Automatic Diagnosis of Sleep Apnea from Biomedical Signals Using Artificial Intelligence Techniques: Methods, Challenges, and Future Works

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Abstract

Apnea is a sleep disorder that stops or reduces airflow for a short time during sleep. Sleep apnea may last for a few seconds and happen for many while sleeping. This reduction in breathing is associated with loud snoring, which may awaken the person with a feeling of suffocation. So far, a variety of methods have been introduced by researchers to diagnose sleep apnea, among which the polysomnography (PSG) method is known to be the best. As a set of biological signals, including electrooculogram (EOG), electromyography (EMG), electroencephalography (EEG), electrocardiogram (ECG), pulse-oximetry results ($S_p o_2$), and breathing signals, are recorded and studied in this method, analysis of PSG signals is very complicated. Many studies have been conducted on the automatic diagnosis of sleep apnea from biological signals using artificial intelligence (AI), including machine learning (ML) and deep learning (DL) methods. This research reviews and investigates the studies on the diagnosis of sleep apnea using AI methods. First, CADS for sleep apnea using ML and DL techniques along with its parts including dataset, preprocessing, and ML and DL methods are introduced. This research also summarizes the important specifications of the studies on the diagnosis of sleep apnea using ML and DL methods in a Table. In the following, a comprehensive discussion is made on the studies carried out in this field. The challenges in the diagnosis of sleep apnea using AI methods are of paramount importance for researchers. Accordingly, these obstacles are elaborately addressed. In another section, the most important future works for studies on the diagnosis of sleep apnea from PSG signals and AI techniques are presented. Ultimately, the essential findings of this study are provided in the conclusion section.

KeyWords: Sleep apnea, Diagnosis, PSG, Detection, Artificial Intelligence, Machine Learning, Deep Learning

1. Introduction

Sleep is a biological phenomenon that involves all body organs and includes sleep with rapid and non-rapid eye movements [1-2]. Scientists have indicated that any individual is asleep for almost one-third of their lifetime, which is called a period for memory consolidation and brain recovery [3-4]. When an individual is asleep, their brain is consolidated, and its function is improved, which facilitates learning, memory recovery, and retention. Thereby, any disorder in sleep interrupts or reduces the functional quality of sleep

[5-6]. Lack of sleep varies in children, teens, and adults. The adults who sleep for less than 8 hours a night suffer from sleep deprivation [7]. According to the conducted studies, the average sleep time of teenagers is lower than the standard sleep time at that age. Despite public belief, teenagers need more sleep than adults [Cite]. According to surveys, 15% of teenagers sleep for 8.5 hours or more, and more than 26% of them sleep for less than 6.5 hours a night [8]. Some sleep disorders are so serious that they can interrupt individuals' natural, spiritual, social, and emotional functions [9-10].

Sleep breathing disorders refer to disorders that lead to short cessation during sleep. Sleep apnea is one of the most common sleep breathing disorders [11]. This disorder happens due to the relaxation of soft tissue in the back of the throat. Loud snoring is one of the symptoms of sleep apnea that is caused by the vibration of soft tissue [12-13]. Sleep apnea causes a sudden and frequent reduction in blood oxygen level, which may lead to awakening from sleep [12-14]. Breathing of patients suffering from sleep apnea during sleep is accompanied by loud snoring and repeated stops and starts. Having a breathing disorder during sleep leads to brain damage, interruption of sleep, reduced sleep time, variation in hormone level in the body, and increased sympathetic nerve activity level [15-16]. This disorder has different types, including Central sleep apnea (CSA) [17], obstructive sleep apnea (OSA) [18], and mixed sleep apnea (MSA) [19].

CSA happens when the brainstem is damaged in the region that controls breathing. The brainstem could be damaged due to an infection or stroke. In this case, the brain cannot send the proper signals to the muscles to control breath [20-21].

Obstructive sleep apnea syndrome (OSAS) is a much more common variety of sleep apnea and happens due to interruption in the airflow in the throat while sleeping [22-24]. OSAS is a form of interruption in breathing while sleep in which the airway through the mouth and nose are completely obstructed for 10 seconds or more [22-24]. This obstruction can be due to large tonsils, tongue, or tissue in the airway [22-24]. Almost 5% of people in the world suffer from OSAS. Besides, OSAS patients experience sleep apnea more than five times per hour of sleep. Due to lack of oxygen and carbon dioxide exchange during sleep apnea, the blood oxygen saturation declines [22-25]. If blood oxygen saturation declines to less than 30% of normal condition during the sleep apnea and continues for more than 15 seconds, this matter will be of paramount importance clinically [22-25]. In addition, hormonal disorders caused by sympathetic activation in the long term can lead to the development of metabolic disorders, such as resistance to insulin, diabetes, and obesity [22-25].

MSA is a combination of central and obstructive sleep apnea. It means that MSA occurs due to interruption in breathing during sleep by both obstructions in the airway and lack of the brain's ability to send signals to the body to breathe [26-28]. On the contrary to OSA that normally happens in the REM phase of sleep, this disorder often happens in the N-REM phase of sleep. However, it must be noted that MSA is not as common as OSA [29]. According to studies, 5% to 15% of sleep apnea patients suffer from this type of sleep apnea [29]. In adults, sleep apnea syndrome is treated based on Continuous Positive Airway Pressure (CPAP), weight loss, and ultimately dental and surgical instruments [30-31]. Initial treatment in children is Aden tonsillectomy. In the cases when surgery in children cannot be done, CPAP is employed [32-33].

So far, physicians have proposed various methods to diagnose sleep apnea, among which the PSG method is the most important [34-35]. PSG is the most useful standard method for diagnosing breathing disorders during sleep, which is used for initial diagnosis, determining the severity of sleep apnea in sleep, and discovering several initial disorders in sleep [34-35]. PSG includes biological signals, such as EOG, EMG, EEG, ECG, $S_p o_2$, and breathing signals [34-35].

PSG recording is extremely complicated, costly, challenging, and requires the presence of a specialist group. Analysis of PSG signals is generally carried out manually, which is a demanding and exhausting task subject to human error [36]. It is because physicians ought to divide long-term signals into 20 to 30-second frames and analyze them afterward [37]. In order to tackle these challenges, it is essential to propose a CADS for sleep apnea detection from PSG signals, including EOG, EMG, EEG, ECG, $S_p o_2$, and breathing signals [35]. Over recent years, many research have been conducted on the diagnosis of sleep apnea using biological signals and AI techniques [38-40]. This study aims to help specialists by proposing solutions to increase accuracy in sleep apnea detection using ML and DL techniques.

In this paper, there will be a comprehensive review in sleep apnea detection from PGG including EOG, EMG, EEG, ECG, $S_p o_2$, and breathing signals using AI methods. In the second section, the search strategy will be provided, and a review of the ML and DL methods will be discussed for sleep apnea detection in the second section. In the fourth section, the CADS based on AI for the diagnosis of sleep apnea will be discussed. In this section, first, the datasets, preprocessing methods, various ML and DL methods will be discussed. Also, the conducted studies in the field of sleep apnea detection will be introduced in this session. The fifth section addresses the most important challenges for sleep apnea detection using AI methods. The discussion of this paper will be provided in the sixth section, where there will be a comprehensive comparison between the ML and DL studies in the diagnosis of sleep apnea. In the following, the future works and conclusions are provided in sections 7 and 8, respectively.

2. Search Strategy

2.1. Paper search

In this section, the paper search is done based on PRISMA guidelines [41]. The published papers search is performed between years 2016 and 2022 in the field of sleep Apnea detection, where the general keywords like Apnea, central sleep apnea, obstructive sleep apnea, and mixed sleep apnea, EOG, $S_p o_2$, EMG, ECG, EEG, PSG, respiration signals, Deep Learning, and Machine Learning have been used. These keywords have been searched in databases like Nature, IEEE Xplore, MDPI, Frontiers, Science Direct, ArXiv, Springer, Wiley, etc. Figure (1) displays the number of paper published in different databases for AI studies.

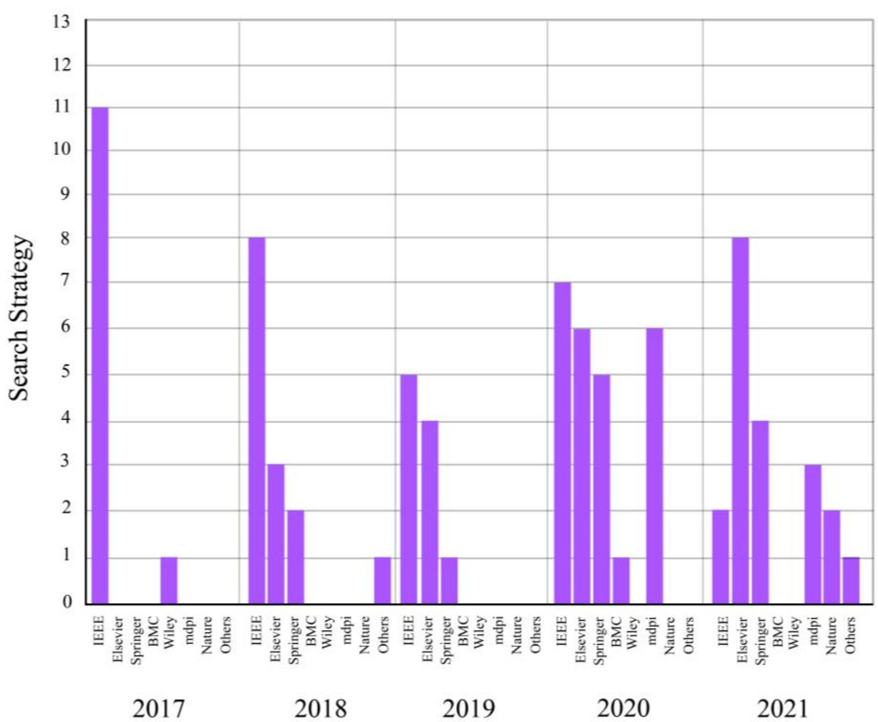


Fig 1a. Number of papers published for sleep apnea detection using ML methods

2.2. Selection of papers

The selection way of important papers for the diagnosis of sleep apnea using AI methods has been provided. In this section, the provided articles between 2016 to 2022 that are related to this research have been investigated and considered. The selection process of the relevant papers has been performed in 3 levels. First, 328 papers were collected, and then 83 papers were filtered out due to irrelevance. In the next step, 49 papers filtered based on input data or biological signals. In the following, 24 other papers were filtered out due to the type of datasets or the used AI methods. Ultimately, 172 papers were chosen for study, the details of each were discussed. The papers selection process has been displayed in Figure (2). In this study, the researchers have investigated all valid papers in the diagnosis of sleep apnea using ML and DL methods. The last investigation of the papers in this field was performed on 16 Jan 2022. Investigation of the papers is based on PRISMA instructions. Also, the input and output criteria have been provided in Table (1).

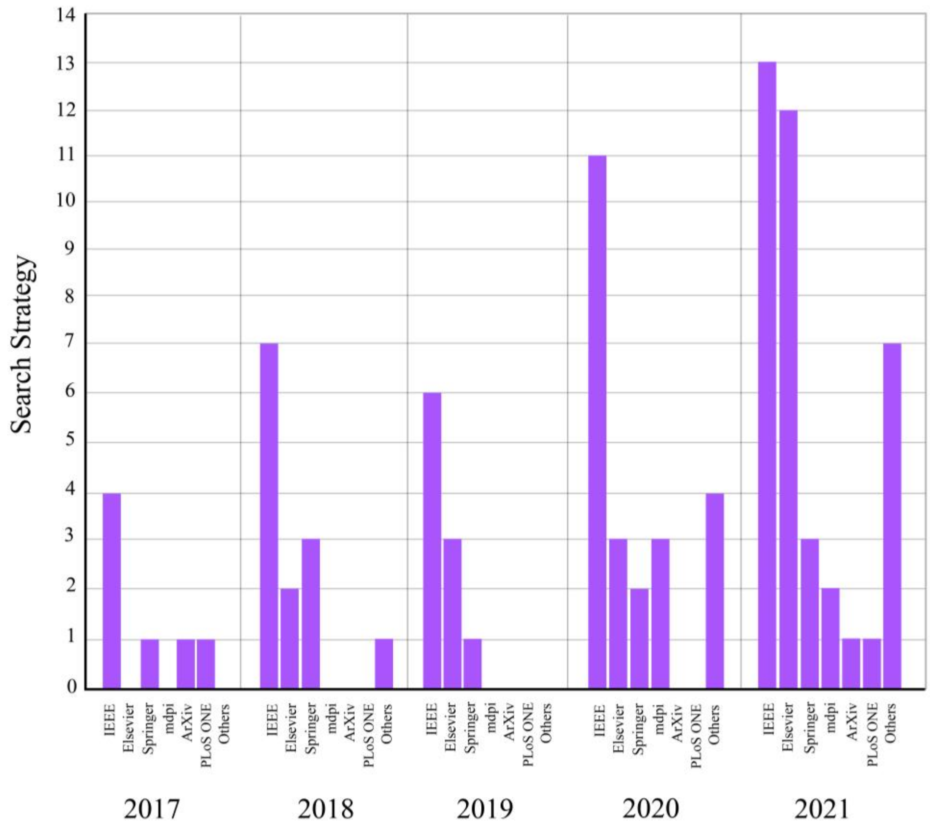


Fig 1b. Number of papers published for sleep apnea detection using DL methods

Table 1. The exclusion and inclusion criteria for diagnosis of sleep apnea

Inclusion	Exclusion
1. polysomnography signals 2. Biological signals and neuroimaging 3. Central sleep apnea, obstructive sleep apnea, mixed sleep apnea. 4. DL models (CNNs, RNNs, AEs, CNN-RNN, CNN-AE, GAN, Transfer Learning, etc.) 5. Feature extraction methods (Times, Frequency, Time-Frequency, Non-Linear) 6. Classification methods (SVM, KNN, RF, MLP, etc.)	1. Treatment of sleep apnea 2. Clinical methods for treatment of sleep apnea 3. Rehabilitation systems for sleep apnea detection (Without AI techniques)

3. Diagnosis of Sleep Apnea Syndrome Using Artificial Intelligence Techniques

In recent years, sleep apnea has been introduced as a dangerous factor for various ailments, e.g., cardiovascular diseases [42-43]. Physicians make the diagnosis of sleep disorders manually, which is time-consuming, exhausting, and dependent on the operator [44]. This leads to difficulty in the diagnosis in most cases. In the AI field, various studies have been conducted in the diagnosis of sleep apnea using ML and DL methods [38-40]. In [45-49], the researchers mainly aim to investigate the papers in the field of sleep apnea detection using ML techniques. In addition, in [50], researchers have provided a review study in sleep apnea detection using DL techniques. In our study, a review is be conducted over whole performed studies in sleep apnea detection using AI techniques. In Tables (2) and (3), the conducted studies in sleep apnea detection using ML and DL methods are provided.

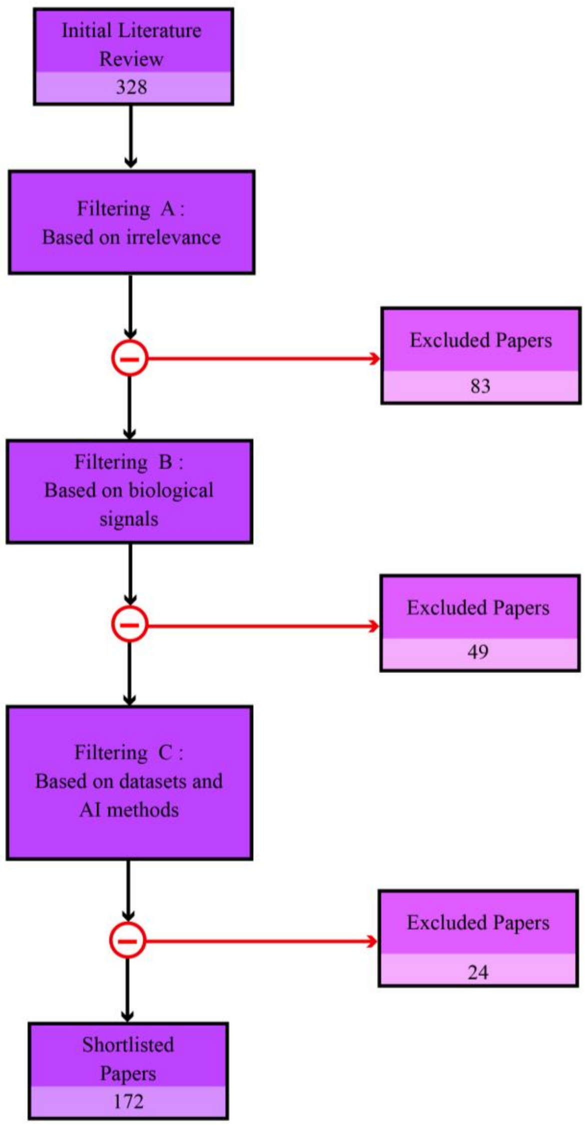


Fig 2. Papers selection process based on the PRISMA guidelines.

4. CADS Based on AI Methods for Detection of Sleep Apnea Syndrome

This section addresses the CADS based on AI for the diagnosis of sleep apnea from PSG data. There are numerous studies regarding the diagnosis of sleep apnea, aiming to achieve a real tool for the rapid diagnosis of such sleep disorders [51-53]. Currently, researchers use ML and DL methods in the implementation of CADS for the diagnosis of sleep apnea and have obtained important results. Generally, the CADS based on AI consists of different sections: datasets, preprocessing, feature extraction, dimension reduction, and classification methods [54-48]. The CADS based on ML implementation is more complicated for the diagnosis of sleep apnea compared to the DL methods. The increasing the accuracy in sleep apnea detection requires great knowledge in the field of machine learning algorithms. On the other hand, the implementation of CADS based on DL is simpler with high performance for the diagnosis of sleep apnea from the biological signals. That is because, unlike ML, the feature selection and dimensions reduction in DL is performed in unsupervised form by deep layers [59-60]. Another merit of DL methods is that their performance is not diminished as the performance increases, though increasing the inputs in ML models leads to the performance reduction and the accuracy decline of diagnosis of sleep apnea. In Fig. (3), the CADS based on AI along with its sections (ML and DL models) have been defined for sleep apnea detection. In the following, first, the CADS based on ML are discussed based on Figure (3). Then, a summary of these papers has been reported in Table (2). Afterward, the most important sections of CADS based on DL techniques are introduced for sleep apnea detection from the biological signals. Finally, a summary of the conducted studies in DL field are provided in Table (3).

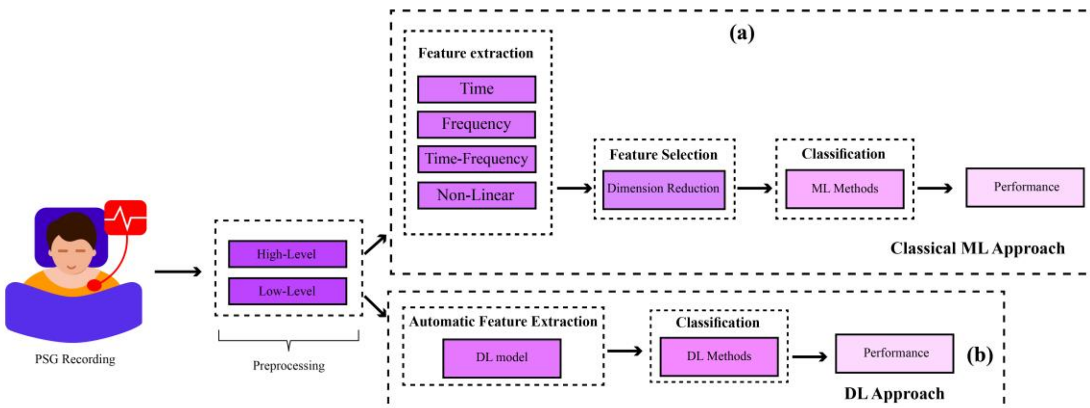


Fig. 3. Illustration of automated diagnosis sleep apnea using of AI methods.

4.1. Datasets

In this section, various available datasets have been introduced for the research in Apnea detection. Each of them has been discussed in the following.

4.1.1. St. Vincent's University Hospital / University College Dublin Sleep Apnea Database

This dataset contains 25 signals of PSG from adult cases with apnea disorder [61]. The cases were selected in a six-month period from the cases visiting the sleep disorders hospital of St Vincent University for the diagnosis of Apnea, obstructive central Apnea, or primary snoring. The number of cases was 25, out of which 21 were male, and four were female. In this dataset, there are various data: ECG, EMG, EOG, EEG, Thermistor,, ribcage movements, abdomen movements, finger SpO2, snoring (tracheal microphone), and body position. In this dataset, sleeping steps have been determined by an experienced sleep technologist according to the Rechtschaffen and Kales standard [61].

4.1.2. Apnea-ECG Database

This dataset includes signals from 70 cases which is equally divided for training and test [62-63]. The signals recording was done in 7-10 hours. Each signals recording includes an ECG signal, a set of interpretations of Apnea by a human expert (according to the simultaneous recording of respiration and signal), and a set of QRS interpretations. In addition, eight records are accompanied by four extra signals, which include respiration signals from the chest, abdomen, nose airflow, and SpO2. More information has been provided in references [62].

4.1.3. Sleep-EDF Database Expanded

In this dataset, PSG recording has been performed from 198 cases, which includes EOG (horizontal), EEG (Fpz-Cz and Pz-Oz), EMG, and event marker. In addition, some of the recordings also have rectal body temperature and oro-nasal respiration. The sleep patterns have been scored manually by the educated experts according to the Rechtschaffen and Kales instructions. More information on this dataset has been indicated in [63-65].

4.1.4. Sleep Heart Health Study PSG Database

The Sleep Heart Health Study (SHHS) has been performed by National Heart, Lung, and Blood Institute to investigate the cardiovascular consequences caused by respiration disorders in sleeping [66]. In the first part of this dataset, the signals recording was performed from 6441 males and females in the age range of 40. This signals recording was done from 1 Nov 1995 to 31 Jan 1998 and is called SHHS Visit 1. In addition, the second part of the signals has been recorded from Jan 2001 to June 2003, where 3295 individuals have participated and are called SHHS Visit 2. The performed PSG recording has various signals: EOG, EMG, thoracic and abdominal excursions, nasal-oral airflow, finger-tip pulse oximetry, ECG, heart rate, body position, and ambient light [66-67].

4.1.5. Multi-Ethnic Study of Atherosclerosis (MESA)

MESA is a research study from 6 centers supported by NHLBI in the field of relevant factors to the subclinical cardiovascular disease development and the process trend from subclinical to clinical cardiovascular disease on 6814 males and females in the age range between 45-84 years on 2000-2002 [68-69]. Also, four other tests have been performed in 2003-2004, 2004-2005, 2005-2007, and 2010-2011. In 2010-2012, 2237 cases participated in the MESA sleep test, out of which the PSG signals, the 7-day wrist actigraphy, and sleep questionnaires were recorded [68-69]. More information from this dataset has been provided in References [68-69].

4.1.6. MIT-BIH Polysomnographic Database

The MIT-BIH dataset is a set of several physiological signals during sleep which is recorded in Boston's Beth Israel Hospital Sleep Laboratory [70]. This dataset includes more than 80 hours of 4-channel, 6-channel, and 7-channel PSG recordings, each of which has EEG, ECG, and respiration signals [70].

4.1.7. PhysioNet/CinC 2018 Challenge

The biological signals of this challenge are collected by Computational Clinical Neurophysiology Laboratory (CCNL), Massachusetts General Hospital (MGH), and the Clinical Data Animation Laboratory (CDAC). This dataset includes 1985 cases that were under surveillance in the MGH sleep laboratory. The sleep steps have been interpreted by the experts in MGH according to AASM instructions. Various physiological signals like ECG, EMG, EOG, EEG, and SpO2 have been recorded from the cases and are placed in this dataset [71].

4.1.8. MrOS sleep study

MrOS is a study regarding osteoporotic fractures among males. Between the years 2000-2002, 5994 males with ages more than 65 registered in 6 clinical centers. Between Dec 2003 to March 2005, 3135 individuals of participants were chosen for the sleep study and were put under actigraphy studies for 3-5 days (without any surveillant). The sleep study aims to understand the relationship between sleep disorders and falling, fracture, mortality, and cardiovascular diseases [72].

4.2. Preprocessing Techniques

The preprocessing is an important step for the biological signals where the CADS based on AI are divided into two low-level and high-level techniques. The lower-level methods in preprocessing the biological signals include steps like noise removal, baseline correction, segmentation, and normalization [73-74]. These methods in improving the performance of CADS based on AI play an important part in the diagnosis of sleep apnea. In addition, researchers use a number of advanced preprocessing methods to increase the performance, which is called high-level preprocessing. In the CADS based on ML, the high-level preprocessing techniques often include the methods in the domain of frequency or time-frequency. The Fast Fourier Transform (FFT) [75] is a high-level preprocessing method in the frequency domain and is used in the some studies. The high-level preprocessing techniques in the time-frequency domain are include Gabor [cite], empirical mode decomposition (EMD) [76], discrete wavelet transform (DWT) [77], continues wavelet transform (CWT) [78], wavelet coefficients Thresholding (WCT) [79], and Bivariate fast and adaptive EMD (FAEMD) [80], which are used in sleep apnea detection. In addition, in the CADS based on DL, the data augmentation (DA) methods exist as one high-level preprocessing [81]. Also, in some research, the DWT [77], Hilbert–Huang transform (HHT) [82], short time Fourier transform (STFT) [83], and Mel-frequency Cepstral coefficients (MFCC) [84] methods were used as a high-level preprocessing step in the diagnosis of sleep apnea.

4.3. Machine Learning Techniques

This section introduces the most important parts of CADS based on ML, where various feature extraction and dimension reduction algorithms are presented. In the following, the feature extraction and dimensions reduction for diagnosis of sleep apnea are introduced.

4.3.1. Feature Extraction Methods

The feature extraction is the most important section in the CADS based on AI for sleep apnea detection, and these methods are divided into four categories in ML: Time-domain, Frequency-domain, Time-Frequency domain, and nonlinear. In Table (2), the research in the sleep apnea detection in the biological signals using ML techniques is provided. As obvious, in a part of Table (2), various feature extraction methods used in each study is demonstrated. Table (2) provides more details of the studies using the feature extraction methods in the diagnosis of sleep apnea. In the following, the feature extraction methods for diagnosis of sleep apnea are provided.

A) Time Domain and Statistical Features

The biological signals have important information, and in case of accurate extraction, we can detect various diseases such as epileptic seizures [85-86], schizophrenia [87-88], and sleep apnea [89] with high performance. Since the biological signals in the time domain demonstrate the body activity during the Apnea, the time-domain and statistical features are powerful tools in analyzing these signals. Also, the time-domain and statistical features are considered as the morphological analyst for investigating the biological signals [90-91]. In references [155, 189], various time-domain and statistical features are used for sleep apnea detection, and satisfactory results have been obtained. In Table (2), a summary of other papers are provided where they have applied the time-domain and statistical feature extraction methods for sleep apnea detection.

B) Frequency-Domain Features

Spectral analysis of the biological signals is done using methods in the frequency domain such as FFT. Accordingly, in most studies, frequency-domain feature extraction methods have been used for the diagnosis of sleep apnea [125]. The most important feature extraction method in the frequency domain is the power spectrum density (PSD) [92].

C) Time - Frequency Domain Features

In order to overcome the issues in the time and frequency domains, the time-frequency domain method are provided, which increases the accuracy and performance of CADS using biological signals [93-94]. In these methods, the times and frequency information are extracted from the biological signals, which are important in the processing of medical signals [93-94]. Some research have used the time-frequency methods, including biorthogonal antisymmetric wavelet filter bank (BAWFB) [95] and tunable Q-factor wavelet transform (TQWT) [96], for sleep apnea detection.

D) Non-Linear Features

The nonlinear features are recognized among the most important feature extraction methods and are used in the diagnosis of various diseases using biological signals [97-98]. The reason behind the tendency to use the nonlinear feature extraction methods by researchers is that most biological signals, e.g., EEG, have nonlinear and chaotic behavior [99]. Thus, the nonlinear feature extraction methods increase the accuracy of diagnosis of the disease in chaotic signals [99]. For the diagnosis of sleep apnea, the researchers have used nonlinear methods for the feature extraction, some of which include various methods such as entropy [100], fractal [101], correlation coefficients (CCE) [102], Lempel-Ziv complexity (LZC) [103], etc.

4.3.2. Dimension Reduction Methods

In the feature matrix, some features lack useful information for classification or have repeated information, which increases computational complexity in classification algorithms. This issue reduces the efficiency of CADS for the diagnosis of sleep apnea. In order to increase generalization and reduce the complexity of classification algorithms, it is necessary to have a dimension reduction step for the feature matrix [104]. For this purpose, a variety of techniques have been introduced that are divided into two categories, including feature reduction and selection. In the CADS based on ML, researchers have employed various techniques for feature reduction or feature selection, which are summarized in Table (2). The principal component analysis (PCA) is one of the most important feature reduction method that is employed in [105]. Besides, other essential feature selection techniques can be forward wrapper approach (FWA) [106], neighborhood components analysis (NCA) [107], normalized auto-correlation (NAC) [108], and sequential feature selection (SFS) [109] in the diagnosis of sleep apnea.

4.4. Deep Learning Methods

In this section, various DL models in the diagnosis of sleep apnea from biological signals are introduced. The DL models in this section include convolutional neural networks (CNN's) [110-112], generative adversarial networks (GANs) [113-114], recurrent neural networks (RNNs) [110-112], Autoencoders (AEs) [110-112], deep belief networks (DBNs) [110-112], CNN-RNN [110-112], and CNN-AE [110-112]. In the following, each one of these methods will be investigated.

4.4.1. Convolutional Neural Networks (CNNs)

CNNs have become the most recognized structure of deep neural nets in recent years, mostly due to their astonishing performance for any image or data processing task. The idea behind these structures has been around since the 1990s [110-112]; however, it was Alexnet's paper [110-112] that started the path of these networks by resolving many base idea shortcomings. Firstly developed on images, these networks take advantage of spatial patterns to create a robust representation of the data at hand; therefore, they can be applied to many types of data such as signals, images, and 3D scans.

A) 2D and 3D CNNs

Two of these structures are of utmost importance in biomedical signal processing, 2D-CNNs, and 3D-CNNs. Given the literature and studies were done on 2D-CNNs, many famous structures of these networks exist for different tasks, making them the best models for benchmarks [110-112]. Moreover, the transformation of many types of data, such as signals, into images is another vastly researched area, all of which help researchers to use these networks easily with a minimum required knowledge of the underlying math. As for 3D models [110-112]. The 3D scans and modalities present utterly useful information for the diagnosis; the performance of each system is deeply dependent on the quality of data, compelling the need for 3D-CNNs. 2D-CNN architecture for diagnosis of sleep apnea from PSG signals is shows in Figure (4).

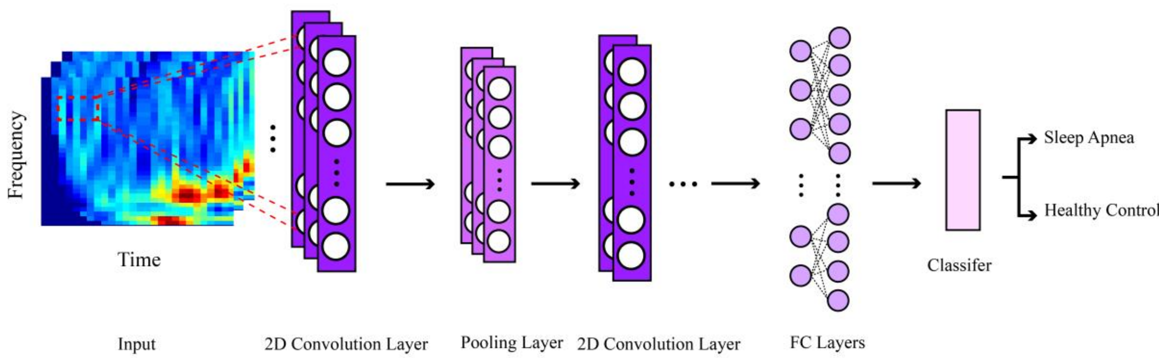


Fig. 4. Block diagram of 2D-CNN model for sleep apnea detection.

B) Transfer Learning

Transfer learning has been shaped to be the heart of many research papers in recent years [110-112]. With improvements in deep neural nets and hardware resources, many researchers have strived toward training new models on small datasets, especially in the field of biomedical data processing [115-116]; however, using transfer learning and pre-trained models has paved the path of using very deep models on small datasets dramatically. In this technique, a neural net is first pre-trained on a large dataset such as ImageNet; then, using trained weights as a starting point, the model is fine-tuned on desired datasets [110-112].

C) Generative Adversarial Networks

With the surge of various social media, data publicity in many fields such as sentiment analysis [113-114] is no longer considered a challenge. However, generative models' importance is two-fold; first, generating data similar to a data set introduces many challenges that solving them helps dramatically in other fields such as representation learning. Secondly, in many tasks such as biomedical data processing, public labeled data availability is still a big challenge. GANs were firstly introduced in 2014 by Ian Goodfellow [113-114]. By using a simple adversarial idea, two networks try to increase the loss of another one, one by generating data non-distinguishable by the other one and the other network by distinguishing the generated data from the original data [113-114]. GAN architecture for diagnosis of sleep apnea from PSG signals is indicated in Figure (5).

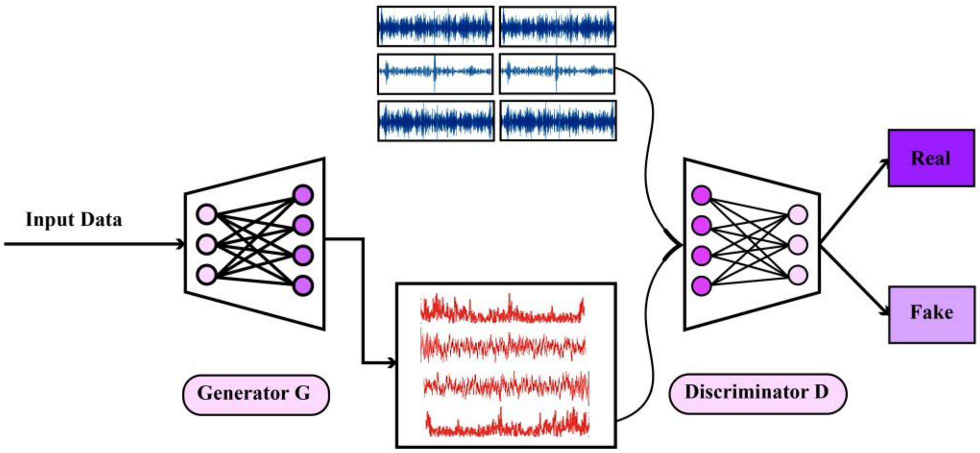


Fig. 5. Block diagram of GAN model for sleep apnea detection.

4.1.2. Autoencoders

Unsupervised learning has always been an arguably more exciting field of study for many researchers. The outcome of those studies has helped toward automation of many tasks, such as feature extraction and representation learning [110-112]. AEs are an example; these networks work by the idea of taking the input data into a latent space and then back to the original space and thus learn a useful encoding for data into the latent space [110-112]. These networks are also among the oldest methods used in neural nets [110-112]. AE architecture for diagnosis of sleep apnea from PSG signals is indicated in Figure (6).

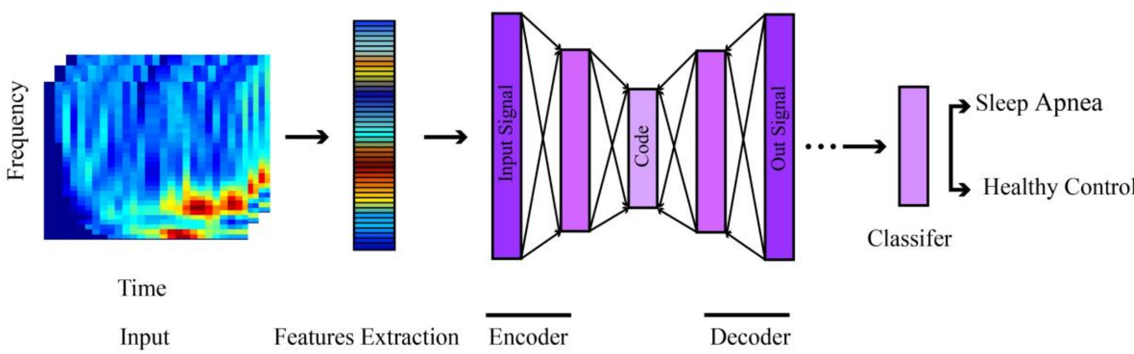


Fig. 6. Block diagram of standard AE model for sleep apnea detection.

4.1.3. Recurrent Neural Networks

Whilst the deep learning methods are widely referred to as representation learning methods, robust representation comes from accurately finding patterns in data. Yet data is presented in many shapes and forms; consequently, it is logical to design different network structures for various forms of data. Time series, such as EEG, ECG, and many other biomedical signals, are among the most primary methods of diagnosis, and proper detection of temporal patterns is essential in order to process these data precisely. Temporal patterns can be shown in the short or long term, and recurrent neural nets are designed with this in mind. The two most famous structures of these networks are LSTM and GRU, and they are extensively used for many tasks such as time-series detection and prediction [117], video processing [118], text generation [119], and epileptic seizure prediction [120], etc. RNN architecture for diagnosis of sleep apnea from PSG signals is indicated in Figure (7).

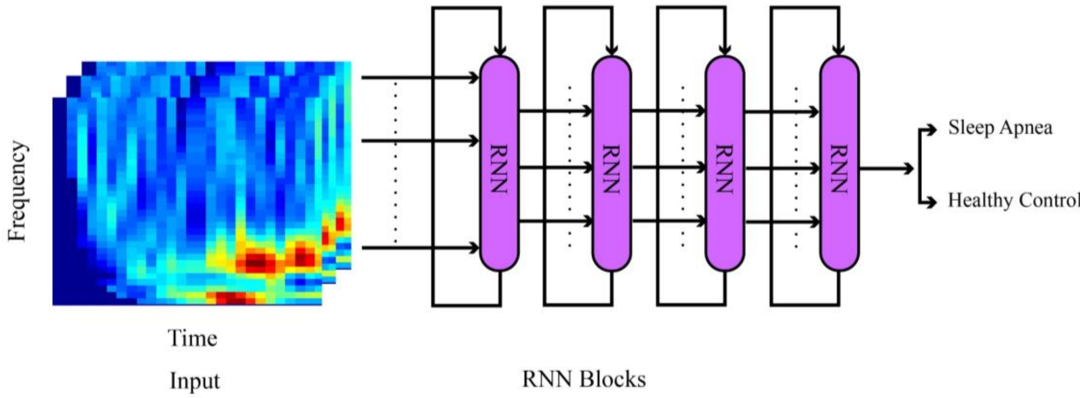


Fig. 7. Block diagram of RNN model for sleep apnea detection.

4.1.2. Deep Belief Networks

Restricted Boltzmann Machine (RBM), the building block of Deep Boltzmann Machine (DBM), is an undirected graphical model [110-112]. The unrestricted Boltzmann machines are also similar; however, they may also have connections between the hidden units. DBNs are unsupervised probabilistic hybrid generative DL models comprising of latent and stochastic variables in multiple layers [cite]. Moreover, a variation of DBN is called Convolutional DBN (CDBN), which is more suitable for images and signals, as it uses the spatial information of data [110-112].

4.1.6. Convolutional Autoencoders

CNN-AEs are a group of DL models that employs unsupervised learning and applies to various medical applications [121-122]. The architecture of these networks is based on AEs that employ Conv layers in the decoder and encoder sections [110-112]. First, images are inserted into the encoder layer, which is based on Conv, and the outputs are like compressed images. There are also Conv layers in the decoder section. This layer receives the images of the encoder section and performs the recovery of the images. CNN-AE architecture for diagnosis of sleep apnea from PSG signals is indicated in Figure (8).

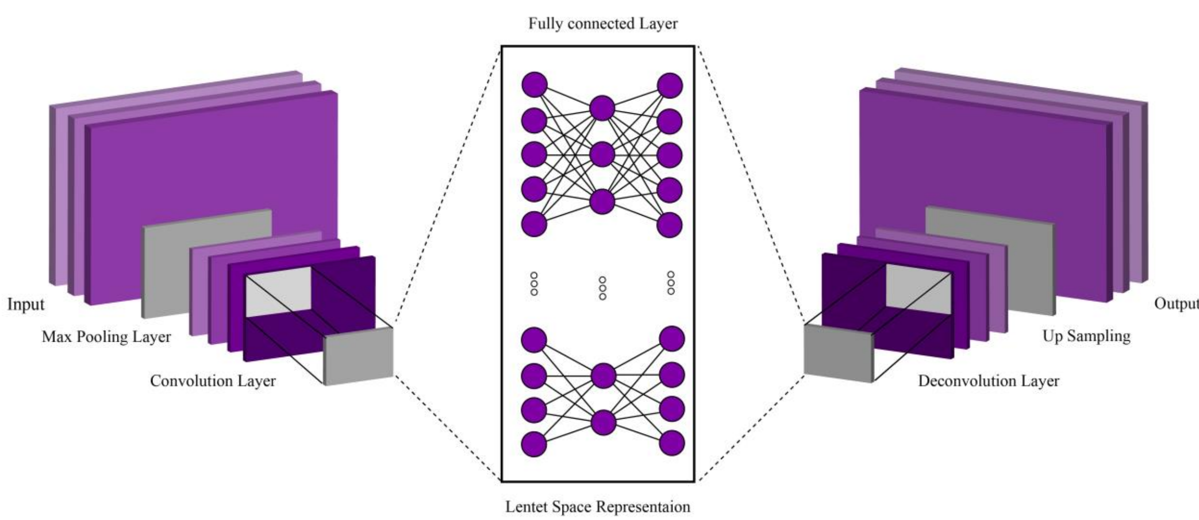


Fig. 8. Block diagram of standard CNN-AE model for sleep apnea detection.

4.1.7. Convolutional Recurrent Neural Networks

Architectures based on CRNN consist of two networks, including CNN and RNN. Due to the capabilities of CNN in learning spatial features and the capability of RNN in learning temporal features, this combined structure has captured lots of interest [110-112]. In CRNN architecture, the signals are first applied on the input of the CNN network and, after passing through several Conv layers, are inserted into the input of the RNN network [110-112]. One CRNN architecture for diagnosis of Apnea from PSG signals is indicated in Figure (9).

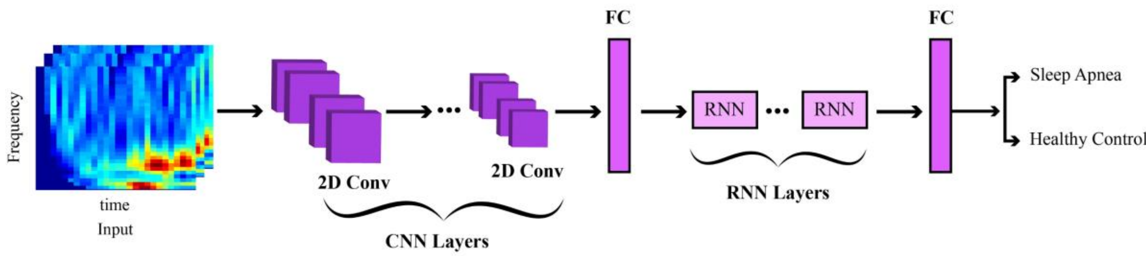


Fig. 9. Block diagram of standard CNN-RNN model for sleep apnea detection.

Table 2. Automatic diagnosis of sleep apnea using ML methods

Work	Datasets	Modalities	Number of Cases	High level Preprocessing	Windowing	Feature Extraction	Feature Selection	Classifier	K fold	Performance Criteria (%)
[123]	MIT Standard Data	ECG	40 Obstructive sleep apnea(OSA)	Discrete wavelet packet decomposition (DWPD)	--	FFT, WPD	NA	SVM	NA	Acc=93.34 Sen=90 Spe=100
[124]	PhysioNet Apnea-ECG database	ECG	35 OSA	Gabor Filters	1 Min	Histograms of Local Descript,1D-LPQ+1D-MLBP	Weighted Histogram Concatenation	LS-SVM	10	Acc=93.31 Sen=93.05 Spe=93.46
[125]	University Hospital Leuven (UZ Leuven)	PPG signal	26 Polysomnographic Recordings	--	40 Sec	STD, the Power at High and Low Frequency (PLF) Bands	FWA	LS-SVM	NA	Acc=72.66 Sen=73.81 Spe=72.55
[126]	PhysioNet Dataset	ECG SpO2	70 Records	NA	--	Multimodal Features	NA	SVM	10	Acc=96.64
[127]	Clinical	ECG RES	15 OCA, 17 Normal	--	--	Time Domain and Frequency Domain Features	Weighted Decision Method	SVM	NA	Acc=80 Sen=60 Spe=100
[128]	MIT/BIH Dataset	EEG	16 Subjects (1195 Normal and 947 Apnea Signals)	Decomposition	--	HFs-based Statistical Features	PSO	LS-SVM	NA	Acc=98.82 Sen=98.66 Spe=99.03
[129]	UCD	ECG	40 Healthy Subjects, 13 Apnea	Alternate Direction Method of Multipliers (ADMM), EMD	--	Energy and RR Interval	NA	SVM	10	Acc=97.5 Sen=95.45 Spe=100
[130]	Clinical	ECG SpO2 BMI	148 OSA, 33 unaffected	Pan–Tompkins	--	Different Features	NA	Multi-Layer FNN	NA	Acc=97.8 Sen=98.6 Spe=93.9
[131]	UCD	SpO2	25 Subjects	--	1 Min	Statistical Features	NA	SVM	10	Acc=90.2 Sen=87.6 Spe=94.1
[132]	UCD Dataset	SpO2	25 Subjects (1457 Apnea Events and 2278 Non-apnea Events)	--	1 Min	Statistical Features	???	SVM	10	Acc=90.2 Sen=87.6 Spe=94.1
[133]	PhysioNet Apnea-ECG database UCD	ECG	95 Single-lead ECG Recordings	DWT	1 Min 30 Sec	Entropy Features	SFFS	SVM	10	Acc=95.71 Sen=95.83 Spe=95.66
[134]	Clinical UCD	Thoracic Respiratory Effort and SpO2 Signals	18 Healthy Individuals, 18 OSA, 18 central sleep apnea (CSA) 25 Subjects	--	--	Different Features	GA	SVM	NA	Acc=90.9 Sen=90.9 Spe=100
[135]		EEG				Multi-Domain Feature Extraction		LS-SVM	6	Acc=97.7 Sen=97 Spe=94.2

[136]	PhysioNet	ECG	70 Records	Wavelet Decomposition, Wavelet Reshaping, QRS Detection	NA	Cubic B-type Interpolation Wavelet Transform	???	SVM	NA	Acc=90.52 Sen=86.1 Spe=93.4
[137]	MIT/BIH Dataset	EEG	16 Subjects	Adaptive Hermit Decomposition	30 Sec	Artificial Bee Colony (ABC)	Fisher-score Ranking Test	ELM	10	Acc=99.53 Sen=99.47 Spe=99.58
[138]	Childhood Aden tonsillectomy Trial (CHAT) Pediatric Department of the Hospital General Universitario of Valencia	SpO2	453 Children (43% of them suffered severe OSAS) 27 Patients	Performing a Standardization Process	--	Different Features	L1 penalty term	LR	15	Acc=79 Spe=96 AUC=90
[139]	PhysioNet Apnea-ECG database	EDR RR-Time-series	70 ECG Recordings	Pan-Tompkins Algorithm, PCA	1 Min	Novel Sparse Residual Entropy (SRE) Features (Sparse Residual Entropy Features)	NA	SVM	10	Acc=78.07 Sen=78.01 Spe=78.13
[140]	PhysioNet Apnea-ECG database Apnea-ECG Dataset Generated for PhysioNet/CinC Challenge 2000	ECG-derived respiration (EDR)	20 Simultaneously Lead II ECG Recording 70 Single-lead (lead II) ECG Recordings	Pan-Tompkins Algorithm, Correcting the RR Series	1 Min	Time and Frequency Domain Features	Temporal Feature averaging	SVM	35	Acc=90.9 Sen=89.6 Spe=91.8
[141]	Apnea-ECG Database	EDR HRV	70 single lead ECG Recordings	Pan-Tompkins Algorithm, PCA	1 Min	FuEn	NA	KELM	10	Acc=76.58 Sen=78.02 Spe=74.64
[142]	Clinical	Pressure-sensitive mats (PSM)	9 Subjects	Occupancy Extraction, SNR-maximizing Sensor Signal Combination Method	30 Sec	Time and Frequency Domain Features	NA	BiLSTM	5	Acc=95.1 Sen=85.7 Spe=96
[143]	PhysioNet Dataset	ECG (EDR, HRV)	70 ECG Recordings	--	1 Min	Different Features	Quintessential Wise Feature Selection	Artificial Neural Network (ANN)	NA	Acc=82.12 Sen=88.41 Spe=72.29
[144]	MIT/BIH Dataset	EEG	16 Subjects (947 Apnea EEG Epochs, 1195 Control Epochs)	TQWT	--	LZC Feature	NA	KNN	10	Acc=96 Sen=95.68 Spe=96.22
[145]	PhysioNet Apnea-ECG database	ECG	32 Subjects (10,480 Normal Epochs, 6513 Apnea Epochs)	BAWFB	1 Min	FuEn, LogEn	KWT	LS-SVM	35	Acc=90.11 Sen=90.87 Spe=88.88
[146]		ECG	35 Subjects		1 Min	FuEn, LogEn	T-Test	SVM	35	Acc=90.87

	PhysioNet Clinc Challenge-2000 Database			Wavelet Frequency-bands (WFBs)			Forward Wrapper Feature Selection			Sen=92.43 Spe=88.33
[147]	Clinical	MRI	3 Subjects (1 Snorer)	FFT, CWT	--	Oscillation Features	NA	NA	NA	NA
[148]	PhysioNet Apnea-ECG database	ECG	35 Subjects with Apnea-hypopnea Index (AHI)	FFT	1 Min	Statistical Features, Entropy	KWT	SVM	NA	Acc=92.59 Sen=89.7 Spe=94.67 Pre=91.27
	MIT-BIH Dataset		--							
	University College Dublin sleep apnea database (UCDDB)		35 Subjects with Apnea-hypopnea Index (AHI)							
[149]	Clinical	Different Signals	213 OSA, 66 No OSA	Data Sampling (SMOTE)	--	Different Features	Permutation Feature Importance	SVM	NA	Acc=83.33 Sen=80.33 Spe=86.96
[150]	MIT-BIH Dataset	EEG	16 Subjects	HHT	30 Sec	Different Features	NA	SVM	NA	Acc=96 Sen=100 Spe=98
[151]	Clinical	Akaike's Information Criterion (AIC)	154 OSA, 96 Without OSA	--	--	Different Features	Stepwise Selection Backward Elimination	SVM	NA	Acc=79.7 Sen=71.4 Spe=84.7
[152]	PhysioNet	ECG	35 Subjects	--	1 Min	Different Features	--	SVM, BPNN, IBPNN	--	Acc: 85%
[153]	MIT-BIH Dataset	EEG, Abdomen Movements, Nasal flow, Ribcage Movements, Snoring	25 Subjects	DWT	30 Min	Statistical Features	--	--	--	--
[154]	Polysomnographic studies (University Hospital Leuven in Belgium)	SpO2	79 Subjects	DWT	--	Phase Space Reconstruction, Convex Hull Algorithm	--	KNN, LS-SVM	--	Acc: 93%
[155]	University of Chicago Medicine Comer Children’s Hospital (Chicago, IL, USA)	SpO2	298 Subjects	DWT	--	Mean, Variance	--	logistic regression (LR)	--	Acc: 81.9%, Sens: 79.1%, Spec:84.1%
[156]	data collection was conducted in the Sleep Center of South Campus of Guang’anmen Hospital, China Academy of Chinese Medical	Snore	14 Subjects	Pre-emphasis technique	Different Times	NSPC, MFCC	PCA	SVM	--	Acc: 87.05%

[157]	MIT-BIH Dataset	ECG	16 Subjects	Filtering	--	Different Features	--	SVM	--	Acc=80.8 Sens=80.6 Spec=79.8
[158]	PhysioNet	ECG	32 Subjects	Data transformation technique	Different Times	Different Statistical Features	--	Different Classifiers	10	Acc= 94.32
[159]	PhysioNet	ECG	35 Subjects	DT-CWT		Statistical Features	ANOVA	Different Classifiers	10	Acc: 84.4
[160]	Clinical	physiological radar monitoring system (PRMS)	5 Subjects	linear demodulation	60 Sec	PSD, packing density and linear envelop error from radar captured paradoxical breathing patterns	--	SVM, KNN, RF	--	Acc=93.75
[161]	PhysioNet Apnea Database	ECG, SAO2, Airflow, Abdominal, Thoracic	8 Subjects	--	Different Times	Time-Domain and Non-Linear Features	ANOVA	SVM	--	AUC = 95.23 Sen = 94.29 spec = 96.17
[162]	recordings of patients referred to the University Hospitals Leuven	SpO2	100 Subjects	Sharp changes and ripples correction	5 Min	143 features and their logarithmic Transformation	--	LS-SVM	--	Acc:76.7
[163]	PhysioNet ECG Apnea Database	ECG	70 Subjects	TQWT	1 Min	CCE	--	MLP, Bagging, RF	10	Acc= 92.78 Spec=93.91 Sens= 90.95
[164]	Tianjin Chest Hospital dataset EEG	EEG	30 Subjects	DWT	10 Sec	ApEn	RFE	KNN, SVM, RF	--	Acc= 94.33% Sens= 93.10 Spec= 95.07
[165]	PhysioNet Apnea-ECG database	ECG	10 Subjects	DWT	2 Sec	Mean RR, RMSSD, SDNN, Variance, LF, HF, LF/HF ranges considered	--	NARX	--	Sens= 93.3 Spec=91.8 Acc= 92.55
[166]	Sleep Neurological Laboratory	ECG	--	Amplitude Respiratory Modulation	--	SSWT, ISSWT	--	--	--	--
[167]	PhysioNet Apnea Database	SpO2	8 Subjects	--	1 Min	Time and Frequency Domain Features	GA	MLP	--	Acc: 97.7
[168]	PhysioBank database, collected at St. Vincent's University Hospital Sleep Disorders Clinic in Dublin	EEG	25 Subjects	DWT, HT	30 Sec	Different Features	ANOVA	FFNN	--	Acc=77.3
[169]	Clinical	ECG	241 Subjects	Different Preprocessing Techniques	300 Sec, 100 Sec	Different Features	PCA	SVM, KNN, OPLS, LDA	--	Acc= 74 Sens= 88 Spec= 61
[170]	PhysioNet Cardiology 2000 Challenge Dataset	ECG	--	RR intervals were constructed (by Pan Tompkins	1 Min	DNN	--	SVM-HMM	--	Acc=84.7

				algorithm), RR intervals were interpolated into 100 points						
[171]	Different Datasets	EEG	--	EMD	--	R peak value, RR interval, peak values of P and T waves	--	SVM	--	Sens=90 Spec=85 Acc=93.33
[172]	PhysioNet and Clinical Dataset	ECG	70 Subjects	Pan-Tompkins algorithm	--	Different Time Features	PCA	SVM, RF, LDA, DT	--	Acc= 95.01 Sens=92.17 Spec=94.79
[173]	Amrita Institute of Medical Sciences Dataset	ECG and Respiratory Effort signals	32 Subjects	HRV, RRV	--	Different Time and Frequency Features	NAP	SVM	--	Acc: 50
[174]	University of Chicago (Chicago, IL, USA)	oronasal airflow (AF), Sp02	946 (records were studied)	DWT	10 Min	ODI3 (spo2), Four statistical moments, maximum minimum amplitude, energy, wavelet entropy	FCBF	Different Classifiers	--	Acc=90.99
[175]	PhysioNet Apnea-ECG database	ECG	32 subjects	Pan-Tompkins Algorithm	5 Min	CgSampEn2D	Different Tests	Different Classifiers	5	Acc=93.3 Sen=92.5 Spec=95
[176]	MIT-BIH Dataset	ECG	10 Recordings	--	1 Min	Mean, Median, Variance, Ratio of 2 Consequent R-R Intervals, Wavelet Entropy		Ensemble-Bagged Tree classifier		Acc= 89.6
[177]	PhysioNet Apnea-ECG database	ECG	70 Recordings	Pan-Tompkins Algorithm, EMD	1 Min	The First Five IMFs, Mean and Variance, Sum of The Amplitudes of Cross Power Spectral Density (CPSD)	--	PSO_MLPNN	--	Acc= 97.66 Sen= 97.78 Spec= 97.96
[178]	Clinical	Respiratory Inductance Plethysmography (RIP), Nasal Airflow, ECG, SpO 2, Accelerometers Data	28 Subjects	--	300 Sec, 5 Min, 20 Sec	Different Features	NCA, NAC	RUSBoosted Trees	--	Acc=89 Sen=80 Spec=100
[179]	Sleep Heart Health Study (SHHS1)	SpO2	5,804 Subjects	--	--	Classic Clinical Features, Statistics and Non-Linear Measures in Time Domain, Frequency Domain Analysis	--	Least-Squares Boosting (LSBoost)		Acc=94.6 Sen=82.2 Spec=96.3
			2,647 Subjects							Acc=91.6 Sen=89.8 Spec=92
	SHHS2 RHUH		322 Patients							Acc=96.6 Sen=99 Spec=63.6

[180]	University of Chicago (UofC) Childhood Adenotonsillectomy Trial (CHAT)	ECG	1738 Pediatric Subjects	FFT	5 Min	Hilbert Transform: Relative Power (RPs)	NA	LDA	NA	Acc=82.8 AUC=79.6 Spe=84.7 Sen=63.8
[181]	Clinical	PPG, SpO_2	96 Signals	--	1 Min	using the Smooth Pseudo Wigner-Ville Distribution (SPWV) and the Lomb Periodogram	T-Test	SVM	10	Acc=92.6
[182]	ISRUC EDF CAP	EEG	89 (57 Sleep Apnea and 32 Normal Subjects) 40 Subjects 20 (4 Sleep Apnea and 16 Normal Subjects)	Decomposition	30 Sec	Entropy, Energy, Heart Rate, Brain Perfusion, Neural Activity, Synchronization	NA	SVM	NA	Acc=90 Sen=100 Spe=83
[183]	Apnea-ECG Dataset	Respiratory Signal	8 Records	HHT	1 Min	time and frequency domain features	NA	RF	NA	Acc=95 Pre=95.1 F1=95.1 Sen=94.4 Spe=96
[184]	Sakarya Hendek State Hospital's Chest Diseases Sleep Laboratory	ECG, EEG	10 OSA Patients	--	30 Sec	Different Features	Fisher Score PCA	Ensemble Classifier	NA	Acc=87.12 Sen=90 Spe=85
[185]	Pediatric Sleep Unit at the Comer Children's Hospital of the University of Chicago	Airflow (AF) Signal	946 AF signals	--	30 Sec	Bispectral Features	Fast Correlation-Based Filter (FCBF)	MLP	NA	Acc=90.15
[186]	MIT-BIH Dataset	EEG	16 Healthy Subjects, 8 Unhealthy Subjects	DWT	1 Min	Energy of Each Coefficients, Mean, Median, Standard Deviation	--	SVM	NA	Acc=98
[187]	PhysioNet Apnea-ECG database SDMCMSH	ECG	70 Recordings 35 Recordings	Different Methods	--	Different Features	PCA	ANN-LM, ANN-SCG	--	???
[188]	Clinical	EEG	30 Patients	Decomposition	--	Sample Entropy, Variance	NCA	RF, KNN, SVM	10	Acc=88.99 Recall=86 Prec=89
[189]	Clinical	PSG	184 Patients	WCT, DWT, SMOTE	--	Statistical Features	ANOVA	Different Methods	10	Acc= 90.18 Prec=78.5 Recall=86.4 F1-Score= 82.3
[190]	PhysioNet Apnea-ECG database	ECG	70 Recordings	DWT	1 Min	Different Features	Different Techniques	LDA, KNN, SVM, RF	10	Acc= 90.3 Sen= 86.6 Spec= 92.59

[191]	Clinical	Single Channel ECG	10 Patients	--	10 Sec	25 Features	Fisher Score, PCA	DT, KNN, SVM, Ensemble Classifiers	--	Acc=85.12 Sen=85 Spec=86
[192]	PhysioNet Apnea-ECG database	ECG	70 Recordings of 32 Subjects	--	5 Min	Frequency Domain Features	--	--	--	Acc= 90 Sen= 87.5 Spec=95
[193]	UCD	SpO2	25	Optimal Duration-Frequency Concentrated (ODFC), WFB	1 Min	Shannon Entropy	--	Ensemble RUSBoosted Trees	10	Acc=89.21
	SAE Dataset		8							Acc= 95.97
[194]	PhysioNet Apnea-ECG database	ECG	70	--	1 Min	AR Coefficients, ACF Based Features	SFFS	Different Classifiers	10	Acc= 93.90
[195]	Clinical	EEG	84	Frequency Band Decomposition	30 Sec	Normalized Symbolic Transfer entropy, Normalized Posterior-Anterior, Statistical Features	F-Score	DT, ANN, KNN, SVM	--	Acc=98.80
[196]	Taichung Veterans General Hospital (TCVGH)	PSG	300	--	--	Waist Circumference, Mean Blood Pressure (BP), Systolic BP	--	EFNN, ANN, Stepwise Regression	5	Different Results
[197]	Tianjin Chest Hospital	EEG	30	DWT	30 Sec	Approximate Entropy	SVM-RFE	KNN, RF	--	Acc=94.33 Sens= 93.10 Spec=95.07
[198]	PhysioNet Apnea-ECG database	ECG	35	--	1 Min	Different Statistical and Frequency Features, SampEn, RenEn,TesEn	SFS	SVM, KNN	10	Acc=81.40
[199]	PhysioNet Apnea-ECG database	ECG	60	--	1 H	Different Statistical and Frequency Features	LDA	ANN	--	Acc=98.30
[200]	EEG PhysioNet	EEG	5	--	10 Sec	Energy, Entropy, Statistical Features	--	Bagging	5	Acc= 95.10 Sens= 93.20 Spec=96.80
[201]	Clinical	Airflow (AF), SpO2	974	--	30 Sec	Different Features	Fast Correlation-Based Filter Method	Multiclass Adaboost	--	Acc= 90.26
[202]	EEG PhysioNet	EEG	31	FAEMD	1 Min	Temporal, Spectral, Time–Frequency Domain Features	Non-Parametric Statistical Test	RF ,SVM	10	Sens= 82.27 Spec= 78.67
[203]	Apnea-ECG Data	ECG	70	--	1 Min	Time Domain Features, Spectral Domain Features	SFS	SFS Algorithm	10	Acc=93.26

Table 3. Automatic diagnosis of sleep apnea using DL methods

Works	Dataset	Modality	Number of Cases	Length Window	High Level Preprocessing	Deep Learning Methods	Classifier	K-Fold	Performance
[204]	PhysioNet Sleep Database	Blood Oxygen Saturation, Oronasal Airflow, Ribcage and Abdomen Movements	25	5 Sec	--	CNN	Fully Connected Layer	--	Avg Acc=79.6
[205]	Sleep Laboratory at the Toronto Rehabilitation Institute	Airflow, SpO2, Chest and Abdominal Movements	80	10 Sec	Morphological Features Extracted	CNN, LSTM	Sigmoid	5	F1 Score (event-by-event detection algorithm): Between 12-71%
[206]	CHA database	SpO2	746	20 Min	--	CNN	Linear	--	Acc=95.1
[207]	Alexandra Hospital, Brisbane, Australia	EEG, EOG	891	30 Sec	--	CNN, LSTM	Softmax	10	Acc=84.5
[208]	PhysioNet Apnea-ECG database	SPO2	8 (apnea-ECG dataset)	1 Min	--	DBN	Softmax	10	Acc=97.64
	UCD database		25 (UCD dataset)						Acc=85.26
[209]	Princess Alexandra Hospital (Brisbane, Australia)	EEG, EOG	717	30 Sec	--	CNN, LSTM	Softmax	--	Acc=83.2
[210]	SHHS-1 dataset	ECG, THOR and ABDO	2100	30 Sec	--	LSTM, FLSTM	Tanh	--	Acc=83.4
[211]	Sleep Data And 3D Scans Were Collected Prom the Patients Appearing to Genesis SleepCare for Different Sleep Issues	Face Image	69	--	--	VGGFace, PAMs	--	--	Acc: 67.42%
[212]	MIT-BIT Dataset	IHR, spo2	--	--	--	LSTM-RNN	--	--	Acc=95.5
[213]	--	PSM	9	30 Sec	--	BiLSTM, TCN	Softmax	--	Acc=95.1
[214]	MrOS Sleep Study	ECG	545	15 Sec	--	1-D CNN, LSTM, DNN	Softmax	10	Acc=79.45
[215]	PhysioNet Apnea-ECG database	ECG	--	--	--	LSTM	Softmax	--	Acc=97.80
[216]	Seoul National University Hospital, Multi-Ethnic Study	Thoracic, abdominal, spo2	129	10 Sec	--	CNN	Sigmoid	--	Average accuracy: 94.9%
	MESA		50						
[217]	--	Abdominal and Thoracic Triaxial Accelerometers, SpO2, ECG	--	--	--	LSTM	Softmax	--	Acc=92.3

[218]	SHHS	ECG	500	5 Min	--	DNN (optimization with Dde)	Relu	--	Acc=72.95
[219]	PhysioNet	ECG	35	1 Min	--	CNN	Relu	--	Acc=98.91 Sen=97.82 Spec=99.20
[220]	Polysomnography (PSG) data for 17 patients recorded at the Interdisciplinary Center of Sleep Medicine in Charité- Universitätsmedizin Berlin in Berlin, Germany	Oronasal thermal airflow (FlowTh), nasal pressure (NPRE), and abdominal respiratory inductance plethysmography (ABD)	17	10 Sec	--	LSTM, Bi-LSTM	Softmax	--	Acc=85 Spec=83.7 Sen=90.3
[221]	Samsung Medical Center (Seoul, Korea).	ECG	86	10 Sec	signal was converted into a 2D	Different Models	Softmax	--	Acc=99
[222]	PhysioNet	ECG	35	1 Min	--	DNN	Relu	--	Acc=67.39
[223]	MESA sleep study	Nasal Airflow	100	30 Sec	--	CNN	Softmax	10	Acc=74.70
[224]	MrOS sleep data	Airflow	520	--	--	DNN	Softmax	10	Acc=63.70
[225]	Physionet/CinC Challenge	EEG, EMG	--	30 Sec	--	CNN	Softmax	5	AUPRC=0.315 AUROC=0.858
[226]	Apnea-ECG database from PhysioNet	ECG	--	1 Min	--	DNN	Logistic Regression	--	Acc=84.7
[227]	MESA	PSG Nasal Airflow Signal	1,507	30 Sec	--	CNN	Softmax	10	Average F1-Score= 79.7
[228]	Physionet Computing in Cardiology (CinC) Sleep Apnea Challenge database MIT BIH Arrhythmia database	ECG	35	--	ECG converted to IHR	LSTM-RNN	--	5	Acc=99.99
[229]	Apnea Database v2.0 Hospital Quirón Salud de Málaga (Spain)	Speech	525	--	--	X-Vectors Embeddings, Domain-Adversarial Training (DAT)	Softmax	15	Acc=76.60
[230]	CapnoBase Vortal	PPG, Respiratory Signal	42 (CapnoBase)	8 Sec	--	ResNet	--	--	--
[231]	PhysioNet Apnea-ECG database	ECG	70	1 Min	--	CNN	Softmax	--	Acc=88.23 Sens=82.74 Spec=91.62
[232]	MIT-BIT Dataset	EEG, EOG	20	150 Sec	Removing Movement Epochs During Sleep	CNN	Softmax	4	Acc=81%
[233]	Sleep Center of Samsung Medical Center (Seoul, Korea).	ECG	86	10 Sec	--	CNN	Softmax	--	F1_Score=87

[234]	Sleep Center of Samsung Medical Center (Seoul, Korea)	ECG	82	10 Sec	--	CNN	Softmax	--	--
[235]	Ziekenhuis Oost-Limburg, a hospital in Belgium, ROBIN bioZ data	Bio-impedance (bioZ) of the chest (ECG data is used for data alignment), Abdominal respiratory, Thoracic respiratory	25	30 Sec	--	KSTM	--	5	Acc=72.8 Sen=58.4 Spec=76.2
[236]	CHAT-baseline Dataset	SpO2	453	1 Min	--	CNN	Softmax	--	Acc=93.6 Spec=96.7
[237]	--	RFID	4	--	--	RNN-AE	--	--	TN: 94%, TP: 92%
[238]	PhysioNet Apnea-ECG database	ECG	35	1 Min	--	CNN, CNN-RNNs	Sigmoid	10	Avg Acc=89.11 Avg Sen=89.91 Avg Spec=87.78
[239]	Human Experiments conducted by team	Sound	4	3.2 Sec	Boosting	CNN, BstCNN	Softmax	--	Sen=89
[240]	EIT datasets were obtained of premature neonate patients provided by the Emma Children's Hospital, Academic Medical Centre (AMC), in the Netherlands	EIT boundary voltage	15	--	--	ResNet50 and SVM	Softmax	--	Acc=99
[241]	SHHS	PSG Records (SpO2 and HR Signals)	5000 Patients	30 Sec	--	Bi-GRU	Softmax, MV	--	Acc=90.13 Sen=94.13 Spec=80.26
[242]	Cleveland Children′s Sleep and Health Study database	EEG, EMG, ECG, Respiratory Channels Including Airflow, Thoracic and Abdominal Breathing	32 Participants	1 Min	--	1D-CNN	Softmax	--	Acc=98.97
[243]	SDB Datasets	Nocturnal PSGs, Single-Lead ECG Recordings	92 SDB Patients	10 Sec	--	RNN	Softmax	--	Acc=99 Sen=99 Spec=99
[244]	Clinical	Respiratory	8 Subjects	--	DWT	LSTM	Softmax	--	Acc=92 Sen=87 Spec=84
[245]	Apnea-ECG Database	ECG	70 ECG	1 Min	Extraction of EDR And HBI Signals, SSA, HHT	--	SVM and SAE-DNN Classifiers	10	Different Results
	UCD Database		--						
	PhysioNet Challenge Database		--						
[246]	Montreal Archive of Sleep Studies (MASS) Dataset Subset 2 (SS2)	PSG	19 Records	20 Sec	CWT	Recurrent Event Detector (RED)	Softmax	10	F1-Score=84:7 Rec=82:6 Pre=88:1
[247]	SHHS Visit 2	Single Channel EEG	2,650 Patients	30 Sec	Critical-Band Masking (CBM) technique	CNN	Softmax	10	Acc=76.7 MCC=54
	UCD		25 Participants						
	MIT-BIH Dataset		16 Patients						

[248]	Diagnostic Imaging Center, Kuopio University Hospital, Kuopio, Finland NeuroCenter, Kuopio University Hospital, Kuopio, Finland	SpO2 signal	1970 77	10 Min	--	CNN	Fully Connected Layer	--	Acc=88.3 Sen=90.9 Spec=95.4
[249]	St. Vincent's University Hospital	EEG	25 patients	10 Sec	Decomposition	LSTM	Dense	--	Acc=81.9
[250]	Sleep Heart Health Study (SHHS) Sleep-EDF Expanded (Sleep-EDFx) healthy Clinical	Single Channel EEG Signals from PSG Recordings.	100 Recordings 100 Recordings 10 Subjects	--	--	CCN-SE	Softmax	5	Acc=88.1 Pre=80.4 Acc=85.3 Pre=75.1
[251]	PhysioNet Apnea-ECG Dataset (PAD) University College of Dublin's Sleep Apnea Dataset (UCDSAD) the Best Apnea Interventions for Research (BestAIR)	Discontinuous RR-Interval Signals	243 Recordings	--	--	FENet	Softmax	--	Acc= 78.25 Rec= 90.64 Pre= 81.54 Spec= 45.18
[252]	PhysioNet Apnea-ECG database	ECG	35 ECG Recorded Apnea Signals	--	Data Augmentation	CNN	Softmax	--	Acc=97.80 Sen=100 Spec=93
[253]	Fırat University Research Hospital Sleep Room PSG Recordings	PTT signals	50 Patients, 50 Healthy	--	Spectrogram	AlexNet, VGG-16	SVM, KNN	10	Acc=92.78 Pre=94.25 Spec=98
[254]	PhysioNet Sleep-EDFx Dataset	Single Channel EEG	42 Subjects	30 Sec, 150 Sec	CWT	SqueezeNet	Softmax		Acc=85.07 Sen=77.06 Spec=95.78
[255]	Sleep-EDF-2013 Sleep-EDF-2018	2 Scalp EEG Signals	39 Recordings from 20 Subjects 153 Recordings	30 Sec	Mapping Label	RL+TCNN+ CRF	Average Ensemble	20 10	Acc=85.39 MF 1=79.27 Kappa=80 Acc=82.46
[256]	Multi-Ethnic Study of Atherosclerosis (MESA) SHHS	Single Lead ECG	1547 Records 1961 Records	--	--	DeepCAD	Sigmoid	--	--
[257]	MIT-BIH	EEG, ECG	18 PSG Signals Obtained From 16 Healthy Adult Subjects	30 Sec	--	Dual-Modal and Multi-Scale DNN	Sigmoid, Softmax	5	???
[258]	St. Vincent's University Hospital	EEG	25 Patients	1 Sec	--	FCNN	DNN	--	Acc=80.2 Sen=82.3 Spec=79.8
[259]	Sleep Disorders Unit, Loewenstein Hospital—Rehabilitation Center, Raanana, Israel	EEG, EOG, Chin EMG Signals	2,014 Patients	--	PSD Estimate, Spectrogram	CNN	Softmax	10	4 Category: Acc=60.6 Binary: Acc=77.2 Sen=76.5 Spec=77.9
[260]	Apnea-ECG Dataset	Single Lead ECG.	70 Recordings	10 Sec	--	CNN-LSTM	Softmax	--	Acc=96.1 Sen=96.1 Spec=96.2

[261]	Apnea-ECG Database	RR Interval from Single Lead ECG Signal	70 Records	1 Min	Christov Algorithm, Median Filter Algorithm, Data Balancing	MSDA-1DCNN	Weighted-Loss Time-Dependent (WLTD)	10	Acc=89.4 Sen=89.8 Spec=89.1
[262]	UCD	Single Channel EEG	25 Recordings From 25 Adult Subjects	30 Sec	HHT, AE	OCNN + SeNet	Softmax	--	Acc=88.4
	MIT-BIH Dataset		16 Recordings, From 16 Male Subjects						Acc=87.6
[263]	MGH-PSG Dataset	4 Scalp EEG Bipolar Channels	6,341 Patients	30 Sec	Bipolar Montage Generation	CNN-RNN	Softmax	5	Different Results
	Ambulatory Scalp EEG Dataset		112 Patients						
[264]	sleep center of the First Affiliated Hospital, Sun Yat-sen University (FAH database)	PSG	405 PSG Records	30 Sec	STFT, Grayscale Transform	Mr-ResNet	Post-Processing and Estimated AHI Values	--	Acc=91.2 Sen=90.8 Spec=90.5
	CMH dataset		45 Patients						
[265]	PhysioNet Apnea-ECG database	ECG	70 Single-lead ECG Recordings	--	DA	Contrastive Learning-based Cross Attention Framework (ConCAD)	Softmax	10	Acc=91.22
	MIT-BIH Dataset								
[266]	UCD	SpO2 Signals	25 patients	11 Sec	--	1D-CNN	Softmax	NA	Acc=97.08 Sen=84.65 Spe=97.42
[267]	Stanford Technology Analytics and Genomics in Sleep (STAGES)	PSG	1366 Patients (1756 Scans)	--	Transforming Scans, Least Squares Solution	ResNet18	Softmax	10	Acc=67 Sen=59 Spe=72
[268]	UCD	PSG, ECG	25 Patients	11 Sec	--	1D-CNN	Softmax	NA	Acc=99.56 Sen=96.05 Spe=99.66
[269]	ST. VINCENT's University Hospital	EEG	25 Patients	--	Variational Mode Decomposition (VMD)	CNN-BiLSTM	Sigmoid	NA	Acc=93.22 Sen=91.71 Spe=93.79
	The PhysioNet Computing in Cardiology Challenge 2018								
	MIT-BIH								
[270]	Clinical	DTI Data, sMRI	553 subjects	--	--	2D-CNN	Sigmoid	3	--
[271]	PhysioNet Apnea-ECG database	ECG	70 Sleep Apnea Patients	1 Min	Transforming ECG Data to IHR Value,	BiLSTM	NA	NA	Acc=82.24 Pre=76.95 Spe=82.95
[272]	Childhood Adenotonsillectomy Trial (CHAT)	SpO_2	3196 SpO_2 Signals	--	--	1D-CNN	LR	NA	Acc=97.8 Sen=83.9 Spe=99.3
	The University of Chicago (UofC)								
	The Burgos University Hospital (BUH)								
[273]	PhysioNet Apnea-ECG database	ECG, SpO_2	70 Recordings	1 Min	--	CNN-BiLSTM	Sigmoid	10	Acc=94.3 Sen=95.1 Spe=93.7
	Clinical		30 Patients						

[274]	PhysioNet Apnea-ECG database	ECG	70 primary records	--	Transformation	CNN-LSTM	Softmax	5	Acc=86.25 Pre=86.55 F1=87.68
[275]	Dataset A: Loewenstein Hospital – Rehabilitation Center	PPG Signal, EEG	2149 PSG Recordings	30 Sec	--	CNN-LSTM	Softmax	NA	Acc=83.3
	Dataset B: Sleep Disorders Centre, Princess Alexandra Hospital		877 Recordings						
[276]	Physionet	Respiratory Signals	25 Recordings	16 Sec	--	LSTM	Softmax	5	Acc=82.04
	SHHS-1		3610 Recordings						
[277]	Clinical	PSG	450 Subjects	30 Sec	STFT and Grayscale Transform	(Mr-ResNet)	NA	NA	Acc=91.2 Sen=90.8 Spe=90.5 F1=90.5
[278]	Apnea-ECG Dataset	ECG	70 PSG Recordings	10 Sec	--	CNN-LSTM	Softmax	NA	Acc=96.1 Sen=96.1 Spe=96.2
[279]	Apnea-ECG Dataset	ECG	70 Recordings	1 Min	--	1D-CNN	NA	NA	Acc=94 Sen=88
[280]	Clinical	ECG	24 Patients	1 Min	Pan-Tompkins Algorithm	LSTM	Sigmoid	5	Sen=100 Spe=100
[281]	Apnea-ECG Benchmark Database	ECG	35 Recordings	--	--	LSTM	Sigmoid	10	Acc=99.8 Sen=99.85 Spe=99.73
[282]	Clinical	36 PSG, IR-UWB Radar Data	40 Subjects	20 Sec	--	CNN-LSTM	Softmax	6	Acc=93 Sen=78.1 Spec=95.6
[283]	A3 Study	Nox-T3 and Flow Data	579 Patients	1 Min	Simple Baseline Adjustment (BLA) Procedure	CNN	--	10	Acc=76.09 Sen=78.33 Spec=72.17
[284]	Clinical	SpO2	1970 HSATs 77 Patients	10 Min	--	CNN	Averaging	--	Acc=88.3 Sen=90.9 Spec=95.4
[285]	Apnea-ECG	PSG	35 Recordings	60, 30 Sec	--	CNN	EPD	--	Different Results
	MIT-BIH		18 Patients						
	UCD		25 patients						
	MrOS-Visit2 Study		1026 Recordings (Visit2)						
[286]	SHIP	MRI	181 Subjects	--	DA	U-Net	--	5	Average Dice Coefficients 89, 87, 79
[287]	INTERSPEECH 2017 ComParE Snoring Sub-Challenge Datasets	Sound	828 Snore Samples	--	MFCC	VGGNet, Inception, ResNet	Softmax	--	Acc= 44.6
[288]	PhysioNet Apnea-ECG database	ECG	70 Subjects	1 Min	Scalogram, STFT, DA	2D-CNN	Softmax	10	Acc= 92.4 Sen= 92.3 Spec= 92.6

[289]	University College Dublin Sleep Apnea Database	EEG, ECG	25 patients	8 Sec	3 Recurrence Plots (RPs)	3 ResNet-50	MV	10	Acc=91.74 Sen=91.55 Spec=91.51
[290]	Apnea-ECG Dataset	ECG	70 Recordings	1 Min	CWT, Hybrid Scalogram Representation (EMD-CWT)	SCNN	Softmax	--	Acc=94.38 Sen=94.30 Spec=94.51
	University College Dublin Sleep Apnea Database		25 Patients						Acc=81.86 Sen=71.62 Spec=86.05
[291]	MIT-BIH Dataset	EEG, ECG, and respiration signals	16 Subjects	8 Sec	3 Recurrence Plots (RPs)	ResNet-18 and ShuffleNet	WMV	10	Acc=90.72 Sen=89.61 Spec=89.42
	St. Vincent's University Hospital/ University College Dublin Sleep Apnea Database	EEG, ECG, and respiration signals	25 Patients 16 Subjects						
[292]	UCD	EEG	128 Samples	NA	--	1D-CNN	Sigmoid	NA	Acc=80.05 Sen=79.53 Spec=80.56
[293]	Clinical	EEG ECG	500 Temporal Data	NA	Welch Method, Average PSD	Modified Fusion Convolution Neural Network (MFCNN)	Softmax	NA	Acc=91.7
[294]	Clinical	Nasal Airflow	500	15 Sec	STFT	Octave CNNs, Res2Net	--	NA	Acc= 91.23 Sens=90.81 Spec= 90.59
[295]	Apnea-ECG Data	ECG	32	1 Min	Data Division	1D-CNN	Softmax	NA	Acc= 97.1 Spec=100 Sens=95.7

5. Challenges

In this section, the most important challenges in the diagnosis of sleep apnea are discussed. These challenges fall into four categories, including PSG and neuroimaging datasets, ML techniques, and DL models. In the following, these challenges will are elaborately addressed.

5.1. Challenges in PSG Datasets

Recording PSG is known as the most important method for diagnosis of sleep apnea, and medical physicians widely use this method. As mentioned earlier, this signal recording method consists of ECG, EEG, EMG, EOG, S_po_2, and breathing signals. Various available PSG datasets are discussed in section 3.1. It can be seen that the presented datasets have a limited number of cases. In addition, some of these datasets lack different types of PSG signals. It is important for researchers to tackle the challenges in this section because they will be able to carry out more applicable studies on the diagnosis of sleep apnea using AI techniques.

5.2. Challenges in Neuroimaging Datasets

EEG is one of the most important biological signals that is employed for the diagnosis of various diseases, including sleep apnea. This modality is known as one of the PSG recordings and is employed to examine the brain function during apnea in sleep. Among the available datasets presented, the EEG modalities are often missing. In some other groups of datasets, this modality is available for researchers with a limited number of cases. On the contrary, EEG recording consists of essential information about functional of the brain [296], and studies in this field can help researchers with a diagnosis of sleep apnea. In addition, a variety of studies on the diagnosis of sleep apnea from magnetic resonance imaging (MRI) modalities are being conducted [297-298]. In clinical studies [297-299], researchers investigate to what point Apnea affects the structure and function of the brain. So far, no dataset containing MRI modalities has been presented, which is a challenge in this field. All in all, the provision of available datasets from various neuroimaging modalities will lay the foundation for interesting studies on the diagnosis of sleep apnea.

5.3. Challenges in ML methods

Diagnosis of sleep apnea using ML techniques is complicated. It is because the selection of feature extraction to classification algorithms for obtaining high accuracy for diagnosis of sleep apnea from PSG signals is significantly time-consuming and requires try and error. Besides, ML models are not very applicable to input data [56]. However, various PSG signals must be examined in the real diagnosis of sleep apnea. These issues create serious challenges in having access to applied software for researchers in the diagnosis of sleep apnea.

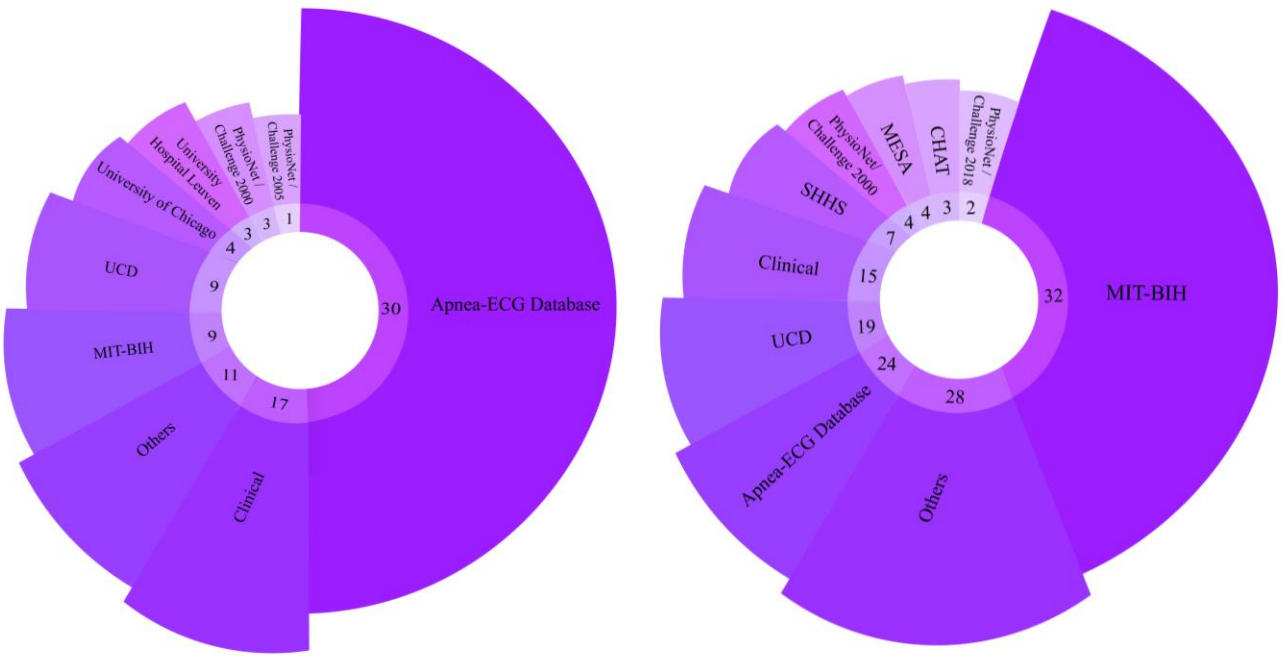
5.4. Challenges in DL Methods

This section addresses the most important challenges in the diagnosis of Apnea using DL methods. In Table (3), the studies on the diagnosis of Apnea from biological signals using different DL models are presented. According to Table (3), researchers have employed standard or simple DL models for the diagnosis of sleep apnea and have obtained acceptable results. Nevertheless, complex DL models, including graph [300-301], attention [302-303], and representation learning [304-305], etc. have not yet been used in the diagnosis of sleep apnea research. It is mainly because of a lack of access to large input data. Lack of access to hardware resources with high efficiency is another challenge that prevents [55-58].

6. Discussion

Apnea is a disorder that prevents breathing at some points in sleep [1-3]. Patients with sleep disorders suffer from a variety of breathing problems and have several problems, including uncomfortable sleep with loud snoring [1-5]. These disorders include three groups of CSA, OSA, MSA, and PSG recording is also used

for diagnosing them. Medical physicians use AI techniques as a suitable solution to diagnose sleep apnea. Many studies have been carried out in this field.
According to the importance of this issue, we conducted a review study to examine the sleep apnea detection using biological signals and AI techniques. Tables (2) and (3) summarized the research on sleep apnea detection using ML and DL techniques. In table (2), the most important information of the studies on the diagnosis of sleep apnea using ML techniques is provided, which includes dataset, preprocessing, feature extraction, dimension reduction, and classification methods. Furthermore, Table (3) demonstrates the information regarding DL studies on the diagnosis of sleep apnea.
In section 2, available datasets containing biological signals are provided along with their details for diagnosis of sleep apnea. Moreover, the employed datasets in ML and DL research for diagnosis of sleep apnea are also presented in a part of Tables (2) and (3). The number of datasets in ML and DL research are displayed in Figure (10). As shown in Figures (10.a) and (10.b), datasets Apnea-ECG database and MIT-BIH are most applicable to ML and DL studies for the diagnosis of sleep apnea, respectively.



(a) ML (b) DL

Fig. 10. Number of MRI dataset used in sleep apnea detection using AI techniques: (a) DL and (b) ML

The types of biological signals based on PSG for sleep apnea detection is also indicated in Tables (2) and (3). Accordingly, the number of biological signals based on PSG recording for ML and DL research are shown in Figure (11). According to Figures (11.a) and (11.b), the ECG signal is most applicable for diagnosis of sleep apnea using ML models. Additionally, compared to other biological methods, ECG recording is used more in DL studies.
Table (2) introduces different feature extraction and dimension reduction algorithms for diagnosis of sleep apnea. As mentioned in the previous sections, the feature extraction methods are divided into four categories, including time-domain, frequency-domain, time-frequency domain, and non-linear features [306-309]. The non-linear techniques are among the most useful feature extraction methods in studies on the diagnosis of sleep apnea. On the other hand, feature extraction in CDAS based on DL is carried out by deep layers. Table (3) demonstrates DL techniques in the diagnosis of sleep apnea. In this section, the number of DL networks for sleep apnea detection is indicated in Fig. (12). According to studies, the CNN

model is the most useful compared to other DL models, which is attributed to their high efficiency in processing applications of biological signals.

(a) ML (b) DL

Fig. 10. Number of biological signals based on PSG used in sleep apnea detection using AI techniques: (a) DL and (b) ML

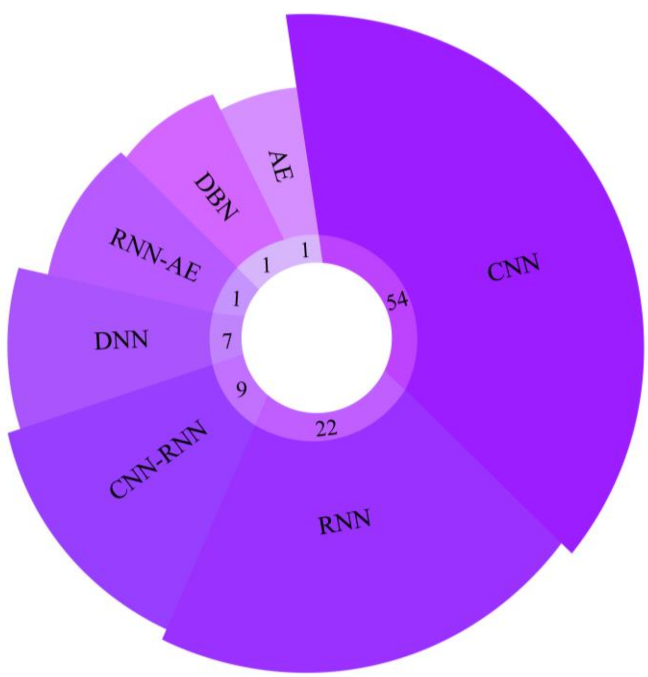
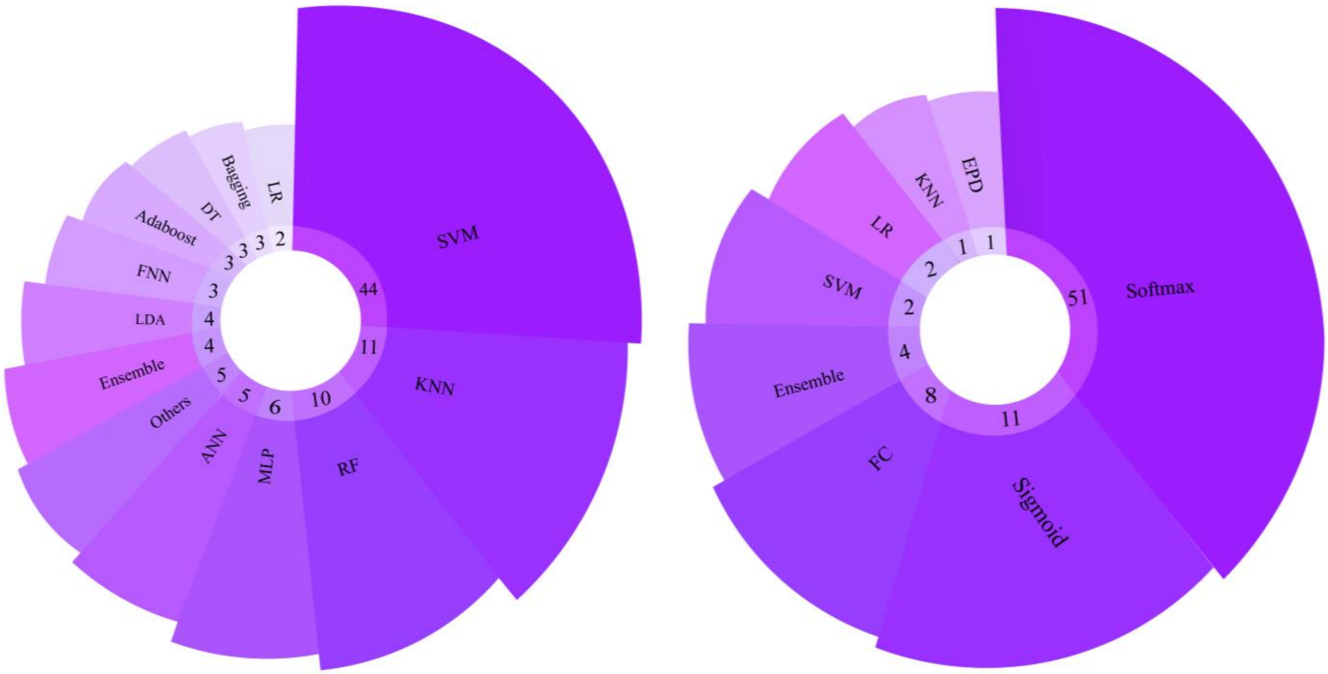


Fig. 12. Number of DL models for sleep apnea detection

The last part of the discussion addresses the classification algorithms. Classification techniques are the last section of CADS based on AI for the diagnosis of sleep apnea. The classification algorithms for the diagnosis of sleep apnea are indicated in Tables (2) and (3). According to DL and ML research, the number of classification algorithms for diagnosis of sleep apnea are shown in Figure (13). As shown in Figure (13.a), the support vector machine (SVM) method is most used in ML applications. Also, the Softmax method is more popular in DL studies than other techniques based on Figure (13.b).



(a) ML (b) DL

Fig. 13. Number of classification methods in sleep apnea detection: (a) DL and (b) ML

7. Future Works

In this section, future works for the diagnosis of sleep apnea in PSG signals using AI methods are proposed. In the first place, future works are allocated to the provision of available datasets containing PSG signals with a high number of cases. In addition, the provision of datasets with a variety of neuroimaging modalities is also discussed. In the second subsection, some of the newest ML techniques in the diagnosis of sleep apnea are proposed as future works. The newest DL techniques for future studies for sleep apnea detection are introduced in the third subsection. Finally, several ideas are mentioned in rehabilitation systems along with diagnosis of sleep apnea based on AI techniques.

7.1. Future Works in Dataset

Datasets are one of the most important sections in CADS for the diagnosis of various diseases. The first future work may provide datasets of PSG recordings with a high number of cases. As mentioned earlier, recording PSG signals includes ECG, EEG, EMG, EOG, $S_p o_2$, and breathing signals. Providing datasets with a high number of cased is of paramount importance for future studies. Furthermore, several clinical studies try to investigate the efficiency of MRI modalities in the diagnosis of Apnea [297-299]. Thereby, researchers' access to datasets of MRI modalities allows them to study the brain function during sleep apnea and compare the patients' brain structure and the function to those of normal individuals.

7.2. Future Works in ML Methods

In Table (2), the conducted studies on the diagnosis of sleep apnea from biological signals using ML methods are summarized. The future works proposed in this section include the provision of new preprocessing, feature extraction, and classification methods. Various techniques for preprocessing biological signals have been introduced. Among the introduced methods, the techniques based on time-frequency domain, such as new DWT [310-312] and EMD [313-315] methods, can be addressed as future work with a preprocessing approach.

In another section of Table (2), different feature extraction methods in studies on the diagnosis of sleep apnea are introduced. The most important future work in this field may be Fuzzy feature extraction [316], functional connectivity [317-318], effective connectivity [319-320], dynamic connectivity [321], graph [322], and new entropy techniques [323]. Using the introduced techniques may increase the accuracy and efficiency of CADS based on ML for sleep apnea detection.

According to Tables (3) and (4), a variety of classification algorithms are employed in the studies on the diagnosis of sleep apnea. However, none of these studies have used classification methods based on Fuzzy theories. As future works, using Fuzzy models type 1 [324-325] and type 2 [326-327] and Fuzzy regression [328] could lead to interesting studies in this field. Moreover, graph theory methods with a classification approach have not also been employed in the diagnosis of sleep apnea. Hence, using the graph theory method could be future work in the classification section [329].

7.3. Future Works in DL Methods

This section introduces several ideas for using the newest DL techniques in future studies on the diagnosis of Apnea. Over the recent years, DL techniques have been significantly evolved, and researchers in this field have been able to develop novel models. A review of the studies on the diagnosis of Apnea using DL techniques is presented in Table (3). As can be seen, the studies on the diagnosis of Apnea, standard or simple DL models are used. For this purpose, some of the newest DL sets for future studies on the diagnosis of Apnea are introduced, graph [300-301], attention [302-303], and representation learning [304-305], etc.

7.4. Future Works in Rehabilitation Systems

This section introduces future works for rehabilitation systems based on AI techniques in the diagnosis of Apnea. CSA happens due to brain dysfunction. Medical physicians use neuroimaging modalities, such as MRI, to diagnose them. Transcranial magnetic stimulation (TMS) and transcranial direct current stimulation (tDCS) are two interventional methods for the rehabilitation of CSA [330-332]. In this treatment method, first, medical physicians detect the regions suspected to cause Apnea using MRI modalities. In the following, the suspected regions are electrically/magnetically stimulated using TDCS/ TMS methods [332-333]. Regions for electrical stimulation must be selected accurately. Otherwise, it may have serious consequences for the patients. As future works, the provision of an accurate classification method for brain regions in MRI data using AI techniques seems necessary. This will increase the accuracy of selecting regions suspected to cause CSA for electric/magnetic stimulation.

8. Conclusion

Sleep apnea is one of the most common disorders many individuals suffer from today. Compared to the low ages, this disorder is more prevalent in adults and is directly correlated with snoring [11-12]. This disorder is prevalent in different ages, leading to irreparable damages to individuals [11-12]. Apnea in children could lead to attention deficit hyperactivity disorder (ADHD) [334]. Also, in older individuals, apnea could bring about diseases such as hypertension [335], cardiovascular diseases [336], and stroke [337]. The PSG is used as a precise method for the diagnosis of sleep apnea, and physicians obtain important information regarding the patients' condition [34-35]. However, the diagnosis of sleep apnea using PSG data is invariably challenging for physicians. Using methods based on AI and PSG data is of paramount importance for diagnosing sleep apnea. For this purpose, many studies are being done in diagnosis of sleep apnea using ML and DL methods.

In this work, a comprehensive review has been conducted on the diagnosis of sleep apnea from biological signals using AI methods. A complete explanation was provided regarding sleep apnea and various diagnostic methods in the introduction part. In addition, in this section, the importance of using AI methods was also investigated in the diagnosis of rapid sleep apnea. The second section introduced the search strategy, which included a paper search mechanism and selection of papers. In this section, the PRISMA instructions were used, which could be interesting for the readers. In the third section, a discussion has been done regarding the research in the field of sleep apnea detection using ML and DL methods. Also, in this section, a comparison has been conducted on the number of performed studies for the diagnosis of sleep apnea using ML and DL methods.

The CADS for sleep apnea detection in biological signals using AI methods was provided in Section 3. First, the available datasets from the PSG data were discussed along with the details. In the following, different low and high-level preprocessing methods for the EOG, EMG, EEG, ECG, S_po_2, and respiration signals are presented. Next, the feature extraction, dimensions reduction, and classification methods in the CADS based on ML are provided, and the research of this field are summarized in Table (2). Finally, the DL methods were discussed, and the sleep apnea detection research using DL models were summarized in Table (3).

In another section, the important challenges in diagnosing sleep apnea from PSG signals and AI methods have been discussed. As discussed, these challenges include dataset, ML methods, and DL models. With a high number of cases, the lack of access to datasets from the EOG, EMG, EEG, ECG, S_po_2, and respiration signals is still a serious challenge. In [297-299], the researchers used MRI modality for the diagnosis of sleep apnea, but the MRI neuroimaging is not provided for free, which is another challenge of the dataset. The diagnosis of sleep apnea using ML methods was provided as another challenge. As discussed, choosing the ML algorithms for the precision enhancement of apnea from the PSG data is difficult. In addition, increasing the input data in most cases leads to the performance decline of the CADS based on ML method. Accordingly, these are the serious challenges for providing the software for the diagnosis of apnea by ML methods. There have been various DL methods, and using advanced models requires numerous input data. This challenge leads to the lack of providing advanced DL methods by researchers. Also, the lack of access to the hardware resources with high performance is another reason behind not using the advanced DL models. In general, the introduced challenges have led to the unavailability of real-time tools for the rapid and accurate diagnosis of sleep apnea.

In the following, the discussion section was introduced along with the subsets. A comparison between ML and DL fields for the diagnosis of sleep apnea was provided in the first subsection. Then, a comparison was made between the number of used datasets in the diagnosis of sleep apnea disorder. In another subsection, the number of used modalities in the ML and DL studies for the diagnosis of sleep apnea disorder was provided and displayed. Ultimately, the number of categorization algorithms in the ML and DL researches for the diagnosis of sleep apnea was investigated. This section assists the researchers achieve the diagnosis of sleep apnea algorithms with high performance.

Future works have been reported in the diagnosis of apnea in section 6. Providing the available PSG datasets with a high number of cases is the first future work. In addition, providing the neuroimaging datasets, e.g., MRI, for the diagnosis of sleep disorder is also another future work. One of the future works is using state-of-the-art ML methods to increase the accuracy of sleep apnea diagnosis. Also, in future studies, using new and advanced DL models will help the precision enhancement of diagnosis of sleep apnea. Of course, using advanced DL models requires the development of hardware resources which will happen in the future. Ultimately, providing the rehabilitation systems in the diagnosis of sleep apnea was defined as the future work. In this section, the idea of providing intervention methods for the treatment of CSA using TMS and tDCS methods was introduced along with the AI methods.

With respect to the advances made in the diagnosis of apnea using AI methods, it is promising that the researchers achieve the real hardware and software platforms for the diagnosis of sleep apnea. In future works, various researchers will address the provided challenges, and the initial samples from the diagnosis of apnea will be provided. These platforms will help the specialists in the hospitals and health centers in the rapid diagnosis and treatment of sleep apnea. In addition, it is expected that in the future, the most important methods in the medical industry, e.g., internet of things (IoT), cloud computing, etc., will be used in the diagnosis and prediction of apnea in the most advanced platforms.

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