Systematic Review of Detecting Sleep Apnea Using Artificial Intelligence: An Insight to Convolutional Neural Network Method

Behnam Samadi[1], Shahram Samadi [2, 3, *], Mehrshad Samadi[4], Sepehr Samadi[5], Mehrdad Samadi[6] and Mahdi Mohammadi[7]

[1]Faculty of Computer Engineering, K.N. Toosi University of Technology, Tehran, Iran
[2]Sleep Breathing Disorders Research Center, Tehran University of Medical Sciences, Tehran, Iran
[3]Anesthesia, Critical Care and Pain Management Research Center, Tehran University of Medical Sciences, Tehran, Iran
[4]Faculty of Management and Accountancy, Allameh Tabatabaei University, Tehran, Iran
[5]Department of Wireless Communication, University of Oulu, Oulu, Finland
[6]Faculty of Electrical Engineering, Iran University of Science and Technology, Tehran, Iran
[7]Department of Medical Physics and Biomedical Engineering, School of Medicine, Tehran University of Medical Sciences, Tehran, Iran

Corresponding author: Sleep Breathing Disorders Research Center, Tehran University of Medical Sciences, Tehran, Iran. Email: shsamadi@yahoo.com

Abstract

Background: Sleep apnea is a prevalent sleep disorder, especially in males and older ages. The common diagnostic methods, including polysomnography (PSG), are expensive, difficult to perform, and time-consuming. Numerous studies are focusing on developing easy-to-perform methods based on artificial intelligence (AI) for the early diagnosis of sleep apnea. This systematic review aimed to gather current methods based on the convolutional neural network (CNN) for the diagnosis of sleep apnea.

Methods: Three international electronic databases (PubMed, Web of Science [WoS], and Scopus) were searched from 2010 to October 2023. All studies that have developed CNN-based methods for the diagnosis of sleep apnea and have accomplished the performance tests were included. Finally, the characteristics of the studies were extracted and summarized.

Results: A total of 36 studies were included in this systematic review. Various physiological signals have been proposed to detect sleep apnea, including electrocardiogram (ECG), blood oxygen saturation (SpO$_2$), sound signals, respiratory signals, electroencephalogram (EEG), and nasal airflow. Electrocardiogram was the most frequently used signal in the studies, followed by SpO$_2$. The highest reported accuracy was achieved by SpO$_2$ or ECG-based methods and with a one-dimensional CNN (1D-CNN) classifier. Using multiple signals did not necessarily increase the performance of test results.

Conclusions: Diagnostic methods based on CNN can be used only as screening tools or home diagnosis of sleep apnea. These methods are easy to perform and can only reduce the diagnostic costs and waiting time for a sleep study in special scenarios. Nevertheless, PSG is still the gold standard for the diagnosis of sleep disorders.

Keywords: Neural Networks, Sleep Apnea, Artificial Intelligence, Systematic Review, Physiological Signals

1. Background

Sleep apnea is defined by the recurrent ceasing of breathing during sleep, affecting ventilation and fragmentation of sleep. Consequent restorative sleep causes excessive sleepiness and tiredness during the daytime and reduced functionality. The apnea-hypopnea index (AHI) has been frequently used in studies to evaluate the severity of sleep apnea or hypopnea based on events per hour (1). In a previous systematic review, the prevalence of moderate and severe obstructive sleep apnea (OSA) based on AHI was estimated to be 6% to 17% of the general adult population, being more prevalent in males (2). However, a great proportion of affected cases remain undiagnosed. It was estimated that 85% of middle-aged women and 92% of middle-aged men with moderate to severe sleep apnea are undiagnosed in the US (3).

Sleep apnea can increase the risk of hypertension and cardiovascular accidents (4). Although sleep apnea is associated with a high burden, there is usually a lack of adequate attention to this phenomenon (5). Additionally, diagnostic tests, such as polysomnography (PSG), portable monitoring, and home sleep apnea testing, are accurate but time-consuming and expensive (6, 7). Polysomnography, the gold standard for sleep apnea

diagnosis, involves the recording of various physiological signals collected from electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG), electrocardiogram (ECG), and respiratory signals (8).

Due to the large number of mentioned sensors, PSG might be considered uncomfortable, difficult to perform, and unavailable for many (9). Many recent pieces of research aim to introduce easy-to-do and cost-effective methods and algorithms based on artificial intelligence (AI) to detect sleep apnea. Artificial intelligence refers to the ability of computers and systems to perform tasks that are usually considered to need human intelligence and mental work, such as decision-making and pattern recognition (10).

Methods that focus on singular bio-signals are hot topics in the field of the diagnosis of sleep apnea using AI. Among multiple AI methods that have been developed, convolutional neural network (CNN) are gaining popularity. The convolution neural network is one of the most effective and successful methods inspired by the vision system. Convolution neural network was first developed to classify images (11). Additionally, CNN automatically detects the significant features of the data without any human supervision, which is the main advantage of CNN compared to its predecessors (12). After that, some studies adapted the concept for signal classification by employing a one-dimensional CNN (1D-CNN) network. A two-dimensional CNN (2D-CNN) was also used in studies that converted the one-dimensional signal to a two-dimensional input (13). The combination of CNN and other methods is also gaining popularity (14).

2. Objectives

This systematic review aims to assess the currently developed methods for detecting sleep apnea using CNN.

3. Methods

The current systematic review is reported based on the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines. The targeted outcomes were the accuracy, sensitivity, and specificity of CNN-based methods and the type of signals used in the diagnosis of sleep apnea. For this purpose, all of the studies that have developed CNN-based methods for the diagnosis of sleep apnea and have accomplished the performance tests were eligible for inclusion.

3.1. Search Strategy

Three international electronic databases (PubMed, Web of Science [WoS], and Scopus) were searched from 2010 to October 2023. This time interval was applied because, based on a previous systematic review, no studies have been found before 2010 for CNN-based methods.

The following key terms were used for searching international databases: (1) "Sleep apnea" or "sleep apnoea"; (2) "neural network" or "deep artificial neural network" or "deep learning" or "convolutional neural network" or "recurrent neural network" or "reinforcement neural network" (Appendix 1). No limitations were applied to language or type of study in the search or the selection process.

3.2. Eligibility Criteria

This review included studies that provided data on the following subjects: (1) a CNN-based method was introduced; (2) the method was developed for the diagnosis or staging of sleep apnea; (3) the study has provided data on the performance of the method in diagnostic tests.

This study excluded studies in which (1) they used methods other than CNN; (2) the accurate signal used was not defined; (3) the performance of the test (specificity [SP], sensitivity [SN], and accuracy [AC]) was indicated; (4) only sleep stage classification was performed; (5) different types of sleep apnea without comparison to normal were distinguished; and (6) breathing disorders other than sleep apnea was diagnosed.

3.3. Screening, Data Extraction, and Quality Assessment

Two researchers independently screened the titles of all search results and selected the studies for the abstract screening step. After the abstract screening, researchers screened the eligible full texts and extracted the data. A third researcher reviewed the extracted data. Any disagreements were resolved via consultation with a fourth reviewer in each stage.

The following information was extracted from eligible studies: Bibliometric information (name of the first author and year of publication), the database used or the setting in which the study was conducted, recording sensors or signals, window size in seconds, classification type (apnea, hypopnea, and OSA), classifier type, sensitivity or recall (%), specificity (%), and accuracy (%).

3.4. Statistical Analyses

Due to the heterogeneity of the included studies, it was impossible to conduct a meta-analysis. The data on the SP, SN, and AC of different studies were entered into

a Microsoft Excel sheet. The plot was created using the R software (version 4.0.5).

4. Results

Figure 1 depicts the flow diagram of the study selection process. The titles and abstracts of 659 records retrieved from online databases were screened after the removal of duplicates. Fifty-three studies fulfilled the eligibility criteria for full-text review and were included.

Seventeen studies were excluded as follows: (1) the full text of 11 studies was not found; (2) 2 studies were on sleep stages in sleep apnea; (3) 1 study was on breathing patterns; (4) 1 study was on classification of sleep apnea; (5) 1 study was on non-apnea sleep arousal; (6) 1 study was in a language other than English. Finally, 36 studies were eligible for data extraction.

4.1. Signals for Sleep Apnea Detection

Numerous physiological signals or sensors have been reported to detect sleep apnea based on a CNN classifier. In this systematic review, we found 11 different signals that can be used for CNN-based algorithms to detect sleep apnea, including ECG, blood oxygen saturation (SpO_2), sound signals (speech and tracheal sounds), respiratory signals (oronasal airflow and chest and abdomen movements), EEG, combined signals, impulse-radio ultra-wideband (IR-UWB), lateral cephalometric radiographs, and pulse transition time (PTT) (Table 1). Figure 2 shows the boxplots of the accuracy of different signals reported in studies.

4.1.1. Signals Based on Electrocardiogram

In electrocardiography, the electrical activity of the heart is mapped by electrodes connected to the skin. These electrodes detect any minor electrical changes in heart muscle during depolarization and repolarization. Electrocardiogram has been used as a signal for detecting sleep apnea since the early 2000s (9). Sleep apnea can affect the ECG through autonomic nervous system response during sleep (63). Some of these changes include variations in the amplitude of R waves, inter-beat (RR) interval, and baseline fluctuation (64). In this systematic review, of 36 included studies, 16 studies used ECG signals. The majority of these studies have used the apnea-ECG database (AED). This database consists of 70 nighttime ECG recordings (and PSG for some cases) conducted at Philipps University, Marburg, and Germany that are available on the PhysioNet site (65).

Alternatively, Banluesombatkul et al. (26) used the osteoporotic fractures in men study (MrOS) database,

which recorded the PSG of 2 991 individuals of 65 years or older at 6 clinical centers (65). Different features of the ECG have been used in this subclass of studies. Heart rate variability (HRV) and RR interval, which is the interval between two successive QRS complexes, are frequently utilized in studies. The RR interval was used by Shen et al. (16), Wang et al. (28), and Liang and Qiao (23). The time window used in ECG-based studies ranged from 10 to 60 seconds, and the sensitivity and specificity ranged from 77.6% to 100% and 80.1% to 99.2%, respectively. The highest accuracy achieved was 99.8% by Liang and Qiao, who used the RR interval (23). Table 2 summarizes the characteristics of datasets used in the included studies.

4.1.2. Signals Based on Blood Oxygen Saturation

Since decreases in blood oxygen levels are associated with apneic events, the SpO_2 signal is a useful and simplified tool to detect these events (66). Blood oxygen saturation could be used as a single signal or in combination with other physiological signals to detect sleep apnea. Databases that are used in this subclass of studies were AED, the HuGCDN2008, childhood adenotonsillectomy trial (CHAT), Massachusetts General Hospital (MGH), sleep laboratory and the sleep heart health study (SHHS), and St. Vincent's University Hospital/University College Dublin Sleep Apnea Database (UCD). HuGCDN2008 database was collected using the VIASYS Healthcare Inc. (Wilmington, MA, USA) device in the University Hospital of Gran Canaria Dr. Negrin. The database has 70 subjects with PSG recordings in addition to the diagnosis of sleep apnea by a physician (67). The CHAT database is composed of PSG studies of 1 900 children, and apneas and hypopneas were scored using AHI (68, 69). Massachusetts General Hospital and SHHS datasets consist of in-lab (MGH) and at-home (SHHS) PSG recordings as part of routine clinical practice consisting of 10 000 and 5 600 recordings, respectively (65). The UCD database had 25 recordings with SpO_2 signals. Four studies have used the SpO_2 signal as a single signal (11, 36-38), and two studies have used the SpO_2 signal in combination with airflow and respiration signals (42, 43). In two studies conducted by Mostafa et al. (11, 36), different window sizes were tested to get the best accuracy. Overall, the sensitivity and specificity ranged from 40% to 92% and 90.5% to 99.6%, respectively. It seems that the specificity of the SpO_2 signal in sleep apnea screening is higher than its sensitivity. Mostafa et al. reached 100% accuracy using the CCN1D classifier in their study (11).

4.1.3. Signals Based on Respiration

Oronasal airflow and respiratory movements are the most direct indicators of breathing disorders and were
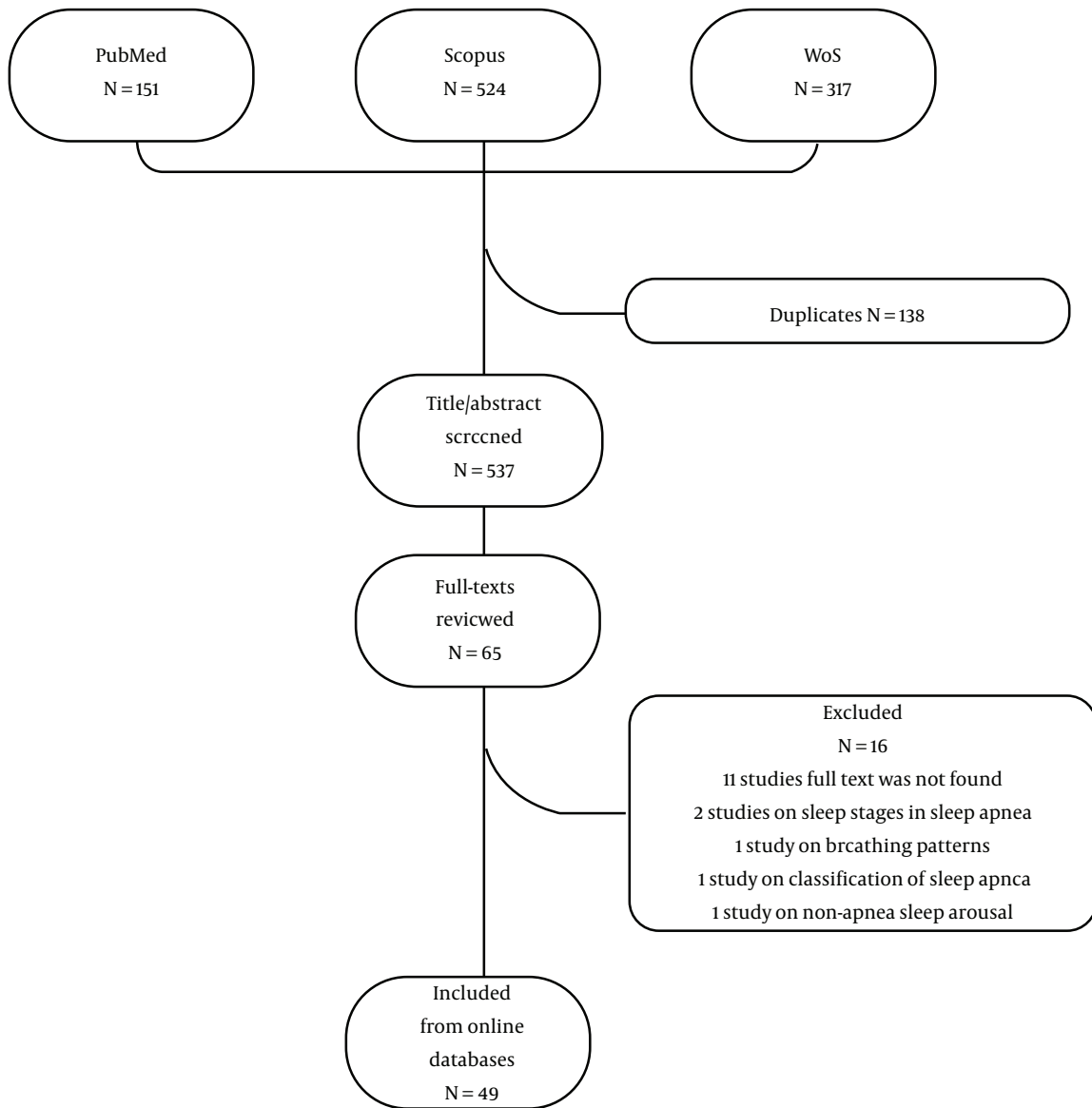
Figure 1. Flow diagram of the study selection process

used by six studies (39-45) to detect sleep apnea. Three studies used nasal airflow as the single signal, and the remaining used a combination of respiratory signals.

The databases used were the multi-ethnic study of atherosclerosis (MESA), MGH, and SHHS datasets. The MESA dataset was collected by the National Sleep Research Resource (NSRR), which includes PSG recordings for 2 200 participants conducted between 2010 and 2011 (65). Each patient was labeled as normal, obstructive apnea, or hypopnea by an expert. By using respiratory signals

for the detection of sleep apnea, the obtained accuracy ranged from 74.7% to 96.6%. Choi et al. achieved the highest accuracy in their study, using nasal airflow signal and CNN1D classifier (41).

4.1.4. Signals Based on Sound

The breathing process produces characteristic sounds that can be used to detect sleep apnea (70). This principle was used in three studies. In these studies, tracheal sound, sleep sound, and speech signals were used (47-49). In
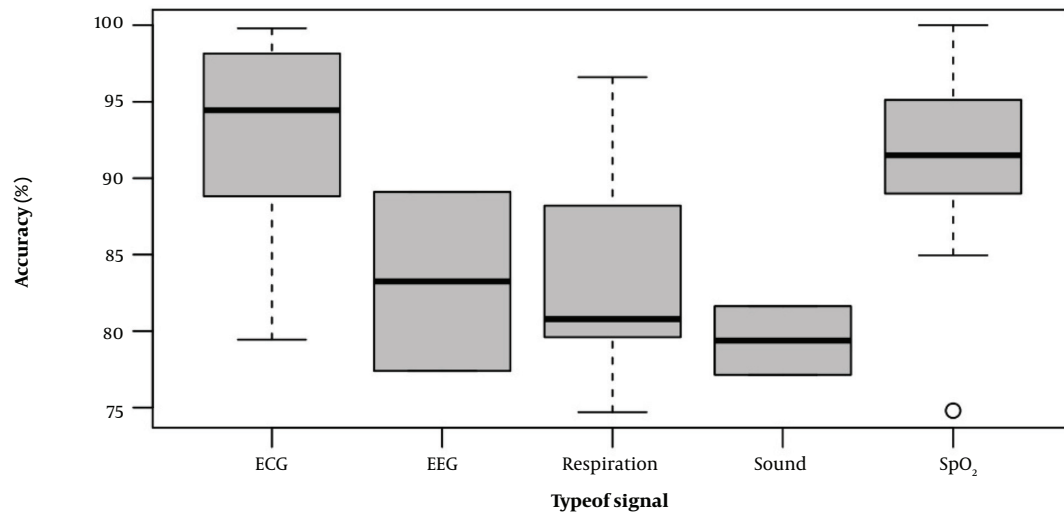
Figure 2. The boxplots of the accuracy of different signals reported in studies

Table 2. Characteristics of Datasets Used in Included Studies

Dataset	Setting	Signals Measured	Number of Subjects	Age (y)	Gender	BMI/Weight
AED	University	ECG, PSG for some patients	70	27 - 63	Both	53 - 135 kg
MrOS	Clinical centers	PSG	2 991	+65	Male	-
HuGCDN2008	University hospital	PSG, diagnosis of sleep apnea by a physician	70	18 - 82	Both	-
CHAT	Multiple clinical centers	PSG	1 900	5 - 10	Both	Mean: 17.1 kg/m^2
MGH	Laboratory	PSG	10 000	42 - 64	Both	27 - 36 kg/m^2
SHHS	At home	PSG	5 600	55 - 72	Both	24.6 - 30.7 kg/m^2
UCD	University hospital	SpO$_2$	25		Both	-
MESA	National Sleep Research Resource	PSG, actigraphy	2 200	45 - 84	Both	
EEG dataset	University hospital	EEG	25	-	Both	-
Physionet Challenge	University hospital	PSG	1 985	-	Both	-
MIT-BIH polysomnographic database	University hospital	PSG	18	32 - 56	Both	-
SHHS2	University hospital	PSG	2 651		Both	-
Apnea-PPG	University hospital	PSG, PPG	110	Mean: 45.25	Both	
ABC	University hospital	PSG	49	18 - 65	Both	35 - 45
HomePAP	University hospital	PSG	243	> 18	Both	-
UofC	University hospital	PSG	974	-	Both	

Abbreviations: BMI, body mass index; AED, apnea-ECG database; MrOS, osteoporotic fractures in men study; CHAT, childhood adenotonsillectomy trial; MGH, Massachusetts General Hospital; SHHS, sleep heart health study; UCD, University College Dublin Sleep Apnea Database; MESA, multi-ethnic study of atherosclerosis; EEG, electroencephalogram; PPG, photoplethysmography; PSG, polysomnography; ECG, electrocardiogram; SpO$_2$, blood oxygen saturation.

this model, a CNN is trained to distinguish respiration sounds from environmental noise, and then the trained model is transferred to recognize respiration sounds in sleep apnea. All three studies were conducted in hospital and medical center settings. The sensitivity ranged from 69.7% to 98%, and the specificity ranged from 70.9% to 79%.

The best-achieved accuracy in this subclass was 81.63% by Luo et al. (48).

4.1.5. Signals Based on Electroencephalogram

Sleep arousal due to sleep apnea can be detected via EEG, which represents sleep arousal as an abrupt shift in EEG waves (71). Three studies have used this signal, and the methods were fully convolutional neural network (FCNN), dense recurrent convolutional neural network (DRCNN), and multi-scale parallel CNN (MSPCNN) as the classifier, respectively (50-52). The databases used in these studies were the EEG dataset of St. Vincent's University Hospital, Physionet Challenge, and MIT-BIH polysomnographic database in that order. The EEG dataset of St. Vincent's University Hospital contains polysomnograms and some other bio-signals of 25 patients. The Physionet challenge is part of the Physionet/computing in cardiology challenge 2018 and includes PSG data from 1 985 subjects who were monitored at the MGH for the diagnosis of sleep disorders (72). The MIT-BIH polysomnographic database, freely available on PhysioNet, includes 18 whole-night PSG recordings (65). The highest accuracy was 89.1%, achieved by Jiang et al. In this study, a sleep apnea detection framework combined with time-frequency analysis for EEG signals and an MSPCNN to learn implicit patterns from time-frequency images were used (50).

4.1.6. Other Signals

Unobtrusive electromechanical film transducer (Emfit) mattress sensor, PTT, IR-UWB, and lateral cephalometric radiographs were used by four studies to detect sleep (56-59). Tsuiki et al. analyzed different parts of lateral cephalometric radiographs to achieve the best performance, and the full image got the best results (57). In this subgroup, sensitivity ranged from 78.1% to 98%, and the specificity was in the range of 82% to 96%. The highest performance was achieved by Arslan with 92.8% accuracy (56).

5. Discussion

In this systematic review, we found different sensors and signals based on CNN algorithms that have been used to detect sleep apnea. Electrocardiogram, SpO$_2$, and respiratory signals were the most utilized signals to detect sleep apnea. Electrocardiogram was frequently used as the single source sensor and was the most studied signal in studies. However, to detect sleep apnea from respiration, it was more common to combine multiple signals. The CNN1D classifier was the most frequently used classifier among various CNN subclasses. The highest accuracy

(100%) was reported by Mostafa, using the SpO$_2$ signal and CNN1D classifier. In this study, the global classification of OSA was also reported (11). The 99.8% accuracy was also achieved by Liang (23) using the RR-interval signal in ECG and a combination of CNN and LSTM classifiers. The maximum sensitivity and specificity were achieved by Erdenebayar et al. (99% each) using ECG signals and CNN1D classifier (24).

Studies that used ECG signals accomplished the highest performance in diagnostic tests. However, the majority of the studies that have used ECG signals were tested in public datasets, which are probably cleaner than ECGs in hospital and medical center settings. This could increase the performance of the algorithms in diagnostic tests (30-35, 73). Although sleep apnea is primarily a breathing disorder, respiratory and sound signals were not as successful as ECG and SpO$_2$ in diagnostic tests. In some parts, it is because the algorithms based on sound and respiratory signals are more susceptible to noises caused by environmental and cardiac sounds (74). The AED database was the only database in the current study whose different features (i.e., ECG, SpO$_2$, and respiratory signals) have been used for detecting sleep apnea in different studies. Merely considering this database, there was no superiority of a signal in detecting sleep apnea over other signals. Additionally, the sleep recordings in the AED database are annotated per minute for detecting sleep apnea events (75); however, most of the databases have annotations per second/sample, which follow the rules of the American Academy of Sleep Medicine (AASM) to annotate sleep recordings (76). As respiratory events can be grouped in clusters, and one sleep minute can contain more than one apnea/hypopnea, this could affect the generalization of the results obtained in AED to other datasets and clinical settings.

Using a combination of respiratory signals did not improve the performance of the algorithms in diagnostic tests in comparison with singular SpO$_2$ signals, as usually one of the signals dominates the algorithm. Further studies are needed in this field to optimize the algorithms that use multiple respiratory signals to detect sleep apnea. However, algorithms that use fewer signals or a singular signal are preferred for their simplicity and ease of implementation (77).

A variety of signals were combined in several studies to detect sleep apnea. For instance, for the diagnosis of obstructive apnea, Alarcon et al. combined SpO$_2$, heart rate, thoracic respiratory effort, and abdominal-respiratory effort; nevertheless, Jimenez-Garcia et al. combined SpO$_2$ and airflow signal (54, 55). Since the test is closer to a full PSG by increasing the received signals, it is evident that the use of combined

signals could increase the sensitivity and specificity of diagnosis. However, the use of combined signals might increase the complexity and cost of the diagnosis and the susceptibility to noise and artifacts. Therefore, the trade-off between the performance and the feasibility of using combined signals should be considered (54, 78).

The convolutional neural network has recently been utilized to diagnose sleep apnea using photoplethysmography (PPG). By examining the changes in the PPG signal that represent the respiratory and cardiac activities, PPG can be utilized to identify sleep apnea (60, 61). To determine the stages of sleep and the arousal events that occur during sleep, PPG can also record the autonomic nervous system's modulation. Photoplethysmography is noninvasive, simple to use, and inexpensive compared to other sleep apnea diagnostic techniques. Photoplethysmography, however, has numerous disadvantages, including a sensitivity to noise, signal quality, and motion artifacts. Consequently, it is necessary to evaluate and compare PPG-based sleep apnea detection techniques to the gold standard, PSG (79, 80). Due to the heterogeneity of the results, it is not clear yet whether CNN-based algorithms are more successful in distinguishing apnea and hypopnea together from normal cases, compared to apnea, hypopnea, or normal separately. There was also no significant difference between the accuracy of CNN methods in apnea diagnosis or determining apnea severity. It was also not possible to determine whether the accuracy and other results from online databases are better than in hospital settings. The reason for the latter is that some confounder factors (e.g., classification method, classifier, and window size) are involved, and a deduction could be possible if any other factors were the same when comparing the setting in which the study is conducted.

The majority of the studies used only one database; some of the subjects in these databases were used for the training phase, and the remaining were used for the test phase. The cross-validation between one or more databases was only applied in a few studies. Using one database without cross-validation can limit the generalization of the test results to other populations and settings (14). This study suggests cross-validation with another population or database for future studies. This study also offers to perform a meta-analysis, including running all mentioned methods on the same hardware, to achieve a fair comparison in terms of accuracy and efficiency.

One-dimensional CNN was the most used classifier in the studies. Combining 2 or more classifiers does not necessarily increase the performance of the algorithms. Some algorithms achieved a good performance, although

using a less complex model. To obtain an algorithm with the highest performance-to-complexity ratio is of special interest. However, further research in this field is needed to reach a definitive conclusion.

Sleep apnea disrupts normal brain signaling and activity. During episodes, lowered oxygen levels and higher carbon dioxide activate sensors in the brainstem. This triggers the brain's attempt to restart breathing. Areas involved in controlling breathing, such as the medulla, pons, and amygdala, are impacted (81). Electroencephalogram directly records these brain pattern changes. Convolutional neural networks are suited for EEG analysis since they can automatically learn the spatial and frequency characteristics distorted by sleep apnea (53). Signals measured during sleep studies provide insight into apnea's neurological effects. Electroencephalogram specifically demonstrates altered wave activity during sleep stages and increased waves with arousal (82). Apneas also affect the timing of signals between EEG electrodes. Convolutional neural network architectures successfully capture abnormalities across electrodes using convolutional and pooling layers, enabling the detection of patterns tied to disrupted breathing (83). Research has achieved over 80% apnea classification accuracy from CNN-processed multi-channel EEG, demonstrating their ability to accurately interpret impacted neural data (84).

Low blood oxygen during apneas influences activity in brain centers controlling breathing. Sensors in the medulla and pons detect oxygen and carbon dioxide changes in blood and brain tissue. This disrupts typical breathing patterns during sleep. Convolutional neural networks learn features in oxygen data linked to these impacts, permitting apnea detection (85). Convolutional neural networks model intricate relationships between oxygen fluctuations and subsequent brain activity.

Abnormal heart rate and rhythms on ECG also reflect neural influences. The autonomic nervous system regulates the heart through pathways originating in the brainstem. Repeated apneas prompt arousals and sympathetic changes are observed as arrhythmias (86). Convolutional neural networks used on ECG can model these control systems and flag irregular rhythms signifying disrupted sleep. This offers insight into apnea's effects on heart function via the brain-heart connection (21).

Advances in CNN design have boosted AI's ability to identify apnea-related brain changes. Deeper CNNs with more convolutional filters can model complex EEG/signal relationships (53). Optimizing CNN structures might further aid in unraveling apnea's neural mechanisms through data analysis (84).

This systematic review provides some insights and suggestions for the future research direction for the diagnosis of sleep apnea using AI methods based on the current literature and the gaps identified in this field. The results of studies in this field can be used to develop home diagnostic tools for sleep apnea, aid clinicians in detecting sleep apnea, and provide a decision support system. Artificial intelligence-based methods demonstrated good feasibility for outpatient application and scalability. However, these methods cannot replace the PSG to date, and PSG is still the gold standard for the diagnosis of sleep apnea in clinical settings.

The current study had some limitations as follows: (1) the studies included in this systematic were heterogeneous and used different sets of signals and classifiers; as a result, conducting a meta-analysis was not possible; (2) this review included studies that used CNN-based algorithms; although the most common and precise type of classifier, it is not the only one; (3) a great number of included studies used online databases, which are public databases from research studies that have met a standardized procedure for recording, annotations, and diagnosis and, therefore, are cleaner than data from clinical settings. As a result, the conclusion regarding the use of AI-based methods for the screening of sleep apnea should be interpreted with caution.

5.1. Conclusions

Algorithms based on a CNN classifier and a singular signal to detect sleep apnea could be recommended as an easy and time-saving approach for aiding clinicians in detecting sleep apnea or home diagnosis. For now, PSG is the gold standard for the diagnosis of sleep disorders, such as sleep-related breathing disorders, in clinical settings. Further studies on the most efficient classifier and cross-validation with clinical settings are needed before AI-based methods can replace the classic approaches.

Supplementary Material

Supplementary material(s) is available here [To read supplementary materials, please refer to the journal website and open PDF/HTML].

Footnotes

References

1. Asghari A, Mohammadi F. Is Apnea-Hypopnea Index a proper measure for Obstructive Sleep Apnea severity? *Med J Islam Repub Iran*. 2013;**27**(3):161–2. [PubMed ID: 24791128]. [PubMed Central ID: PMC3917481].

2. Senaratna CV, Perret JL, Lodge CJ, Lowe AJ, Campbell BE, Matheson MC, et al. Prevalence of obstructive sleep apnea in the general population: A systematic review. *Sleep Med Rev*. 2017;**34**:70–81. [PubMed ID: 27568340]. https://doi.org/10.1016/j.smrv.2016.07.002.

3. Barroso-Garcia V, Fernandez-Poyatos M, Sahelices B, Alvarez D, Gozal D, Hornero R, et al. Prediction of the Sleep Apnea Severity Using 2D-Convolutional Neural Networks and Respiratory Effort Signals. *Diagnostics (Basel)*. 2023;**13**(20):3187. [PubMed ID: 37892008]. [PubMed Central ID: PMC10605440]. https://doi.org/10.3390/diagnostics13203187.

4. Phillips CL, O'Driscoll DM. Hypertension and obstructive sleep apnea. *Nat Sci Sleep*. 2013;**5**:43–52. [PubMed ID: 23750107]. [PubMed Central ID: PMC3666153]. https://doi.org/10.2147/NSS.S34841.

5. Stores G. Clinical diagnosis and misdiagnosis of sleep disorders. *J Neurol Neurosurg Psychiatry*. 2007;**78**(12):1293–7. [PubMed ID: 18024690]. [PubMed Central ID: PMC2095611]. https://doi.org/10.1136/jnnp.2006.111179.

6. Kapur VK, Auckley DH, Chowdhuri S, Kuhlmann DC, Mehra R, Ramar K, et al. Clinical Practice Guideline for Diagnostic Testing for Adult Obstructive Sleep Apnea: An American Academy of Sleep Medicine Clinical Practice Guideline. *J Clin Sleep Med*. 2017;**13**(3):479–504. [PubMed ID: 28162150]. [PubMed Central ID: PMC5337595]. https://doi.org/10.5664/jcsm.6506.

7. Foroughi M, Razavi H, Malekmohammad M, Adimi Naghan P, Jamaati H. Diagnosis of Obstructive Sleep Apnea Syndrome in Adults: A Brief Review of Existing Data for Practice in Iran. *Tanaffos*. 2016;**15**(2):70–4. [PubMed ID: 27904537]. [PubMed Central ID: PMC5127617].

8. Bsoul M, Minn H, Tamil L. Apnea MedAssist: real-time sleep apnea monitor using single-lead ECG. *IEEE Trans Inf Technol Biomed*. 2011;**15**(3):416–27. [PubMed ID: 20952340]. https://doi.org/10.1109/TITB.2010.2087386.

9. de Chazal P, Penzel T, Heneghan C. Automated detection of obstructive sleep apnoea at different time scales using the electrocardiogram. *Physiol Meas*. 2004;**25**(4):967–83. [PubMed ID: 15382835]. https://doi.org/10.1088/0967-3334/25/4/015.

10. Goldstein CA, Berry RB, Kent DT, Kristo DA, Seixas AA, Redline S, et al. Artificial intelligence in sleep medicine: background and implications for clinicians. *J Clin Sleep Med*. 2020;**16**(4):609–18. [PubMed ID: 32065113]. [PubMed Central ID: PMC7161463]. https://doi.org/10.5664/jcsm.8388.

11. Mostafa SS, Mendonca F, Ravelo-Garcia AG, Julia-Serda G, Morgado-Dias F. Multi-Objective Hyperparameter Optimization of Convolutional Neural Network for Obstructive Sleep Apnea Detection. *IEEE Access*. 2020;**8**:129586–99. https://doi.org/10.1109/access.2020.3009149.

12. Alzubaidi L, Zhang J, Humaidi AJ, Al-Dujaili A, Duan Y, Al-Shamma O, et al. Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. *J Big Data*. 2021;**8**(1):53. [PubMed ID: 33816053]. [PubMed Central ID: PMC8010506]. https://doi.org/10.1186/s40537-021-00444-8.

13. O'Shea T, Hoydis J. An Introduction to Deep Learning for the Physical Layer. *IEEE Trans Cogn Commun Netw*. 2017;**3**(4):563–75. https://doi.org/10.1109/tccn.2017.2758370.

14. Mostafa SS, Mendonca F, Ravelo-Garcia AG, Morgado-Dias F. A Systematic Review of Detecting Sleep Apnea Using Deep Learning. *Sensors (Basel)*. 2019;**19**(22):4934. [PubMed ID: 31726771]. [PubMed Central ID: PMC6891618]. https://doi.org/10.3390/s19224934.

15. Zhang J, Tang Z, Gao J, Lin L, Liu Z, Wu H, et al. Automatic Detection of Obstructive Sleep Apnea Events Using a Deep CNN-LSTM Model. *Comput Intell Neurosci*. 2021;**2021**:5594733. [PubMed ID: 33859679]. [PubMed Central ID: PMC8009718]. https://doi.org/10.1155/2021/5594733.

16. Shen Q, Qin H, Wei K, Liu G. Multiscale Deep Neural Network for Obstructive Sleep Apnea Detection Using RR Interval From Single-Lead ECG Signal. *IEEE Trans Instrum Meas*. 2021;**70**:1–13. https://doi.org/10.1109/tim.2021.3062414.

17. Niroshana SMI, Zhu X, Nakamura K, Chen W. A fused-image-based approach to detect obstructive sleep apnea using a single-lead ECG and a 2D convolutional neural network. *PLoS One*. 2021;**16**(4):e0250618. [PubMed ID: 33901251]. [PubMed Central ID: PMC8075238]. https://doi.org/10.1371/journal.pone.0250618.

18. Urtnasan E, Park JU, Joo EY, Lee KJ. Identification of Sleep Apnea Severity Based on Deep Learning from a Short-term Normal ECG. *J Korean Med Sci*. 2020;**35**(47):e399. [PubMed ID: 33289367]. [PubMed Central ID: PMC7721560]. https://doi.org/10.3346/jkms.2020.35.e399.

19. Thompson S, Fergus P, Chalmers C, Reilly D. Detection of Obstructive Sleep Apnoea Using Features Extracted from Segmented Time-Series ECG Signals Using a One Dimensional Convolutional Neural Network. *2020 International Joint Conference on Neural Networks (IJCNN)*. 19-24 July 2020; Glasgow, UK. 2020. p. 1–8.

20. Sharan RV, Berkovsky S, Xiong H, Coiera E. ECG-Derived Heart Rate Variability Interpolation and 1-D Convolutional Neural Networks for Detecting Sleep Apnea. *Annu Int Conf IEEE Eng Med Biol Soc*. 2020;**2020**:637–40. [PubMed ID: 33018068]. https://doi.org/10.1109/EMBC44109.2020.9175998.

21. Chang HY, Yeh CY, Lee CT, Lin CC. A Sleep Apnea Detection System Based on a One-Dimensional Deep Convolution Neural Network Model Using Single-Lead Electrocardiogram. *Sensors (Basel)*. 2020;**20**(15):4157. [PubMed ID: 32722630]. [PubMed Central ID: PMC7435835]. https://doi.org/10.3390/s20154157.

22. Singh SA, Majumder S. A Novel Approach Osa Detection Using Single-Lead Ecg Scalogram Based on Deep Neural Network. *J Mech Med Biol*. 2019;**19**(4):1950026. https://doi.org/10.1142/s021951941950026x.

23. Liang X, Qiao X, Li Y. Obstructive Sleep Apnea Detection Using Combination of CNN and LSTM Techniques. *2019 IEEE 8th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*. 24-26 May 2019; Chongqing, China. 2019. p. 1733–6.

24. Erdenebayar U, Kim YJ, Park JU, Joo EY, Lee KJ. Deep learning approaches for automatic detection of sleep apnea events from an electrocardiogram. *Comput Methods Programs Biomed*. 2019;**180**:105001. [PubMed ID: 31421606]. https://doi.org/10.1016/j.cmpb.2019.105001.

25. Dey D, Chaudhuri S, Munshi S. Obstructive sleep apnoea detection using convolutional neural network based deep learning framework. *Biomed Eng Lett*. 2018;**8**(1):95–100. [PubMed ID: 30603194]. [PubMed Central ID: PMC6208553]. https://doi.org/10.1007/s13534-017-0055-y.

26. Banluesombatkul N, Rakthanmanon T, Wilaiprasitporn T. Single Channel ECG for Obstructive Sleep Apnea Severity Detection Using a Deep Learning Approach. *TENCON 2018 - 2018 IEEE Region 10 Conference*. 28-31 October 2018; Jeju, Korea (South). 2018. p. 2011–6.

27. Urtnasan E, Park JU, Lee KJ. Multiclass classification of obstructive sleep apnea/hypopnea based on a convolutional neural network from a single-lead electrocardiogram. *Physiol Meas*. 2018;**39**(6):65003. [PubMed ID: 29794342]. https://doi.org/10.1088/1361-6579/aac7b7.

28. Wang X, Cheng M, Wang Y, Liu S, Tian Z, Jiang F, et al. Obstructive sleep apnea detection using ecg-sensor with convolutional neural networks. *Multimed Tools Appl*. 2018;**79**(23-24):15813–27. https://doi.org/10.1007/s11042-018-6161-8.

29. Urtnasan E, Park JU, Joo EY, Lee KJ. Automated Detection of Obstructive Sleep Apnea Events from a Single-Lead Electrocardiogram Using a Convolutional Neural Network. *J Med Syst*. 2018;**42**(6):104. [PubMed ID: 29687192]. https://doi.org/10.1007/s10916-018-0963-0.

30. Mukherjee D, Dhar K, Schwenker F, Sarkar R. Ensemble of Deep Learning Models for Sleep Apnea Detection: An Experimental Study. *Sensors (Basel)*. 2021;**21**(16):5425. [PubMed ID: 34450866]. [PubMed Central ID: PMC8399151]. https://doi.org/10.3390/s21165425.

31. Hu S, Wang Y, Liu J, Yang C, Wang A, Li K, et al. Semi-Supervised Learning for Low-Cost Personalized Obstructive Sleep Apnea Detection Using Unsupervised Deep Learning and Single-Lead Electrocardiogram. *IEEE J Biomed Health Inform*. 2023;**27**(11):5281–92. [PubMed ID: 37566509]. https://doi.org/10.1109/JBHI.2023.3304299.

32. Bahrami M, Forouzanfar M. Deep Learning Forecasts the Occurrence of Sleep Apnea from Single-Lead ECG. *Cardiovasc Eng Technol*. 2022;**13**(6):809–15. [PubMed ID: 35301676]. https://doi.org/10.1007/s13239-022-00615-5.

33. Chen J, Shen M, Ma W, Zheng W. A spatio-temporal learning-based model for sleep apnea detection using single-lead ECG signals. *Front Neurosci*. 2022;**16**:972581. [PubMed ID: 35992920]. [PubMed Central ID: PMC9389170]. https://doi.org/10.3389/fnins.2022.972581.

34. Nasifoglu H, Erogul O. Obstructive sleep apnea prediction from electrocardiogram scalograms and spectrograms using convolutional neural networks. *Physiol Meas*. 2021;**42**(6):65010. [PubMed ID: 34116519]. https://doi.org/10.1088/1361-6579/ac0a9c.

35. Mashrur FR, Islam MS, Saha DK, Islam SMR, Moni MA. SCNN: Scalogram-based convolutional neural network to detect obstructive sleep apnea using single-lead electrocardiogram signals. *Comput Biol Med*. 2021;**134**:104532. [PubMed ID: 34102402]. https://doi.org/10.1016/j.compbiomed.2021.104532.

36. Mostafa SS, Baptista D, Ravelo-Garcia AG, Julia-Serda G, Morgado-Dias F. Greedy based convolutional neural network optimization for detecting apnea. *Comput Methods Programs Biomed*. 2020;**197**:105640. [PubMed ID: 32673899]. https://doi.org/10.1016/j.cmpb.2020.105640.

37. Vaquerizo-Villar F, Alvarez D, Kheirandish-Gozal L, Gutierrez-Tobal GC, Gomez-Pilar J, Crespo A, et al. Automatic Assessment of Pediatric Sleep Apnea Severity Using Overnight Oximetry and Convolutional Neural Networks. *Annu Int Conf IEEE Eng Med Biol Soc*. 2020;**2020**:633–6. [PubMed ID: 33018067]. https://doi.org/10.1109/EMBC44109.2020.9176342.

38. Vaquerizo-Villar F, Alvarez D, Kheirandish-Gozal L, Gutierrez-Tobal GC, Barroso-Garcia V, Campo FD, et al. Convolutional Neural Networks to Detect Pediatric Apnea-Hypopnea Events from Oximetry. *Annu Int Conf IEEE Eng Med Biol Soc*. 2019;**2019**:3555–8. [PubMed ID: 31946646]. https://doi.org/10.1109/EMBC.2019.8857934.

39. McCloskey S, Haidar R, Koprinska I, Jeffries B. Detecting Hypopnea and Obstructive Apnea Events Using Convolutional Neural Networks on Wavelet Spectrograms of Nasal Airflow. In: Phung D, Tseng V, Webb G, Ho B, Ganji M, Rashidi L, editors. *Advances in Knowledge Discovery and Data Mining. PAKDD 2018. Lecture Notes in Computer Science*. **Vol. 10937**. Cham: Springer; 2018. p. 361–72. https://doi.org/10.1007/978-3-319-93034-3_29.

40. Haidar R, McCloskey S, Koprinska I, Jeffries B. Convolutional Neural Networks on Multiple Respiratory Channels to Detect Hypopnea and Obstructive Apnea Events. *2018 International Joint Conference on Neural Networks (IJCNN)*. 8-13 July 2018; Rio de Janeiro, Brazil. 2018. p. 1–7.

41. Choi SH, Yoon H, Kim HS, Kim HB, Kwon HB, Oh SM, et al. Real-time apnea-hypopnea event detection during sleep by convolutional neural networks. *Comput Biol Med.* 2018;**100**:123–31. [PubMed ID: 29990645]. https://doi.org/10.1016/j.compbiomed.2018.06.028.

42. Cen L, Yu ZL, Kluge T, Ser W. Automatic System for Obstructive Sleep Apnea Events Detection Using Convolutional Neural Network. *Annu Int Conf IEEE Eng Med Biol Soc.* 2018;**2018**:3975–8. [PubMed ID: 30441229]. https://doi.org/10.1109/EMBC.2018.8513363.

43. Biswal S, Sun H, Goparaju B, Westover MB, Sun J, Bianchi MT. Expert-level sleep scoring with deep neural networks. *J Am Med Inform Assoc.* 2018;**25**(12):1643–50. [PubMed ID: 30445569]. [PubMed Central ID: PMC6289549]. https://doi.org/10.1093/jamia/ocy131.

44. Haidar R, Koprinska I, Jeffries B. Sleep Apnea Event Prediction Using Convolutional Neural Networks and Markov Chains. *2020 International Joint Conference on Neural Networks (IJCNN).* 19-24 July 2020; Glasgow, UK. 2020. p. 1–8.

45. Haidar R, Koprinska I, Jeffries B. Sleep Apnea Event Detection from Nasal Airflow Using Convolutional Neural Networks. In: Liu D, Xie S, Li Y, Zhao D, El-Alfy ES, editors. *Neural Information Processing. ICONIP 2017. Lecture Notes in Computer Science.* **Vol. 10638**. Cham: Springer; 2017. p. 819–27. https://doi.org/10.1007/978-3-319-70139-4_83.

46. Wang E, Koprinska I, Jeffries B. Sleep Apnea Prediction Using Deep Learning. *IEEE J Biomed Health Inform.* 2023;**27**(11):5644–54. [PubMed ID: 37669207]. https://doi.org/10.1109/JBHI.2023.3305980.

47. Simply RM, Dafna E, Zigel Y. Diagnosis of Obstructive Sleep Apnea Using Speech Signals From Awake Subjects. *IEEE J Sel Top Signal Process.* 2020;**14**(2):251–60. https://doi.org/10.1109/jstsp.2019.2955019.

48. Luo J, Liu H, Gao X, Wang B, Zhu X, Shi Y, et al. A novel deep feature transfer-based OSA detection method using sleep sound signals. *Physiol Meas.* 2020;**41**(7):75009. [PubMed ID: 32559754]. https://doi.org/10.1088/1361-6579/ab9e7b.

49. Nakano H, Furukawa T, Tanigawa T. Tracheal Sound Analysis Using a Deep Neural Network to Detect Sleep Apnea. *J Clin Sleep Med.* 2019;**15**(8):1125–33. [PubMed ID: 31482834]. [PubMed Central ID: PMC6707047]. https://doi.org/10.5664/jcsm.7804.

50. Jiang D, Ma Y, Wang Y. A Multi-Scale Parallel Convolutional Neural Network for Automatic Sleep Apnea Detection Using Single-Channel EEG Signals. *2018 11th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI).* 13-15 October 2018; Beijing, China. 2018. p. 1–5.

51. Pourbabaee B, Patterson MH, Patterson MR, Benard F. SleepNet: automated sleep analysis via dense convolutional neural network using physiological time series. *Physiol Meas.* 2019;**40**(8):84005. [PubMed ID: 31349239]. https://doi.org/10.1088/1361-6579/ab3632.

52. Mahmud T, Khan IA, Ibn Mahmud T, Fattah SA, Zhu WP, Ahmad MO. Sleep Apnea Event Detection from Sub-frame Based Feature Variation in EEG Signal Using Deep Convolutional Neural Network. *Annu Int Conf IEEE Eng Med Biol Soc.* 2020;**2020**:5580–3. [PubMed ID: 33019242]. https://doi.org/10.1109/EMBC44109.2020.9176433.

53. Barnes LD, Lee K, Kempa-Liehr AW, Hallum LE. Detection of sleep apnea from single-channel electroencephalogram (EEG) using an explainable convolutional neural network (CNN). *PLoS One.* 2022;**17**(9):e0272167. [PubMed ID: 36099242]. [PubMed Central ID: PMC9469966]. https://doi.org/10.1371/journal.pone.0272167.

54. Alarcon AS, Madrid NM, Seepold R, Ortega JA. Obstructive sleep apnea event detection using explainable deep learning models for a portable monitor. *Front Neurosci.* 2023;**17**:1155900. [PubMed ID: 37521695]. [PubMed Central ID: PMC10375719]. https://doi.org/10.3389/fnins.2023.1155900.

55. Jimenez-Garcia J, Garcia M, Gutierrez-Tobal GC, Kheirandish-Gozal L, Vaquerizo-Villar F, Alvarez D, et al. A 2D convolutional neural network to detect sleep apnea in children using airflow and oximetry. *Comput Biol Med.* 2022;**147**:105784. [PubMed ID: 35797888]. https://doi.org/10.1016/j.compbiomed.2022.105784.

56. Arslan Tuncer S, Akilotu B, Toraman S. A deep learning-based decision support system for diagnosis of OSAS using PTT signals. *Med Hypotheses.* 2019;**127**:15–22. [PubMed ID: 31088639]. https://doi.org/10.1016/j.mehy.2019.03.026.

57. Tsuiki S, Nagaoka T, Fukuda T, Sakamoto Y, Almeida FR, Nakayama H, et al. Machine learning for image-based detection of patients with obstructive sleep apnea: an exploratory study. *Sleep Breath.* 2021;**25**(4):2297–305. [PubMed ID: 33559004]. [PubMed Central ID: PMC8590647]. https://doi.org/10.1007/s11325-021-02301-7.

58. Kwon HB, Son D, Lee D, Yoon H, Lee MH, Lee YJ, et al. Hybrid CNN-LSTM Network for Real-Time Apnea-Hypopnea Event Detection Based on IR-UWB Radar. *IEEE Access.* 2021;**10**:17556–64. https://doi.org/10.1109/access.2021.3081747.

59. Perez-Macias JM, Adavanne S, Viik J, Varri A, Himanen SL, Tenhunen M. Assessment of support vector machines and convolutional neural networks to detect snoring using Emfit mattress. *Annu Int Conf IEEE Eng Med Biol Soc.* 2017;**2017**:2883–6. [PubMed ID: 29060500]. https://doi.org/10.1109/EMBC.2017.8037459.

60. Wei K, Zou L, Liu G, Wang C. MS-Net: Sleep apnea detection in PPG using multi-scale block and shadow module one-dimensional convolutional neural network. *Comput Biol Med.* 2023;**155**:106469. [PubMed ID: 36842220]. https://doi.org/10.1016/j.compbiomed.2022.106469.

61. Jiang X, Ren Y, Wu H, Li Y, Liu F. Convolutional neural network based on photoplethysmography signals for sleep apnea syndrome detection. *Front Neurosci.* 2023;**17**:1222715. [PubMed ID: 37547138]. [PubMed Central ID: PMC10400763]. https://doi.org/10.3389/fnins.2023.1222715.

62. He S, Su H, Li Y, Xu W, Wang X, Han D. Detecting obstructive sleep apnea by craniofacial image-based deep learning. *Sleep Breath.* 2022;**26**(4):1885–95. [PubMed ID: 35132533]. https://doi.org/10.1007/s11325-022-02571-9.

63. da Silva SP, Hulce VD, Backs RW. Effects of obstructive sleep apnea on autonomic cardiac control during sleep. *Sleep Breath.* 2009;**13**(2):147–56. [PubMed ID: 18949500]. https://doi.org/10.1007/s11325-008-0228-0.

64. Bacharova L, Triantafyllou E, Vazaios C, Tomeckova I, Paranicova I, Tkacova R. The effect of obstructive sleep apnea on QRS complex morphology. *J Electrocardiol.* 2015;**48**(2):164–70. [PubMed ID: 25541278]. https://doi.org/10.1016/j.jelectrocard.2014.12.007.

65. Dean II DA, Goldberger AL, Mueller R, Kim M, Rueschman M, Mobley D, et al. Scaling Up Scientific Discovery in Sleep Medicine: The National Sleep Research Resource. *Sleep.* 2016;**39**(5):1151–64. [PubMed ID: 27070134]. [PubMed Central ID: PMC4835314]. https://doi.org/10.5665/sleep.5774.

66. Singh S, Khan SZ, Singh D, Verma S, Talwar A. The uses of overnight pulse oximetry. *Lung India.* 2020;**37**(2):151–7. [PubMed ID: 32108601]. [PubMed Central ID: PMC7065557]. https://doi.org/10.4103/lungindia.lungindia_302_19.

67. Iber C, Ancoli-Israel S, Chesson Jr AL, Quan SF. *The AASM manual for the scoring of sleep and associated events: Rules, terminology, and technical specifications.* 2007. Available from: https://www.sleep.pitt.edu/wp-content/uploads/2020/03/The-AASM-Manual-for-Scoring-of-Sleep-and-Associated-Events-2007-.pdf.

68. Marcus CL, Moore RH, Rosen CL, Giordani B, Garetz SL, Taylor HG, et al. A randomized trial of adenotonsillectomy for childhood sleep apnea. *N Engl J Med.* 2013;**368**(25):2366–76. [PubMed ID: 23692173]. [PubMed Central ID: PMC3756808]. https://doi.org/10.1056/NEJMoa1215881.

69. Redline S, Amin R, Beebe D, Chervin RD, Garetz SL, Giordani B, et al. The Childhood Adenotonsillectomy Trial (CHAT): rationale, design, and challenges of a randomized controlled trial evaluating a standard surgical procedure in a pediatric population. *Sleep.* 2011;**34**(11):1509–17. [PubMed ID: 22043122]. [PubMed Central ID: PMC3198206]. https://doi.org/10.5665/sleep.1388.

70. Jiang Y, Peng J, Zhang X. Automatic snoring sounds detection

from sleep sounds based on deep learning. *Phys Eng Sci Med*. 2020;**43**(2):679–89. [PubMed ID: 32378124]. https://doi.org/10.1007/s13246-020-00876-1.

71. Chen K, Zhang C, Ma J, Wang G, Zhang J. Sleep staging from single-channel EEG with multi-scale feature and contextual information. *Sleep Breath*. 2019;**23**(4):1159–67. [PubMed ID: 30863994]. https://doi.org/10.1007/s11325-019-01789-4.

72. Howe-Patterson M, Pourbabaee B, Benard F. Automated Detection of Sleep Arousals From Polysomnography Data Using a Dense Convolutional Neural Network. *Comput Cardiol*. 2018;**45**:1–4. https://doi.org/10.22489/CinC.2018.232.

73. Bolboaca SD. Medical Diagnostic Tests: A Review of Test Anatomy, Phases, and Statistical Treatment of Data. *Comput Math Methods Med*. 2019;**2019**:1891569. [PubMed ID: 31275427]. [PubMed Central ID: PMC6558629]. https://doi.org/10.1155/2019/1891569.

74. Abougabal MM, Diaa Moussa N. A novel technique for validating diagnosed respiratory noises in infants and children. *Alex Eng J*. 2018;**57**(4):3033–41. https://doi.org/10.1016/j.aej.2018.05.003.

75. Penzel T, Moody GB, Mark RG, Goldberger AL, Peter JH. The apnea-ECG database. *Computers in Cardiology 2000. Vol.27 (Cat. 00CH37163)*. 24-27 September 2000; Cambridge, MA, USA. 2000. p. 255–8.

76. Berry RB, Budhiraja R, Gottlieb DJ, Gozal D, Iber C, Kapur VK, et al. Rules for scoring respiratory events in sleep: update of the 2007 AASM Manual for the Scoring of Sleep and Associated Events. Deliberations of the Sleep Apnea Definitions Task Force of the American Academy of Sleep Medicine. *J Clin Sleep Med*. 2012;**8**(5):597–619. [PubMed ID: 23066376]. [PubMed Central ID: PMC3459210]. https://doi.org/10.5664/jcsm.2172.

77. Mendonca F, Mostafa SS, Ravelo-Garcia AG, Morgado-Dias F, Penzel T. A Review of Obstructive Sleep Apnea Detection Approaches. *IEEE J Biomed Health Inform*. 2019;**23**(2):825–37. [PubMed ID: 29993672]. https://doi.org/10.1109/JBHI.2018.2823265.

78. Lv X, Li J, Ren Q. MCFN: A Multichannel Fusion Network for Sleep Apnea Syndrome Detection. *J Healthc Eng*. 2023;**2023**:5287043. [PubMed ID: 36726772]. [PubMed Central ID: PMC9886480]. https://doi.org/10.1155/2023/5287043.

79. Yilmaz G, Ong JL, Ling LH, Chee MWL. Insights into vascular physiology from sleep photoplethysmography. *Sleep*. 2023;**46**(10):zsad172. [PubMed ID: 37379483]. [PubMed Central ID: PMC10566244]. https://doi.org/10.1093/sleep/zsad172.

80. Liu PK, Ting N, Chiu HC, Lin YC, Liu YT, Ku BW, et al. Validation of photoplethysmography- and acceleration-based sleep staging in a community sample: comparison with polysomnography and Actiwatch. *J Clin Sleep Med*. 2023;**19**(10):1797–810. [PubMed ID: 37338335]. [PubMed Central ID: PMC10545987]. https://doi.org/10.5664/jcsm.10690.

81. Prabhakar NR, Peng YJ. Peripheral chemoreceptors in health and disease. *J Appl Physiol (1985)*. 2004;**96**(1):359–66. [PubMed ID: 14660497]. https://doi.org/10.1152/japplphysiol.00809.2003.

82. Broderick M, Guilleminault C. Neurological aspects of obstructive sleep apnea. *Ann N Y Acad Sci*. 2008;**1142**:44–57. [PubMed ID: 18990120]. https://doi.org/10.1196/annals.1444.003.

83. Liu H, Cui S, Zhao X, Cong F. Detection of obstructive sleep apnea from single-channel ECG signals using a CNN-transformer architecture. *Biomed Signal Process Control*. 2023;**82**:104581. https://doi.org/10.1016/j.bspc.2023.104581.

84. Shi J, Liu X, Li Y, Zhang Q, Li Y, Ying S. Multi-channel EEG-based sleep stage classification with joint collaborative representation and multiple kernel learning. *J Neurosci Methods*. 2015;**254**:94–101. [PubMed ID: 26192325]. https://doi.org/10.1016/j.jneumeth.2015.07.006.

85. Biswal S, Kulas J, Sun H, Goparaju B, Westover MB, Bianchi MT, et al. SLEEPNET: automated sleep staging system via deep learning. Preprint. *arXiv*. Posted online July 26, 2017. https://doi.org/10.48550/arXiv.1707.08262.

86. Yeghiazarians Y, Jneid H, Tietjens JR, Redline S, Brown DL, El-Sherif N, et al. Obstructive Sleep Apnea and Cardiovascular Disease: A Scientific Statement From the American Heart Association. *Circulation*. 2021;**144**(3):e56–67. [PubMed ID: 34148375]. https://doi.org/10.1161/CIR.0000000000000988.

Table 1. Characteristics of Included Studies

Authors	Year	Database/Setting	Target Group	Recordings	Sensors/Signals	Window Size (s)	Classification Type	Classifier Type	Sensitivity/Recall (%)	Specify (%)	Accuracy (%)
ECG Signal											
Zhang et al. (15)	2021	AED	Adults	70	ECG	10	OA/N	LSTM, CNN	96.1	96.2	96.1
Shen et al. (16)	2021	AED	Adults	70	RR-ECG	-	OA/N	MSDA-DCNN + WLTD	89.8	89.1	89.4
Niroshana et al. (17)	2021	AED	Adults	70	ECG	60	OA/N	CNN2D	92.3	92.6	92.4
Urtnasan et al. (18)	2020	Medical center	Adults	144	ECG	30	OAS/N	CNN	99.25	98.5	99
Thompson et al. (19)	2020	AED	Adults	35	ECG	50	OA/N	CNN1D	97	97.2	-
Sharan et al. (20)	2020	AED	Adults	70	ECG (HRV)	60	A/N	CNN1D	82.74	91.62	88.23
Chang et al. (21)	2020	AED	Adults	70	ECG	60	A/N	CNN1D	81.1	92	87.9
						Per recording	A/N	CNN1D	95.7	100	97.1
Singh and Majumder (22)	2019	AED	Adults	70	ECG	60	OA/N	CNN2D	90	83.82	86.22
Liang et al. (23)	2019	AED	Adults	70	RR-ECG	-	OA/N	LSTM, CNN	98.97	96.94	99.8
Erdenebayar et al. (24)	2019	Medical center	Adults	86	ECG	10	AH/N	CNN1D	99	99	98.5
								CNN2D			95.9
								DNN	93	94	93
Dey et al. (25)	2018	AED	Adults	35	ECG	NA	OA/N	CNN1D	97.82	99.2	98.91
Banluesombatkul et al. (26)	2018	MrOS	Adults	545	ECG	15	Severe OA (AHI ≥ 30)/N	CNN1D, LSTM, DNN	77.6	80.1	79.45
Urtnasan et al. (27)	2018	Medical center	Adults	86	ECG	10	OA/H/N	CNN1D	87	87	90.8
Wang et al. (28)	2018	AED	Adults	86	RR-ECG	35	OA/N	CNN	100	93	97.8
Urtnasan et al. (29)	2018	Medical center	Adults	82	ECG	10	OA/N	CNN1D	96	96	96
Mukherjee et al. (30)	2021	AED	Adults	70	ECG	240	OA/N	CNN, MLP	84.43	88.26	85.58
Hu et al. (31)	2023	AED	Adults		Raw ECG, RA, RRI, and RRID	NA	OA/N	CNN	-	-	90.3
Bahrami and Forouzanfar (32)	2022	AED	Adults	70	RR-ECG, R-peak	60	A/N	CNN	93.92	95.63	94.95
Chen et al. (33)	2022	AED, UCD	Adults	95	ECG	60	A/N	CNN	86.48	94.16	91.22
Nasifoglu and Erogul (34)	2021	ABC, HomePAP	Adults	292	ECG	30	OA/N	CNN2D	Scalogram images: 83.2; spectrogram images: 81.9	Scalogram images: 82.2; spectrogram images: 77.2	Scalogram images: 82.3; spectrogram images: 80.1
Mashrur et al. (35)	2021	AED, UCD	Adults	95	ECG	60	OA/N	CNN	AED: 94.3; UCD: 71.62	AED: 94.51; UCD: 86.05	AED: 94.38; UCD: 81.86
SpO2 Signal											
Mostafa et al. (11)	2020	HuGCDN2008	Adults	70	SpO2	180	OA/N	CNN	74.4	94.1	89.5
		UCD		25		180			67.35	90.51	84.96
		AED		8		300			88.58	93.67	91.5
Mostafa et al. (36)	2020	HuGCDN2008	Adults	70	SpO2	300	A/N	CNN1D	73.64	93.8	88.49
		HuGCDN2008		70		180	AHS		71.47	94.07	95.71
		AED		7		180	A/N		92.36	97.08	95.14
		AED		7		180	AHS		92.36	97.08	100
Vaquerizo-Villar et al. (37)	2020	CHAT	Pediatrics	746	SpO2	-	AHS/N	CNN (AHI = 1)	40	98.6	74.8

Table 1. Characteristics of Included Studies (Continued)

Study	Year	Dataset	Population	Sample	Signal	No.	Event	Method			
Vaquerizo-Villar et al. (38)	2019	CHAT	Pediatrics	453	SpO2	60	AH/N	CNN(AHI=5)	46	98.6	90.7
								CNN(AHI=10)	54.2	99.6	95.1
								CNN1D	56.5	96.7	93.6
Respiratory Signals											
McCloskey et al. (39)	2018	MESA	Adults	1507	Nasal airflow	30	A/H/N	CNN1D	77.6	-	77.6
								CNN2D	79.7	-	79.8
Haidar et al. (40)	2018	MESA	Adults	1507	Nasal airflow, abdominal and thoracic plethysmography	30	OA/H/N	CNN1D	83.4	-	83.5
Choi et al. (41)	2018	Hospital	Adults	179	Nasal pressure	10	AH/N,G	CNN1D	81.1	98.91	96.6
Cen et al. (42)	2018	UCD	Adults	23	SpO2, oronasal airflow, ribcage, and abdomen movements	1	OAH/N	CNN2D	-	-	79.6
Biswal et al. (43)	2018	SHHS	Adults	5804	Airflow, chest and abdomen movements, SpO2	1	AHS	RCNN	-	-	88.2
		MGH		10 000					-	-	88.2
Haidar et al. (44)	2020	MESA	Adults	1507	Nasal flow, abdominal and thoracic plethysmography	30	A/N	Predictive CNN	81.73	80.63	80.78
Haidar et al. (45)	2017	MESA	Adults	100	Nasal airflow	30	OA/N	CNN1D	754.7		74.7
Wang et al. (46)	2023	MESA	Adults	1507	Nasal airflow, abdominal and thoracic expansion	30	OA/N	CNN1D, CNN2D, LSTM	81.73	86.59	83.90
Sound Signals											
Simply et al. (47)	2020	Medical center, university students	Adults	398	Speech signals	2	OAH/G	LSTM, CNN	75	79	77.14
Luo et al. (48)	2020	Hospital	Adults	132	Sleep sound	5	OA/N	CNN	69.7	70.9	81.63
Nakano et al. (49)	2019	Hospital	Adults	1548	Tracheal sound	60	AH/N	DNN(AHI=5)	98	76	
								DNN(AHI=15)	97	90	
								DNN(AHI=30)	92	94	
EEG Signals											
Jiang et al. (50)	2018	MIT-BIH polysomnographic database	Adults	18	EEG	30		MSPCNN	93.1	82.9	89.1
Pourbabaee et al. (51)	2019	Physionet challenge	Adults	994	EEG	120	AH/N	DRCNN	-	-	62
Mahmud et al. (52)	2020	EEG dataset	Adults	25	EEG	5	A/N	FCNN	83.6	77.3	77.4
Barnes et al. (53)	2022	SHHS2, EEG dataset	Adults	2675	EEG	30	A/N	CNN	-	-	69.9
Combined Signals											
Alarcon et al. (54)	2023	SHHS2	Adults	163	SpO2, heart rate, thoracic respiratory effort, and abdominal-respiratory effort	30	OA/N	CNN1D	82.5	86	92.1
Jimenez-Garcia et al. (55)	2022	CHAT, UofC	Pediatrics	2612	SpO2, airflow signal	300	OA/N	CNN	CHAT:82.4; UofC:95.2	CHAT:99.1; UofC:93.5	CHAT:94.4; UofC:90.3
Other Signals											
Arslan Tuncer et al. (56)	2019	Hospital	Adults	100	PTT	0.048	A/N	CNN	98	94.25	92.78

Table 1. Characteristics of Included Studies (Continued)

Study	Year	Setting	Population	Data	Sample	Full Image	Severe OA (AHI ≥ 30)/N	Model			
Tsuiki et al. (57)	2021	Sleep Center	Adults	Lateral cephalometric radiographs	1389			DCNN	87	82	-
						Main region			88	75	-
						Head only			71	63	-
						Manual cephalometric analysis			54	80	-
Kwon et al. (58)	2021	Hospital	Adults	IR-UWB	36	20	AHS/N	LSTM, CNN	78.1	95.6	93
Perez-Macias et al. (59)	2017	Hospital	Adults	Emfit mattress	30	30	A/N	CNN2D	92	96	94
Wei et al. (60)	2023	Apnea-PPG	Adults	PPG	110	Per segment	OA/N	MS-Net	74.4	85.1	82
						Per recording			80	97.6	93.6
Jiang et al. (61)	2023	Hospital	Adults	PPG	59	NA	OA/N	CNN1D	98.24	86.74	90.75
He et al. (62)	2022	Hospital	Adults	Craniofacial photos	393	NA	OA/N	CNN	AHI ≥ 5: 95; AHI ≥ 15: 91	AHI ≥ 5: 80; AHI ≥ 15: 73	AHI ≥ 5: 90; AHI ≥ 15: 83.1

Abbreviations: A, apnea; H, hypopnea; N, normal; S, severity (based on AHI, OSA is classified as follows: (1) none: AHI < 5 per hour; (2) mild: AHI ≥ 5, but < 15 per hour; (3) moderate: AHI ≥ 15, but < 30 per hour; (4) severe: AHI ≥ 30 per hour); O, obstructive; AHI, apnea-hypopnea index; CNN, convolutional neural network; DCNN, deep convolutional neural network; DNN, deep neural network; RCNN, recurrent convolutional neural network; DRCNN, dense recurrent convolutional neural network; WLTD, weighted-loss time-dependent; MSPCNN, multi-scale parallel CNN; AED, apnea-ECG database; CHAT, childhood adenotonsillectomy trial; EEG, electroencephalogram; MESA, multi-ethnic study of atherosclerosis; SHHS, sleep heart health study; MGH, Massachusetts General Hospital; UCD, University College Dublin Sleep Apnea Database; PTT, pulse transition time; RA, R-peak amplitude; RRID, RR interval first-order difference; MS-Net, combined multiscale-one-dimensional convolutional module (shadow module); MrOS, osteoporotic fractures in men study; PPG, photoplethysmography; ECG, electrocardiogram; SpO₂, blood oxygen saturation; IR-UWB, impulse-radio ultra-wideband; HRV, heart rate variability; FCNN, fully convolutional neural network.