CHALLENGES

It's not easy to record sounds overnight. An ordinary microphone set in the bedroom can pick up spoken words and other family members' conversations. Hence, it can be said that ideally, noise should be processed right on the device, with only the necessary features and risk scores kept from what was recorded. Additionally, any medical information that gets stored in the cloud comes with its own terms and regulations depending on the region.

There are also issues related to safety and fairness. For instance, if a model is trained mostly on people of one age, gender, or body shape, it may show low efficiency when detecting apnea in different people, which represents a false negative scenario. Moreover, it is important for users to understand that receiving risk scores means that they should consult a doctor, and this does not mean that they have received a diagnosis. Finally, constant data recording may cause battery and storage problems with smartphones, which means that the development of the app has to be oriented towards the creation of energy-efficient models.

X. RESEARCH GAPS

In my viewpoint, the most critical challenge is the absence of vast, diverse, balanced datasets that are acquired in the actual sleep environment. If the model is built on restricted or unbalanced data, then it will not be able to recognize the sleep problem correctly in all cases of different people and environments of sleep. As a result, it may lead to false alarms or missed cases, which puts patients at risk. Therefore, acquisition of real bedroom recordings, as well as the testing of the models on different patient demographics, should be the priority for the creation of effective and applicable systems for detecting the sleeping pathology..

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XI. FUTURE DIRECTION

The voids imply specific design criteria for upcoming projects. An appropriate system would execute a small audio model on board, ideally through either pruning or quantization methods such as CNN or CRNN to ensure minimum delay and battery use. It should integrate snoring sounds with at least one cheap physiological parameter like SpO_2 or heart beat in order to transition from merely detecting the snoring to estimating the risk. Fig. 4 illustrates such a design..

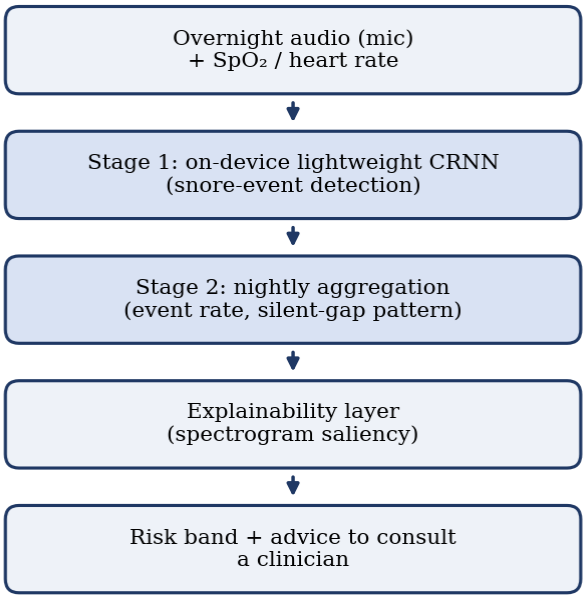


Fig. 4. Proposed two-stage, on-device design for future work (conceptual; not implemented or evaluated in this paper).

From the perspective of data, the training process should utilize the recordings gathered from multiple sites and devices, and testing should employ subject-wise data rearrangements in order to avoid obtaining optimistic outcomes. In the case of privacypersisting training, such as federated learning, it would be possible to use big data with no need to transfer any of it. Saliency methods would help significantly on the task of interpreting the results too. Thus, a two-step procedure where snore detection happens in the first step and snore results are aggregated into a risk category during each night would ease the interpretation as well.

In the end, this kind of system has to be studied in comparison with PSG when it comes to creating claims about the efficiency of the screening process.

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Potential Applications

If the gaps above are closed, several uses become realistic. A phone or wearable could act as a first-line home screen that advises people with persistent loud snoring to book a sleep study. Primary-care clinics could use short overnight recordings to prioritize patients for PSG, reducing waiting lists. Telemedicine services could track snoring and risk trends over weeks to judge whether lifestyle changes or treatment are helping. In each case the system supports, rather than replaces, clinical diagnosis.

Limitations of This Review

Once the existing gaps are filled, multiple applications become possible. A mobile phone or wearable device may serve as an initial home screen for informing individuals suffering from loud snoring to take up a sleep study. Primary care clinics may take advantage of short recordings made during the night in order to prioritize patients on PSG waiting lists. A telemedicine service may observe the patterns of snoring and risk over the course of weeks in order to evaluate whether lifestyle changes or treatment prescribed to the patients are effective. In all these instances the system promotes clinical diagnosis instead of being an alternative..

XII. CONCLUSION

This paper reviews the most advanced deep learning technologies which can be used for the detection of snores and the prediction of sleep apnea. Studies indicate that CNNs and the mixed models are capable of accurately recognizing snores and the patterns of the sleep apnea. In addition, use of smartphones and wearable devices can serve as an effective and cheaper method of performing screening instead of PSG. Numerous issues emerge despite the advances in technology, such as limited access to large datasets, high computational requirements, absence of meaningfulness in these technologies, and difficulties associated with data privacy and validation. As a result, all future studies should consider the creation of new sources of data and methods of obtaining efficient technology..

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