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TOPICAL REVIEW

Deep and Shallow Learning Model-Based Sleep Apnea Diagnosis Systems: A Comprehensive Study

ROKSANA AKTER RAISA[1], **AYESHA SIDDIKA RODELA**[1], **MOHAMMAD ABU YOUSUF**[2], **AKM AZAD**[3], **SALEM A. ALYAMI**[3], **(Member, IEEE), PIETRO LIÒ**[4], **MD ZAHIDUL ISLAM**[5], **GANNA POGREBNA**[6], **AND MOHAMMAD ALI MONI**[6]
[1]Department of Information and Communication Technology, Bangladesh University of Professionals, Mirpur, Dhaka 1216, Bangladesh
[2]Institute of Information Technology, Jahangirnagar University, Savar, Dhaka 1342, Bangladesh
[3]Department of Mathematics and Statistics, Imam Mohammad Ibn Saud Islamic University (IMSIU), Riyadh 11564, Saudi Arabia
[4]Department of Computer Science and Technology, University of Cambridge, CB2 1TN Cambridge, U.K.
[5]School of Computing, Mathematics and Engineering, Charles Sturt University, Bathurst, NSW 2795, Australia
[6]Artificial Intelligence and Cyber Futures Institute, Charles Sturt University, Bathurst, NSW 2795, Australia

Corresponding author: Mohammad Ali Moni (mmoni@csu.edu.au)

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ABSTRACT Sleep apnea (SA) is one of the most prevalent sleep-related problems, impacting more than 100 million people worldwide. A full-night Polysomnography (PSG) is an effective SA diagnosis strategy. However, it requires multiple wearable devices and the patient staying overnight to collect the findings, rendering it both a time-consuming and costly option. Research attempts to develop non-invasive, sensor-based, or automated solutions for diagnosing SA are also made in recent years. In this study, we analyzed a total of 85 papers, shortlisted from an initial collection of 954 articles published in reputable scientific repositories, e.g., IEEE Xplore, PubMed Central (PMC), Springer, Elsevier etc., where each chosen study was thoroughly examined to determine its contribution and performance. A detailed analysis of data preprocessing, feature extraction and classification algorithm is also addressed. It is found that most of the studies are based on signal analysis for identifying sleep apnea, which yields results with substantial reliability, while contemporary research emphases have been on heart rate variability and pulse oximetry outcomes.

INDEX TERMS Sleep apnea, electrocardiogram (ECG), deep learning, machine learning, pulse oximetry, cloud computing, Internet of Things (IoT), smartphone, wearable devices.

I. INTRODUCTION

Sleep apnea (SA) is a ubiquitous illness that can develop with or without symptoms and has significant cardiovascular and neurological consequences. SA is more common in men [1], [2] and is seen to grow in prevalence up to age 55 before levelling off. Moreover, SA is milder in the elderly compared to the young [3]. Despite significant progress in elucidating the pathophysiology and clinical effects of the condition, the vast majority of persons who suffer from it remain untreated [4]. Diagnoses are challenging because the early indicators of SA are not detected by the patient himself but rather by others since symptoms may include snoring, daily sleepiness, night sweats, dry mouth, disturbances in mood, or cognitive impairments [5]. In fact, daytime sleepiness has been closely associated with a variety of contradictory outcomes, including low academic performance, relationship or marital issues, job loss, and auto accidents. Indeed, drowsiness during the day is strongly associated with several unfavourable outcomes [6]. Numerous health issues might

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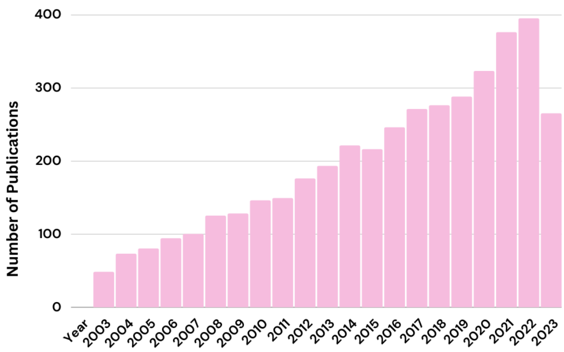


FIGURE 1. The number of studies, articles, and journals on Sleep Apnea published per year is increasing continuously. The data for 2023 have only been collected through June. Therefore there will be more publications by the end of the year.

develop if SA is left untreated. It is seen that when total sleep time is less than five hours, there remains an 80% risk of having Hypertension (HTN) [7], [8]. Some potential risk factors for stroke are linked to SA as reported by [9] and [10]. It is thought that SA may also contribute to the cause and disperse of cardiac failure [11], [12], [13]. SA also had a twice higher risk of Flavored Disorder (FD) following propensity score screening [14]. In a nutshell, SA is associated with a greater probability of cardiovascular problems, both fatal and non-fatal, and may raise the chance of sudden cardiac death [4], [15]. It can be loosely classified into three categories:

- Central Sleep Apnea (CSA), which happens due to an absence of central nervous system input after a stroke, or in people with neuro-muscular illnesses, heart failure, lung problems and others.
- Obstructive Sleep Apnea (OSA) happens due to the upper airway collapse, which occurs when soft tissues in the back of the throat compress while sleeping, followed by hypopnea.
- Hypopneas can be described as partial obstruction or narrowing of the upper airway during sleep, leading to reduced airflow, whereas OSA denotes the cessation of breathing entirely for over 10 seconds.

Additionally, another classification of sleep apnea exists, known as Mixed Sleep Apnea (MSA). Mixed apneas (MA) are identified by the initial absence of both respiratory effort and airflow, succeeded by respiratory effort unaccompanied by airflow. The pathophysiological basis is rooted in concurrent instability in ventilatory control and collapsibility of the upper airway. There is a metric used to quantify the severity of sleep apnea known as the Apnea-Hypopnea Index (AHI). AHI represents the average number of sleep apnea and hypopnea events per hour. AHI categorizes sleep disturbances as follows: 1. Healthy group: AHI $<$ 5 events/h 2. Apneic group: AHI $>$ 5 events/h. As per the American Academy of Sleep Medicine (AASM), it is classified into mild (5-15 events per hour), moderate (15-30 events per hour), and severe (more than 30 events per hour) [16].

The AASM hypopnea criteria mandate either a 30% decrease in airflow paired with a 4% oxygen desaturation or a 50% reduction in airflow alongside a 3% oxygen desaturation or arousal. However, the previous standard for scoring hypopneas, which required a $\geq$4% oxygen desaturation from the pre-event baseline, has been updated to an optional criterion in the AASM Manual Scoring 3.0.

Not surprisingly, 75% of cases of disrupted sleeping go undiagnosed. Between 2% and 5% of females and between 3% and 7% of males are reported to have SA, indicating that the occurrence of SA is twice as common in males compared to females [17]. Even though 20% of children snore, only 1% to 8% of kids between the ages of 2 and 8 suffer obstructive sleep apnea, which affects about 26% of adults aged 30 to 70 [18]. The studies on this topic are increasing daily, which can be seen in Fig. 1.

Polysomnography (PSG) is a frequent approach to detect SA, which involves measuring about sixteen signals, including Electrocardiogram (ECG), blood oxygen saturation (SpO2), Electroencephalogram (EEG), Electroocoulogram (EOG), chest-abdominal breathing movements, Electromyography (EMG), and so on. At the same time, the patient is monitored in the clinic for the entire night [19], [20]. OSA is diagnosed when a patient reports the symptoms and the incidence of no fewer than five obstructed respiratory episodes during an hour of sleep as recorded by PSG. Patients must wear many cables and electrodes, and a specialist must monitor them for manual scoring [21]. In uncomplicated individuals with signs and symptoms of OSA, Home Sleep Apnea Tests (HSAT) can be used instead of PSG to diagnose OSA [22]. Since numerous facilities are needed and the patient must be monitored overnight in the hospital for an OSA diagnosis using PSG or HSAT, the cost is higher, and the diagnostic scope is significantly reduced globally. Because of this, implementing this public health policy is challenging. Another non-invasive and easy-to-use method for diagnosing SA is Pulse-oximetry (SpO2). Desaturation (i.e., a drop in oxygen saturation level) and subsequent reoxygenation (O2) are hallmarks of apnea and hypopnea [23], which makes it widely used for screening SA.Snoring is one of the earliest indicators of SA, specifically OSA, and since snoring sounds differently in healthy and suspicious individuals, analyzing the frequencies of snoring can distinguish patients based on the severity of Obstructive Sleep Apnea Syndrome (OSAS), which is another promising way for diagnosing SA in general [24]. The lack or diminution of sound during apnea or hypopnea is easily detectable in audio recordings [25]. Smartphones have been increasingly ubiquitous over the past few years. Several initiatives have been to employ smartphone apps to keep track of health and sleep disruptions, but most of them just serve as a monitoring and alerting system.

Sleep apnea presents differently in each age group, with adults and children having different needs. It is largely caused by obesity, aging, and anatomical predispositions in adults. It frequently manifests as symptoms like loud snoring and exhaustion during the day, and if ignored, it increases the risk of cardiovascular problems. On the other hand, larger tonsils and adenoids can contribute to upper airway obstruction during sleep, leading to symptoms such as sleep fragmentation. This sleep fragmentation can result in non-restorative sleep, which may cause excessive daytime sleepiness and cognitive impairment in younger populations.

Recently, significant advancements have been made in devising learning-based (ML) approaches, which are based on feature engineering and the use of signals like ECG, Airflow (AF), SpO2, Heart Rate Variability (HRV), or respiratory signals. These include modelling algorithms like neural networks (NN), decision trees (DT), ensemble learning, regression, and so on [26] and [27]. As a result of the constraints in feature engineering, deep learning models (DL) are currently being given a greater emphasis, and approaches that are primarily CNN-based (Convolutional Neural Networks) are being deployed extensively [28], [29]. Most publications combine classifiers to create hybrid models to obtain high accuracy. Recent studies have shown that SA, a type of sleeping condition, is a serious issue as the amount of research is increasing day by day. A careful examination of current research reveals that most of them heavily rely on ECG signal analysis, SpO2 and respiratory data. Many ML or DL models have been proposed with public or custom-made private datasets, and the results have been substantially promising.

This review conducts an analysis based on the SA detection techniques researchers have employed using various data sources. Some research uses signal-based analysis, others use wearable devices to collect data, and some use smartphone technology to find SA. This evaluation also includes a performance analysis that identifies the best approaches for detection. This article also gives a list of commonly used datasets and a description of each one. The descriptions include information about the population or other factors considered when collecting participant data.

II. METHODOLOGY

This article analyzes SA detection-related research works published between 2017 and 2023. This paper's protocols and searching criteria follow PRISMA guidelines [30]. Several publications, journals, and conference proceedings from publishers, including IEEE, Springer and Elsevier. are included in the study. The search was conducted using the terms "apnea detection and ML," "apnea and DL," "sleep apnea detection," "ECG-based Sleep apnea detection," "ECG and SA," "respiration analysis and SA," "smartphone application and SA," and "pulse oximetry and SA". The search terms adopted a streamlined approach to focus on the core concepts of deep learning (DL) and machine learning (ML). The acronyms "DL" and "ML" were utilized instead of their full forms, given their extensive familiarity within the research community. This ensured relevance and precision in the search results, allowing for a comprehensive overview of the current state-of-the-art in deep and shallow learning models. This approach aimed to capture relevant studies across various facets of sleep apnea detection. The focus of

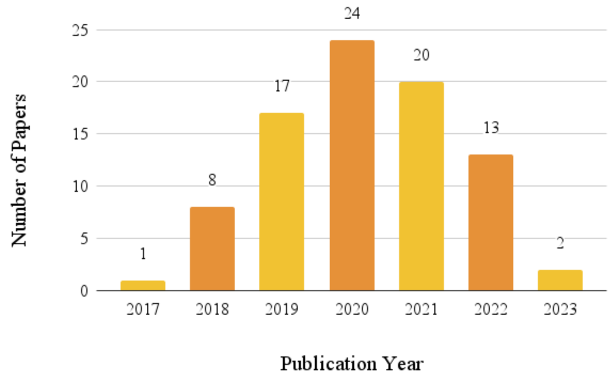


FIGURE 2. Distribution of reviewed articles included in this study according to their publication year (from 2017 till 2023).

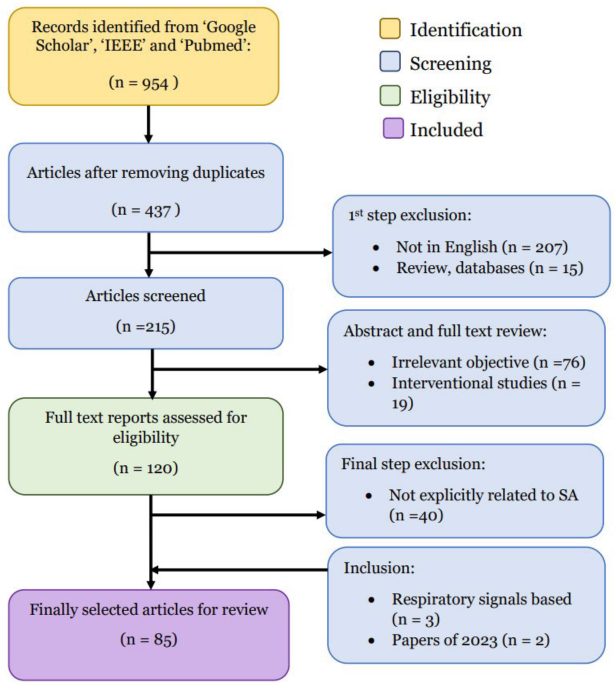


FIGURE 3. Effective article search strategy using PRISMA technique: inclusion and exclusion criteria.

this study could be articulated as any alternative methods for detecting SA to the conventional PSG technique, including hardware and software analysis. Fig. 2. depicts the division of the reviewed papers or articles according to their publication year.

The presentation of different algorithms that had not only been validated by one inquiry (minimum) but also concentrated on the performance of SA identification with data retrieved from polysomnography done in hospitals or readily accessible in databases was the inclusion requirement of the articles for this review. 954 articles were found after searching literature databases, as shown in Fig. 3. Due to linguistic variations in papers, review papers, or conference papers, duplicates were eliminated, resulting in the deletion of around 650 articles. The next phase of exclusion involved looking at the remaining 215 papers, which were not directly connected to sleep apnea and interventional studies. Consequently, they were omitted since they did not align with our purpose. 120 publications were identified as being eligible for evaluation after a study of abstracts and their full-text accessibility. However, 40 works were excluded that could potentially be adapted for detecting sleep apnea but were not initially intended for that purpose. These papers lacked rigorous testing or validation specifically for sleep apnea detection, so they were excluded to ensure the integrity and relevance of our findings. Moreover, three papers were included to address the necessity of mentioning respiratory signals, alongside the incorporation of two recent papers. Finally, 85 papers were chosen for this study, while recent publications were added to focus on cutting-edge research techniques.

Depending on the source data and the signals, technologies, or gadgets utilized, the studied articles are categorized into different groups, such as ECG, SpO2, EEG, respiration, and mixed techniques. Here the classifiers used for screening SA in different papers were also observed. Section III explains the general framework for identifying SA, including dataset management, data preparation techniques, obtaining and selecting features, and classification algorithms. Section IV includes an extensive review of the approaches used in the 85 publications that were selected.

III. GENERAL FRAMEWORK FOR SLEEP APNEA DETECTION

The overall architecture for SA detection is covered in this section alongside dataset management, feature extraction, the method used to choose them, and classification techniques. The analysis steps are depicted in Fig. 4 based on the studied articles.

Out of the 85 studies that were selected, 72.5% of articles used open-access public datasets, and the remaining 27.5% used private datasets obtained from various sources, including hospitals or simulation-based data generated using their system. Physionet's Apnea ECG (PAE), University College Dublin (UCD), ECG-ID, Sleep EDF, and other datasets were applied in 72.5% of the papers that used public datasets. Features were incorporated in different domains, such as time, frequency, and nonlinearity. Temporal features were further categorised into short-term, long-term, and statistical features. Many papers use only one feature, but both features are occasionally used. Some authors didn't fully specify or use simplistic calculations. Lastly, 47.5% of the authors used DL methods, 37.5% used ML methods, and the remaining 15% of them used other methods as their classifier. Among 47.5% DL methods, CNN, ANN, LSTM, and MLP were mostly used. And for 37.5% ML methods, SVM, RF, KNN, DT, and Regression were used. The study of these percentages is roughly shown in Fig. 5 using a pie chart.

A. DATASET MANAGEMENT

The descriptions of the most prominent datasets for detecting apnea are presented in this section. Table 1 compiles data acquisition sources alongside key attributes such as age range, number of recordings, utilized signals or sensors, detectable categories of sleep apnea, and the assessment method employed.

Table 1 has been carefully revised to encompass a comprehensive array of datasets that may potentially be incorporated into the studies reviewed thus far. The inclusion criteria for papers listed in this table are those featuring unique databases intended to showcase the breadth of available datasets for researchers interested in sleep apnea detection. By highlighting a diverse range of databases, this table serves to inform researchers about the variety of resources at their disposal for conducting studies in this field.

Here, it is observed that among all the public datasets, PAE database [31], [32], [33], [34], [35] and UCD database [36], [37], [38], [39], [40] are the two most well-known public datasets. In addition to this, the Sleep Heart Health Study (SHHS) obtained from National Sleep Research Resource (NSSR) [41], [42] and Childhood Adenotonsillectomy Trial (CHAT) database [43], [44] are also extensively used. Other datasets were gathered from several hospitals [45], [46] or created by the researcher using the sensors utilized in the developed system [47], [48], [49], [50], [51]. Moreover, the ratio of types of databases implemented is widely represented in Fig. 5. Also, the datasets used for identifying sleep apnea (SA) in children and adults are distinct. While most datasets diagnose SA in adults aged from 18 to 80, with a median age of around 50, the CHAT and UofC databases focus specifically on detecting SA in children aged from 0 to 18. However, the NSSR database encompasses both adults and children aged from 1 to 81. Overall, most databases are tailored for adults, reflecting the greater relevance of SA in this demographic This section includes a few available dataset sources for SA detection. Nevertheless, the databases most commonly discussed are elaborated upon in detail below.

1) MIT-BIH POLYSOMNOGRAPHIC DATABASE (MBP DATABASE)

The MBP Database [52], [53] is a group of recordings made while people slept of various physiological signs. The database contains over 80 hours of polysomnographic recordings, consisting of four, six, and seven channels. Every recording contains a beat-by-beat analyzed ECG signal, breathing signals, EEG signals, and annotations for various sleep stages and apnea. The database comprises 18 records.

Taran and Bajaj [54], Mahmud et al. [55], Vimala et al. [56], Bhattacharjee et al. [57], some other researchers used this dataset in their studies.

2) PHYSIONET APNEA-ECG DATABASE (PAE DATASET)

There are 70 records total in the data [53], [58], out of which 35 were allocated to the learning set, while the remaining 35 were assigned to the test set.

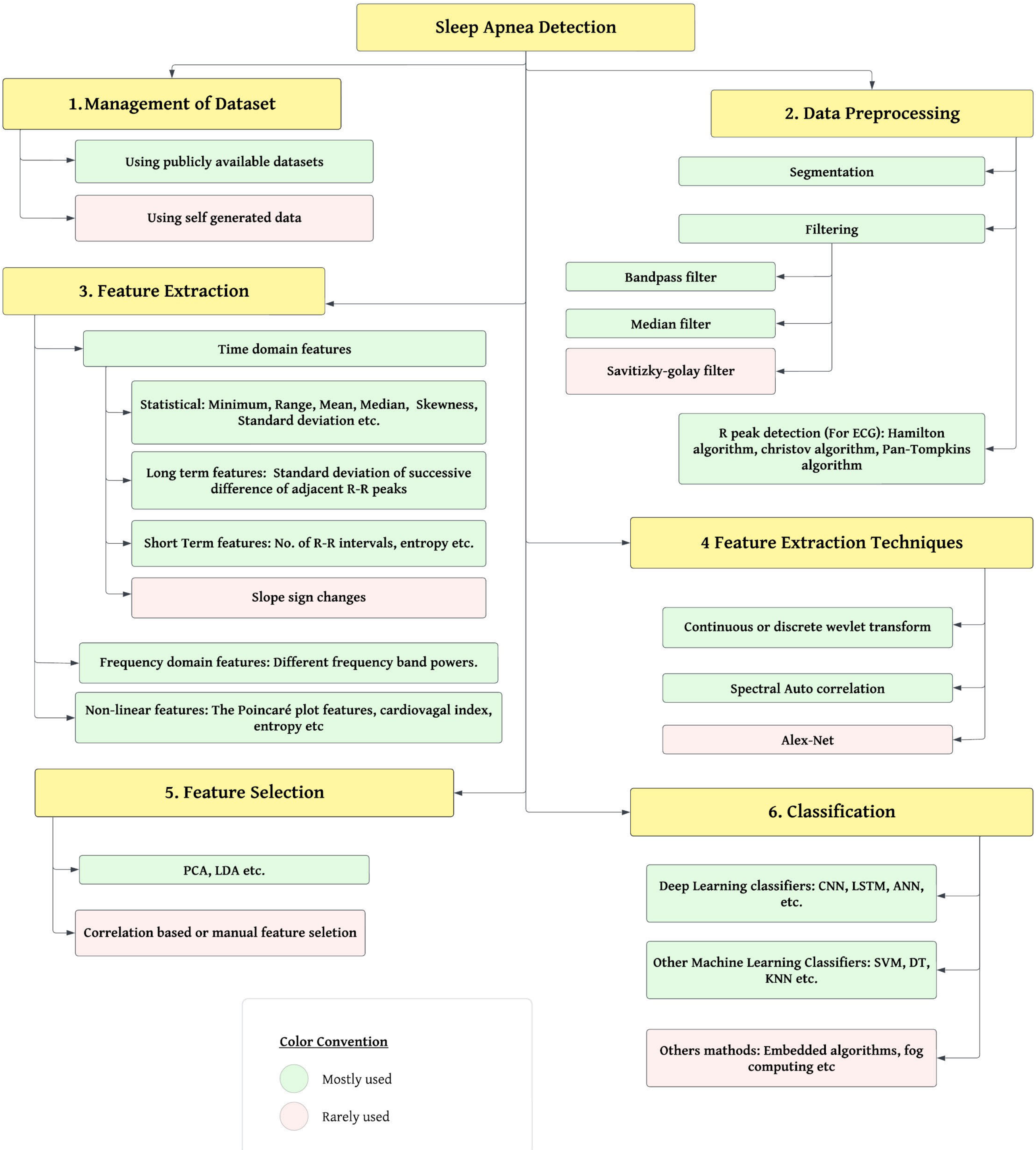


FIGURE 4. Step by step Sleep Apnea Detection procedure. Every step is further broken down into examples or applicable methods. Combinations of colours represent options that are frequently and rarely used.

3) UNIVERSITY COLLEGE DUBLIN SLEEP APNEA DATABASE (UCD DATASET)

UCD [53], [91] dataset contains 25 complete overnight polysomnograms from adult participants with suspected sleep-disordered breathing, together with simultaneous three-channel Holter ECG recordings. Over six months, subjects were chosen at random from sleep-disordered patients from the clinic at St. Vincent's

TABLE 1. Databases used in several recent researches demonstrate the diversity of dataset gathering, including those acquired through hospitals and private and public databases.

Reference	Data Acquisition	Age Range (y)	Recordings/ Subjects	Signals/ Sensors	Category of SA	Assessment of SA
A. Iwasaki *et al.*, 2019, [59]	SUMS Hospital, PSG datasets	18 - 80	59	HRV	SA syndrome	AHI $\geq$ 15
M. K. Moridani *et al.*, 2019, [36]	UCD Dataset [53]	28 - 68 (mean- 49.96 ± 9.55)	25	ECG, EEG, EMG	OSA	-
K.N. Rajesh *et al.*, 2021, [60]	PAE Dataset [58]	29 - 63	70	ECG	OSA	AASM criteria
E. Urtnasan *et al.*, 2020, [61]	A polysomnographic amplifier was used to collect data	47 - 55	144	ECG	SAS	AASM criteria
M. Qatmh *et al.*, 2022, [62]	PAE Dataset [58], ECG-ID Database [63]	29- 63, 13 - 75	70, 310	ECG	Apneic ECG signal	-
Mashrur *et al.*, 2021, [64], A Zarei *et al.*, 2022, [65]	PAE Dataset [58], UCD Dataset [53]	29 - 63, 28 - 68 (mean- 49.96 ± 9.55)	70, 25	ECG	OSA	AHI >5
Y. Wang *et al.*, 2021, [66]	PSG data obtained from patients with apnea at Tianjin Chest Hospital	39 - 77	25	ECG, HRV, RR interval	OSA	-
S. Taran *et al.*, 2019, [54],	MBP Database [52]	32 - 56	18	EEG	Apnea events	-
T. Mahmud *et al.*, 2021, [55]	UCD Dataset [53], MBP Database [52], and You snooze, you win [67]	28 - 68 (mean- 49.96 ± 9.55), 32 - 56, -	25, 18, 1983	EEG	Apnea frames	-
R. Gupta *et al.*, 2021, [40]	UCD Dataset [53]	28 - 68	25	EEG	SAS	-
Henri *et al.*, 2020, [68]	Sleep EDF [69]	median - 55.8	-	EEG	OSA	Sleep stages, (N1 - N4)
V. Thorey *et al.*, 2019, [70]	PSG recordings from Stanford Sleep Medicine Center	45.6 ± 16.5	52	Airflow, AHI	OSA	AASM criteria
A.Onargan *et al.*, 2021, [71]	Collected	-	4	EEG	OSA	sleep stages
M.M. Moussa *et al.*, 2022, [72]	UAE nationals, NSRR	1 - 81	118	EEG, ECG	OSA	-
P. Sharma *et al.*, 2022, [41]	SHHS1, SHHS2 [73]	$\geq$ 40	5424, 2644	SpO2, PR	Apnea events	AASM standards
F. Vaquerizo-Villar *et al.*, 2021, [43]	CHAT [74], UofC and BUH datasets	0 - 18	1638, 980, 578	SpO2	pediatric OSA	AHI, cohen's kappa
M Sharma *et al.*, 2022, [42]	SHHS database [73] from the NSRR [75], data of 2 groups	$\geq$ 40	5,793 and 2,651	Airflow, SpO2		
M Sharma *et al.*, 2022, [76]	PAE Dataset [58], UCD Dataset [53]	29 - 63, 28 - 68	70, 25	SpO2		
J Jim´enez-García *et al.*, 2022, [44]	CHAT [74], clinical database	0 - 18	1683, 974	SpO2, Airflow	OSA	AHI: 1 and 5 e/h
A Leino *et al.*, 2021, [77]	HSAT, subjects with TIA or stroke recorded in Neurocenter, Finland	-	1970, 77	SpO2	Severity of SA	REI>5e/h and REI>15 e/h. AHI >15 e/h

TABLE 1. ***(Continued.)*** **Databases used in several recent researches demonstrate the diversity of dataset gathering, including those acquired through hospitals and private and public databases.**

R. Lazazzera *et al.*, 2020, [78]	Sleep Laboratory, University Hospitals Leuven (UZ Leuven, Belgium)	-	96	PPG, SpO2	OSA, CSA	-
H. Yoon *et al.*, 2020, [45]	Collected from Hospitals		15		Apneic event	-
Y. Jeon *et al.*, 2020, [47]	Used five sleep apnea patients and three normal people as subjects to collect data	-	8	HRV, SpO2, PPG	-	AASM criteria
O. Hassan *et al.*, 2020, [79]	Used PVDF sensor to generate data and Pulse oximetry data from Physionet	-	-	PVDF sensor	Apnea event	-
G. Lyon *et al.*, 2019, [80]	Records collected at the ASR in Berlin, Germany using their system	-	178	ResMed sensor	SDB	AHI $\geq$ 15
X. L. Hoppenbrouwer *et al.*, 2019, [46]	The Alar dataset was obtained at MST with ethical approval under study protocol K17039,	-	42	Airflow	OSA	AHI $\leq$ 5 and AHI $\geq$ 10
Y Castillo Escario *et al.*, 2019, [81]	DBI, acquired using Android app	24 - 83	13	Microphone, SpO2, AF	OSA	AASM criteria
Lluis *et al.*, 2021, [49]	Acquired using a 'Grael PSG' device and Samsung S5	38 - 78	19	PSG, Triaxial accelerometer	sleeping position of OSA patients	5 $\leq$ AHI <30
A. John *et al.*, 2021, [39]	UCD Dataset [53]	28 - 68 (mean- 49.96 ± 9.55)	25	ECG	Apnea episodes	-
G. Cay, 2020, [48]	Used sensors to store data in a .csv file	-	-	Respiration rate	OSA	-
VM Anu *et al.*, 2022, [82]	Collected using sensors	-	-	ECG	OSA	-
A. R. Dhruba *et al.*, 2021, [83]	Four males and one female patient were examined	5 - 50+	5	ECG, HRV, SpO2, skin response	OSA	SpO2 value $\leq$ 90%
A. Channa *et al.*, 2020, [84]	A Pressure Map Dataset is available on Physionet	19 -34, mean- 26.9	13	Pressure mattress	OSA	-
L. Haoyu *et al.*, 2019, [85]	UCD Dataset [53], volunteers	28 - 68, 20 - 51	25, 10	HRV, SpO2	SA	consecutive seconds of AH events
H. Azimi *et al.*, 2020, [86]	Volunteers from various communities	-	9	PSM	CSA	-
Yüzer *et al.*, 2020, [50]	Formed their study group	mean- 36.3	10	Acceleration sensor, AF, Thoracic movement	Apnea event	Time delay etc.
F Baty *et al.*, 2020, [87]	241 individuals with suspected sleep apnea at the Cantonal Hospital St. Gallen lab provided whole-night ECG signals.	median - 52	241	ECG, RR Interval	OSA, CSA, MSA	AHI mean- 21 per hr, ODI 17 per hr
A Manoni *et al.*, 2020, [88]	One patient in a hospital consented to volunteer	-	1	PPG	OSA, CSA, MSA	AHI=104
E Zancanella *et al.*, 2022, [51]	They arbitrarily split the patients into two groups of twenty.	>18	40	SpO2, HRV, EEG	-	AHI mean =17.7 (± 19.9)
M. Baboli *et al.*, 2019, [89]	A custom-built radar	mean - 49	10	Doppler radar	Apnea event	-
T. Van Steenkiste *et al.*, 2020, [90]	Traditional polysomnography data	58 - 70	25	ECG	Apnea event	-

University Hospital in Dublin. The following signals were captured: ECG, EEG, EMG, oxygen saturation, body positions, etc. Due to its inclusion in several publications (included in this study), it can be claimed that the UCD Dataset is the second most commonly used dataset.

4) SLEEP-EDF DATABASE EXPANDED

The Sleep-EDF dataset [69], [92] consists of 197 whole-night sleep recordings obtained through PSG. Furthermore, occasional measurements of respiration and temperature were recorded. Additionally, it is possible to access corresponding sleeping patterns that were individually assessed using the Rechtschaffen and Kales manual [93]. Some of the researchers used this dataset. This dataset is suitable for EEG-based analysis. Besides these, many other datasets were used for evaluation purposes, many of which were privately gathered from hospitals or created by the researchers themselves. In Fig. 5, we see the breakdown of how many people use public versus private databases.

B. PREPROCESSING TECHNIQUES

Data preprocessing prepares the raw data to be used in another format that is simple to use for further procedures. The authors used a variety of preprocessing approaches, which are discussed in this section.

1) FILTERING

Filtering signals for diagnosing sleep apnea is a complex process that requires expertise in signal processing, biomedical engineering, and sleep medicine to ensure accurate and reliable results for diagnosis and treatment planning. Filters are applied to data after sampling on the studies that employ raw signals like ECG, EEG, and SpO2. Filtering removes noise, artefacts, or other contaminants in the signal to acquire an accurate result. Some common approaches for filtering data are listed below:

- Bandpass Filtering: Bandpass filtering isolates frequency components within a specific range, allowing researchers to focus on respiratory-related signals and discard noise and artefacts. This was implemented by [21], [44]
- Wavelet Transform: Wavelet transform decomposes signals into different frequency components at various scales, enabling the identification of transient events and subtle changes in physiological signals [42], [76].
- Empirical Mode Decomposition (EMD): EMD decomposes signals into intrinsic mode functions (IMFs) representing different oscillatory modes, allowing for the separation of physiological components and noise as used in [64].

Also, [77], [94] used a Median filter to remove uninterpretable data points. Butterworth filters [56], [81] and Savitizky-golay filters have also been implemented in some of the works. Moreover, authors in a study [64] have used a Chebyshev Type II bandpass filter. These approaches offer various ways to preprocess and extract relevant information from physiological signals to aid in diagnosing and managing sleep apnea.

2) SEGMENTATION

Segmentation involves dividing continuous physiological signals recorded during sleep into smaller, discrete segments or epochs. This process facilitates further analysis and improve the accuracy of apnea detection algorithms. These segments typically correspond to specific time intervals, allowing for the analysis of localized physiological patterns and events. Some common approaches of segmentation may be:

- Fixed-length segmentation: Divide the continuous signal into fixed-length segments or epochs of equal duration. Example may include dividing a continuous EEG signal into 30-second epochs. In some studies segmentations were done in 5-s epochs, 60-s epoch, into 1-min segments or in 10-min segments [44], [64], [77], [85]
- Event-based segmentation: Segment the signal based on specific events or annotations, such as respiratory events, apnea/hypopnea events, or arousal events. Segmenting an ECG signal based on detected heartbeats or R-wave peaks is an example.
- Adaptive segmentation: Dynamically adjust segment boundaries based on signal characteristics or features, such as amplitude, frequency, or variability. For instance, segmenting a respiratory effort signal based on changes in amplitude or frequency.

3) HEART RATE (R-R PEAKS)

Heart rates from ECG signals are often calculated from RR intervals, which represent the time duration between successive R-peaks in the ECG signal. Common methods include calculating R-R intervals from ECG signals, using peak detection algorithms for automatic peak identification, applying Fourier transform or time-frequency analysis to extract frequency components, measuring heart rate indirectly via pulse oximetry (PPG), and employing machine learning models for prediction. Among the reviewed works, one study [94] detected R peaks using Hamilton Algorithm [95]. Another study [59] calculated the RR interval for HRV analysis using the RRI sensor. Authors in a study [47] used pulseoximeter for obtaining heart rate and SpO2 signals, while some studies [83], [85] extracted HRV signals as well.

C. FEATURE EXTRACTIONS AND SELECTIONS

In this study, feature extraction and selection are two vital techniques within the ML and DL models of SA detection. While feature selection chooses a subset of the most crucial features to enhance the performance of machine learning algorithms, feature extraction turns raw data into a set of features that are more meaningful and practical for analysis. These methods can enhance interoperability, decrease overfitting, and increase model efficiency and accuracy, leading to more accurate predictions and trustworthy data analysis insights.

Table 2 summarises a few features and the accompanying feature extraction and selection methods based on SA detection. The selection of papers featured in this table was

TABLE 2. Features extraction and features selection techniques of SA detection or classification.

Author, Year	Features	Feature Extraction and Selection Technique
M. Bahrami *et al.* [96], 2022	HRV parameters (Time domain. frequency domain, and non-linear features are extracted)	Principal component analysis (PCA)
Mashrur *et al.* [64], 2021	Deep Features from ECG Segments	Automatic feature extraction using the proposed SCNN pipeline.
R. Gupta *et al.* [40], 2020	Different features like entropy, energy, mean absolute deviation (MAD), kurtosis etc, from EEG signal	Feature extraction Technique based on subbands
Y. Wang *et al.* [66], 2021	Lempel-Ziv complexity analysis, HRV, multiscale entropy etc	Discrete Wevlet Transform
M. Deviaene *et al.* [97], 2018	143 time-domain features, desaturation severity, quasi-periodical and statistical were extracted from the SpO2 signals	Removing highly correlated features, applying mRMR algorithm, backward wrapping
A. Zarei *et al.* [98], 2018	A non-linear feature	Decomposing ECG using wavelet transform coefficient.
A. Bhattacharjee *et al.* [57], 2018	Different statistical features, multiband entropy etc	A multi-band feature extraction scheme is applied
C. Wang *et al.* [99], 2019	different features from the signal obtained by the UWB Al mattress.	Principal Component Analysis (PCA)
D Padovano *et al.* [100], 2022	Different time domain and frequency domain features like mean, median, VLF, LF etc.	2 sequential feature selection algorithms, SFFS and SBFS, were implemented
A. Pinho *et al.* [35], 2019	A total of 84 features were obtained by extracting 50 features from the HRV and 34 from the EDR signal.	Discriminant Relevance (DR) method

guided by their utilization of various features and methods of feature extraction. To maintain conciseness, specifically few papers were chosen that employ commonly used feature extraction and selection methods frequently adopted by researchers in the field. This approach ensures that the table remains manageable while still providing valuable insights into prevalent techniques employed in sleep apnea detection studies.

Extracting features can be challenging for sleep apnea (SA) diagnosis. Features are extracted from input data like ECG, EEG, Photoplethysmography (PPG). For instance, in the case of ECG signals, common features of interest include R-R intervals, which provide insights into heart rate variability (HRV), and morphological characteristics such as QRS complex duration and amplitude.

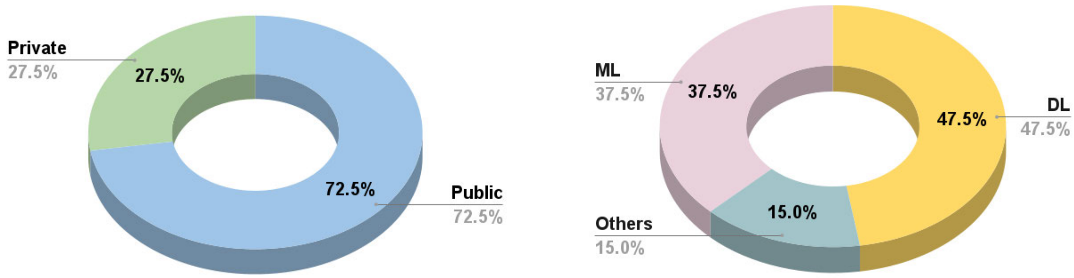
These features are crucial for assessing cardiac function and identifying abnormalities associated with sleep apnea. Similarly, PPG signals offer unique features such as pulse amplitude and pulse transit time, which can indicate changes in peripheral vascular resistance and arterial stiffness, which may be relevant to sleep apnea diagnosis. Furthermore, EEG signals provide valuable information regarding brain activity during sleep, with features such as delta, theta, alpha, beta, and gamma power spectral densities of particular interest. These features help characterize sleep stages and detect abnormalities in sleep architecture associated with sleep apnea. Features can be typically categorized into the time domain, frequency domain [101], and time-frequency domain, each briefly outlined below.

1) TIME DOMAIN FEATURES

Time domain features are statistical characteristics computed directly from the time-domain representation of a signal, providing insights into its behaviour over time across different physiological signals. These features capture attributes such as mean, standard deviation, and variance, which are fundamental measures applicable to various physiological signals. For instance, in electrocardiography (ECG), time domain features can describe properties of the cardiac cycle intervals, while in respiratory signals, they may characterize breathing patterns. Similarly, in electroencephalography (EEG), time domain features can describe characteristics of brain activity patterns, and in pulse oximetry (SpO2), they may reflect oxygen saturation levels over time. Statistical methods involve more complex calculations based on instantaneous values or cycle intervals recorded over longer periods, typically 24 hours. Geometric methods, on the other hand, convert signal data into geometric patterns, enabling measures such as HRV triangular index and Triangular Interpolation of NN interval histogram (TINN), which can be applied across different physiological signals to assess their variability and dynamics. Some of the studies [33], [39], [96], [102] etc. included these features along with other feature sets.

2) FREQUENCY DOMAIN FEATURES

Frequency domain features analyze the distribution of signal power across different frequencies. They provide insights into periodic patterns and rhythmic components present in the signal. These features are valuable for understanding physiological processes such as heart rate variability, respiratory patterns, and other oscillatory phenomena observed in signals like ECG, EEG, SpO2, and airflow recordings. Power spectral density (PSD) analysis reveals how power (variance) distributes across different frequencies. PSD calculation methods can be classified as nonparametric or parametric,



(a) Dataset (b) Classifiers

FIGURE 5. A percentage breakdown of accessibility-based dataset categories and frequently utilized classification algorithms in 80 analyzed articles.

offering comparable results. Short-term recordings typically reveal three main spectral components: very low frequency (VLF), low frequency (LF), and high frequency (HF). The measurement of these components can be in absolute values or normalized units. Long-term recordings additionally include an ultra-low frequency (ULF) component. These features were utilized by some of the authors in their research [86], [99].

3) TIME-FREQUENCY DOMAIN FEATURES

Time-frequency domain features analyze how signal characteristics evolve over time and across different frequencies. These provide insights into dynamic changes and transient events in non-stationary signals such as EEG or HRV. The wavelet transform has gained significant popularity as an effective method of analysis, demonstrating strong performance in both the time and frequency domains, which can be seen to be used in the research in [46], [49], and [87].

4) NON-LINEAR FEATURES

Advanced diagnostic algorithms are greatly aided by non-linear characteristics, which capture complex relationships and patterns in the data. Approximate Entropy (ApEn) and Sample Entropy (SampEn), which measure the regularity and complexity of signals, are two frequently utilised nonlinear characteristics. Recurrence plot analysis shows recurrent patterns throughout time, whereas Detrended Fluctuation Analysis (DFA) evaluates long-range correlations in the data. Signals' self-similarity is measured by the fractal dimension, and their long-term memory is described by the Hurst exponent. Entropy measurements such as Shannon entropy also shed light on the uncertainty and information content of signals. Some works such as [56] and [102] included such features in their studies.

For the feature selection procedure, Principal component analysis (PCA), Linear Discriminant Analysis (LDA), Wavelet Transform (WT), Discrete Wavelet Transform (DWT), Discriminant Relevance (DR) and different correlation-based techniques are used.

D. CLASSIFICATION METHODS

This section contains some of the classifiers most frequently used in this study's articles, papers, or journals. Fig. 6 presents a visual representation of the study's research schematic emphasizing commonly utilized classification algorithms. ML-based methods encompass traditional machine learning techniques, including linear and logistic regression for regression-based and binary classification-based approaches, respectively. In this category, linear regression serves as an example of regression-based methods, while logistic regression represents binary classification. DL-based methods utilize deep neural networks for advanced feature learning and pattern recognition.

1) CONVOLUTIONAL NEURAL NETWORK (CNN)

CNN, or Convolutional Neural Network, is a DL algorithm designed for processing and analyzing visual data such as images and videos. It is inspired by the organization of the animal visual cortex, which consists of interconnected layers of neurons that detect and respond to different visual patterns. CNNs are widely used in various applications, including computer vision, image recognition, object detection etc. During training, a CNN learns to recognize patterns and objects by iteratively adjusting the weights and biases of its layers. This is typically done through a process called back-propagation. This training process allows CNN to automatically learn hierarchical representations of the input data, making it highly effective in tasks involving visual information.

In the field of biomedical signals, CNNs are a type of deep learning model that excels at learning hierarchical representations from sequential data, such as time-series biomedical signals. They employ convolutional layers to automatically extract relevant features from the input signals, enabling them to effectively capture complex patterns and relationships within the data. This makes CNNs particularly well-suited for tasks such as signal classification, anomaly detection, and feature extraction in biomedical applications, including sleep apnea detection.

Most researchers have used CNN as their classification model [29], [33], [41], [96], [103], [104] etc. Additionally, modified CNN models including SCNN [64], LeNet5 [94], FCNN [105], and DCNN [34] were also employed. John et al. [106] used 1D CNN in their research.

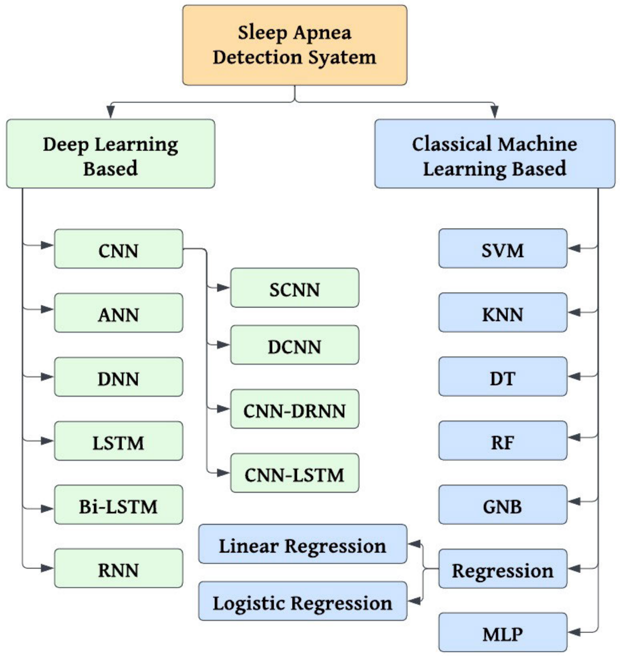


FIGURE 6. The categorization of broad approaches for classifying sleep apnea. ML-based methods include traditional techniques whereas DL-based methods utilize deep neural networks for advanced feature learning and pattern recognition.

2) ARTIFICIAL NEURAL NETWORKS (ANN)

An Artificial Neural Network (ANN) is a computational model inspired by the structure and functioning of the human brain. It is a versatile approach that can operate within both ML and DL paradigms for feature learning and pattern recognition. In our classification, ANN is grouped under the DL-based category due to its capacity as a complex model. The basic building block of an ANN is the artificial neuron, also known as a node or perceptron. Each neuron receives input signals, applies weights to those signals, performs a mathematical operation, and produces an output signal.

One advantage of ANNs is their ability to learn and generalize from large amounts of data, extracting meaningful features and relationships. They can handle complex and nonlinear relationships between inputs and outputs, making them suitable for tasks that involve intricate patterns. However, ANNs can also suffer from overfitting if not properly regularized or if the training data is insufficient or noisy.

Moridani et al. [36], Wang et al. [21], Yacchirema et al. [107], Pombo et al. [32] and many other researchers [35], [62] etc. implemented ANN in their research for SA detection.

3) DEEP NEURAL NETWORKS (DNN)

In general, a DNN is an ANN with several hidden layers, including hundreds or even thousands of hidden layers, intending to mimic how the brain functions to perform sophisticated calculations. It learns new skills through practice using a variety of samples. They excel in image recognition, natural language processing, and recommender systems. DNNs accurately classify objects in image recognition, aiding autonomous vehicles and surveillance systems. In NLP, they enable speech recognition, language translation, and chatbots. DNNs also power recommender systems, providing personalized suggestions.

This classifier is utilized in [108], where in their models, they have used DNN and SVM to create a hidden Markov model (HMM).

4) RECURRENT NEURAL NETWORK (RNN)

Recurrent neural networks (RNNs), a specific type of ANN, are created to be used with data from time series or data that includes sequences. Feed-forward neural networks are generally only appropriate for independent datasets. If the data are arranged in a series so that each data point varies based on the one before it, it is necessary to modify the neural network to account for the interconnections between these data points. RNNs possess a unique capability called ''memory'', which enables them to retain information or details from previous inputs. This memory feature allows RNNs to utilize past context when generating subsequent outputs within a sequence.

Among the reviewed articles, Iwasaki et al. [59] implemented RNN in their study combined with LSTM.

5) LONG SHORT TERM MEMORY (LSTM)

LSTM networks are a type of RNN that can learn order dependency in sequence prediction challenges. By default, LSTM may retain information for an elongated amount of time. It is employed in processing time series data, prediction, and categorization. The unique design of LSTM allows it to mitigate the vanishing or exploding gradient problem commonly encountered in traditional RNNs, enabling more effective learning and modelling of sequential data. LSTM has proven particularly effective in speech recognition, language modelling, sentiment analysis, and generating textual content.

LSTM is seen to be used in various works. The models of [59], [68], [103], and [109] etc. were implemented using this classifier. Also, the use of BiLSTM is observed in [105]. The researchers utilized a hybrid model using CNN and biLSTM.

6) BIDIRECTIONAL LONG SHORT TERM MEMORY (BILSTM)

A Bidirectional LSTM, or biLSTM, differs from a standard LSTM by processing input in both forward and backward directions. It comprises two LSTM layers, each handling input in one direction. This model enhances the network's access to information, enhancing contextual understanding, such as knowing the surrounding words in a sentence. BiLSTM is seen to be used in combination with CNN as a hybrid model in [55] and [110]. Also, in [86] this classifier is used alongside Support Vector Machine (SVM) and Time-based Convolutional Network (TCN) but the highest accuracy was obtained using BiLSTM.

7) SUPPORT VECTOR MACHINE (SVM)

SVM, or Support Vector Machine, is a popular supervised ML algorithm for classification and regression tasks. It operates by finding an optimal hyperplane that separates data points into different classes or predicts continuous values. In SVM, data points are represented as feature vectors in a high-dimensional space, and the algorithm aims to find a hyperplane that maximizes the margin between the support vectors—data points closest to the decision boundary. This margin represents the confidence in the classification/regression decision and helps achieve better generalization. SVMs are utilized in the sciences and for text, image, and handwriting classification.

Among all the reviewed articles included in this study, [98], [108], [111] employed this classifier directly in their models, whereas [54] used a slightly modified approach called Least Square SVM. It was also noted that the majority of the authors used SVM to compare their contributions.

8) MULTILAYER PERCEPTRON (MLP)

A Multilayer Perceptron (MLP) is a type of ANN that consists of multiple layers of interconnected artificial neurons. It is a feed-forward neural network, meaning the information flows in one direction, from the input layer through the hidden layers to the output layer. The MLP neural network is also used in a variety of medical specialities, such as oncology, cardiology, and haematology, as well as in special care, biometrics, dentistry, surgery, and other fields, to address the issues of clinical detections, analyzing medical images and signals, and survival prediction.

Many researchers, including Wang et al. [21], Qatmh et al. [62], and Pombo et al. [32], etc used MLP along with ANN in their studies.

9) GAUSSIAN NAIVE BAYES (GNB)

Gaussian Naive Bayes (GNB) is a simple and widely used probabilistic machine learning algorithm based on Bayes' theorem and feature independence assumption. It is primarily used for classification tasks. GNB assumes that features are continuous and follow a Gaussian (normal) distribution. During training, GNB estimates the mean and variance of each feature for each class.

In this review, Tang and Liu [102] has used GNB in their proposed study.

10) K-NEAREST NEIGHBOR (KNN)

The k-nearest neighbours algorithm (KNN) is a variational, supervised learning classifier that employs proximity to classify or forecast data point groupings. It works because similar points are close together and can be utilised for regression/classification tasks.

In this review, KNN is used by Rajesh et al. [60], Vimala et al. [56], Bhattacharjee et al. [57], Onargan et al. [71], Channa et al. [84], Haoyu et al. [85], Jeon et al. [47], Baty et al. [87], Wang et al. [99] and Tang and Liu [102]

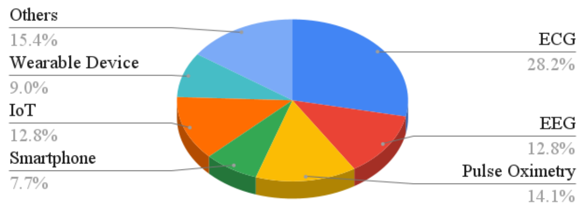


FIGURE 7. Different types of Input data from the reviewed papers.

IV. VARIOUS SIGNALS, SENSORS, AND DEVICES

Several algorithms have been proposed to detect SA. In certain scenarios, this is likely because the complexity of the utilised algorithms makes it difficult for them to run on systems with constrained resources effectively. However, this study focuses on various algorithms and methodologies for screening SA based on input signals like ECG, EEG, IoT-based signals, etc. The literature reviews in this paper are systematically organized by the types of signals or sensors used, rather than strictly by ML or DL approaches. This strategic choice was made to offer a more comprehensive and nuanced representation of studies across various modalities, ensuring a thorough and insightful overview of the field. This approach aims to highlight the diverse methodologies researchers are employing to detect, diagnose, or monitor sleep apnea. Some studies focus on signals or relevant data to identify the disease, others on sleep staging to aid in detection, and yet others on sleep positions to monitor the health of affected individuals. This underscores the wide range of sleep apnea research being conducted globally. Fig. 7 exemplifies the range of inputs, whether data or technology.

A. ECG SIGNALS-BASED

Iwasaki et al. [59] proposed an ECG signals-based study for developing a SA detection approach by using LSTM and HRV. The raw RR Intervals from ECG are used to separate the subjects who have or don't have sleep apnea syndrome (SAS) to obtain better sensitivity and specificity. A robust algorithm for SA is proposed by Moridani et al. [36] utilizing a Multilayer Perceptron (MLP) classifier. The algorithm combines EEG, ECG, and EMG data to improve the screening process's accuracy. This study gives an accuracy of 98.09 ± 2.15, a specificity of 96.87 ± 1.78 and a sensitivity of 97.14 ± 2.24.

Jayanthy et al. [31] suggested a study to analyze OSA utilizing ECG data. This paper aspires to simplify the tools used to analyze sleep apnea using parameters like Power Spectral Density, Correlation, and R-R peak interval. It is observed that the spectrogram estimation method produces the best possible results yielding an accuracy of over 90%. Urtnasan et al. [61] suggested a novel CNN-based method for determining SA severity autonomously. The model yielded a 98% test set F1-score. Using this approach, it is possible to identify mild and moderate SA with a 99.0% accuracy rate.

Qatmh et al. [62] presented a model using an Artificial Neural Network (ANN). Before acquiring level one

TABLE 3. An overview of studies conducted based on the ECG signals.

Author, Year	Objectives	Classifier/Technology	Results
A.Iwasaki *et al.* [59], 2019	To perceive SA using RRI input based on LSTM and HRV	RNN-LSTM	This algorithm has achieved 100% sensitivity and specificity when used on clinical data
M. K. Moridani *et al.* [36], 2019	To detect the SA from ECG, EMG and EEG data combined with MLP classifier	MLP, ANN	The algorithm achieved its optimum scores on specificity, accuracy, and sensitivity as 96.87 ± 1.78, 98.09 ± 2.15, and 97.14 ± 2.24, respectively
A.K. Jayanthy *et al.* [31], 2020	To streamline SA analysis by utilizing ECG signals and analyzing 3 parameters of the signal	Cross-Correlation Coefficient	The correlation technique is capable of detecting OSA episodes with an accuracy exceeding 75%
E. Urtnasan *et al.* [61], 2020	To automatically evaluate SA severity using CNN from short-term, healthy ECG data	CNN	The test set achieved an F1-score of 98.0% with an accuracy of identifying mild and moderate SA to be 99.0%
M. Qatmh *et al.* [62], 2022	To identify SA using the ECG signal and discrete wavelet transform technique with an ANN-based model	ANN	In testing, an accuracy of 92.3% was obtained by this model
M. Bahrami *et al.* [96], 2022	Comparing various ML and DL algorithms to detect SA utilizing a single-lead ECG	CNN-DRNN	Hybrid deep models, notably hybrid CNN-DRNN, are superior at detecting sleep apnea, with 88.13% accuracy, 84.26% sensitivity, and 92.27% specificity
K. Ivanko *et al.* [111], 2020	To identify HRV features for sleep apnea detection in ECG and find the best classification method	SVM	The SVM model with a quadratic kernel attained the best accuracy score of 98.7% and 100% true positive rate for apnea detection
N. Pombo *et al.* [32], 2020	To identify SA utilizing minute-to-minute ECG data comparing the accuracy of different classifiers	ANN	The study achieved 82.12% accuracy, with specificity of 72.29% and sensitivity of 88.41% using ANN with 20 features
S. A. Singh *et al.* [33], 2019	To detect OSA based on Alexnet, which was previously trained from a single channel ECG-scalogram	CNN	The suggested method attained an accuracy rate of 86.22% and a 90% sensitivity in per-minute segment OSA categorization
Q. Shen *et al.* [34], 2021	To detect OSA based on a Weighted-Loss Time-Dependent (WLTD) classification model and a multi-level dilation attention module with 1-D CNN architecture	WLTD, DCNN	The proposed method achieved 89.8% sensitivity rate, 89.4% accuracy, and specificity rate of 89.1% in segment identification
A. Sheta *et al.* [103], 2021	To diagnose OSA from ECG Signals Using ML and DL Classifiers	CNN, LSTM	In the validation stage, the suggested model achieved an accuracy of 86.25%.
A. Pinho *et al.* [35], 2019	To detect SA employing the ECG signal to obtain HRV and EDR, then compared various classifiers using selected feature techniques	ANN	The highest level of accuracy attained was 82.12%. Also, the testing performance had an 88.41% sensitivity and a 72.29% specificity level using ANN
Mashrur *et al.* [64], 2021	To automatically diagnose SA using SCNN (Scalogram-based) and ECG signals with single channel	Scalogram-based CNN	The PAE dataset demonstrated strong performance with 94.30% accuracy, 94.30% sensitivity, 94.51% specificity, and 95.85% F1-score for per-segment classification
T. Wang *et al.* [94], 2019	To use modified LeNet-5 for detecting SA, utilizing ECG segments	Modified LeNet5 CNN	For per-segment analysis, the model has the best sensitivity of 83.1%, specificity of 90.3%, accuracy of 87.6%, and AUC score of 95 %

TABLE 3. ***(Continued.)*** **An overview of studies conducted based on the ECG signals.**

K. Li *et al.* [108], 2018	It was proposed to identify OSA based on DNN and HMM, where decision fusion was also used to increase accuracy	DNN, SVM, ANN	The OSA detection accuracy was nearly 85% with a sensitivity reaching 88.9% for per-segment
T. Wang *et al.* [21], 2019	To use single-lead ECG data's temporal dependence and a time window ANN to detect SA	ANN-MLP	Their approach outperformed conventional non-time window approaches with 87.3% accuracy rate and 88.7% sensitivity
Y. Wang *et al.* [66], 2021	To categorize and identify apnea and hypopnea events from ECG signals using conventional ML algorithms as practical and effective methods	Decision Tree, Random Forest	The classification F1-score, accuracy, specificity, and sensitivity for OSA were 92.20%, 91.78%, 91.30%, and 92.21%, respectively
A. Zarei *et al.* [98], 2018	To suggest a way through which using only the ECG signals from a single lead can achieve a highly precise detection of OSA	SVM	For per-minute classification, an SVM classifier using an RBF kernel had a 94.63% accuracy rate (with a sensitivity rate of 94.43% and 94.77% specificity)
J. Zhang *et al.* [109], 2021	To create a deep CNN-LSTM model to automatically detect OSA and validate the model with a dataset of polysomnography recordings	CNN-LSTM	The proposed model demonstrates a sensitivity, specificity, and accuracy of 96.1%, 96.2%, and 96.1%, respectively, using the PAE dataset
O. Faust *et al.* [112]	To develop an accurate sleep apnea detection method using RR interval signals and LSTM networks	LSTM	The LSTM classifier achieved 99.80% accuracy, 99.85% TPR, and 99.73% TNR with cross-validation
K.N. Rajesh *et al.* [60], 2021	To detect OSA using statistical features derived from discrete wavelet transform from single-led ECG data	SVM, LDA, RF, KNN	k-NN and RF achieved 89% and 90% accuracy, respectively and 96% area under ROC.
A. Zarei *et al.* [65], 2022	To detect OSA, the authors combined two DL algorithms for feature extraction and classification	CNN, LSTM	For the PAE dataset, their model achieved 97.21% accuracy, along with 93.7% accuracy for the UCD dataset.
K. Feng *et al.* [113], 2020	To identify sleep apnea, an inexpensive, time-independent method based on unsupervised learning utilizing single-led ECG	Softmax HMM	The outcome of classifying each segment individually resulted in a specificity of 84.4%, a sensitivity of 86.2%, and an accuracy of 85.1%

decomposition characteristics, continuous wavelet transform (CWT) broke down the ECG signal. The final results revealed a 92.3% accuracy rate. Bahrami and Forouzanfar et al. [96] introduced a model after thoroughly comparing various ML and DL algorithms to detect sleep apnea within a unified framework using a single-lead ECG. DL models outperformed conventional ML methods.

Hybrid models have the optimal detection accuracy, with the highest accuracy of 88.13%, 84.26% sensitivity, and specificity of 92.27%. Ivanko et al. [111] proposed an approach to use ML to detect instances of SA in ECG data. Spectral-temporal, wavelet and single-lead ECG data were used to detect OSA in time and frequency domains. The 9 predictor model had the maximum classification accuracy, with a total accuracy of 98.7% and a sensitivity of 100.0%. Pombo et al. [32] presented the study, which illustrates a comparison of different classifier's accuracy rates and presents a study of the efficacy of classifier implementation to identify sleep apnea moments utilizing per-min of ECG signals. This study showed that the ANN with 20 features, which had an 82.12% accuracy rate, 88.41% sensitivity and 72.29% specificity, was the most accurate model.

Singh and Majumder [33] put forward an OSA classification method based on DL that has already been trained (Alexnet) in this paper. CNN model classified OSA based on time-frequency characteristics using scalogram images from per-minute ECG data. The proposed method yielded 86.22% accuracy and 90% sensitivity. To identify OSA using single-lead ECG signals, a novel scalogram-based convolutional neural network (SCNN) is proposed by Mashrur et. al. [64]. Their goal is to categorize normal and apneic people using ECG time-frequency analysis automatically. They removed signal noise via filtering, segmentation, and noise epoch removal. Conventional and hybrid scalograms created time-frequency images for each epoch. They created a time- and space-efficient model with a segment classification accuracy of 94.30%.

A modified LeNet-5 CNN architecture for SA identification that has adjacent segments is suggested by Wang et al. [94] by extracting features from RR intervals. The modified LeNet-5 was created to address the character recognition issue with one-dimensional data, and they utilized the Hamilton algorithm and cubic interpolation for preprocessing. In per-segment analysis, their modified CNN model had a prediction accuracy of 87.6% for SA. A proposes a novel approach for detecting apnea using ECG data utilizing wearable devices. John et. al. [106] The authors used network pruning techniques and binarization to reduce complexity and primarily created a 1D CNN to reduce the number of feature extraction stages. They created a patient-specific model which led to an accuracy of 99.56%. Li et al. [108] proposed employing single-lead ECG readings with a sparse auto-encoder to train a DNN and Hidden-Markov model (HMM) to diagnose OSA. They employed decision fusion to improve accuracy and overcome the limitation of a single classifier. Their model yielded 84.7% accuracy.

Wang et al. [21] created a quick and portable detection strategy employing single-lead ECG data and proposed a temporal window ANN method for SA detection. They employed a 1-minute slice to detect SA with 12 RR interval-derived features and 6 R-peak amplitude-derived features,

achieving 87.3% accuracy when the time window size was 7. Shen et al. [34] presented a study where a weighted-loss time-dependent (WLTD) model of classification and a multiscale dilation attention 1D CNN (MSDA-1DCNN)-based OSA detection technique is proposed. The network's final classification section used the loss function and HMM to correct data imbalance and improve classifier accuracy. Here, the accuracy, true positive rate, and specificity are 89.40%, 89.80%, and 89.10%, respectively, for segment identification. Sheta et al. [103] proposed a study to detect OSA from ECG data employing ML and DL classifiers. CNN-LSTM combination outperformed other OSA diagnosis methods in this research yielding 86.25% accuracy.

Pinho et al. [35] suggested a study to identify SA more accurately employing ECG signals. This study modelled ECG signals to calculate HRV and respiration signals as input in classifiers like ANN and SVM. This model achieves an 82.12% accuracy rate, 88.41% sensitivity and specificity of 72.29%. Wang et al. [66] recommended an ML-based effective model for the identification of apnea and hypopnea instances utilizing ECG data. 25 subjects were used for the research purpose. The categorization among hypopnea instances and any apnea instances, according to the model's results, has an accuracy rate of more than 90%.

Zarei and Asl [98] proposed a study that extracts nonlinear features from ECG signal decomposition Wavelet Transform (WT) coefficients to detect OSA automatically. For minute-to-minute and subject-to-subject classifications, an SVM classifier with an RBF kernel achieves an accuracy of 94.63% and 95.71%, respectively. A DL model for the automatic recognition of OSA episodes by combining CNN-LSTM networks is presented by Zhang et al. [109]. The algorithm was trained on a large polysomnography dataset and outperformed existing approaches in recognizing apnea occurrences. Another study proposed by Faust et al. [112] also proposed an LSTM-based process to detect SA using RRI signals.

Rajesh et al. [60] used discrete wavelet transform statistical features to detect obstructive sleep apnea. It aims to test and compare its accuracy and efficiency to existing methods and explore its potential for clinical use [60]. Feng et al. [113] proposed a study that introduced a method for detecting SA using a classification model that combines Frequential Stacked Sparse Auto-Encoder (FSSAE) and Time-Dependent Cost-Sensitive (TDCS) techniques.

An approach for extracting features automatically was proposed in the work of Zarei et. al. [65]. The authors combined two DL algorithms, i.e. 2D CNN and LSTM architectures, to obtain diverse features for better classification. Additionally, to reduce computational complexities, they combined algorithms to achieve the best result. Their proposed model achieved the highest accuracy rate of 97.21%, outperforming other detection methodologies.

Table 3 summarizes the studies on ECG signals, highlighting the aim of the study, employed classifiers and results of the studied works.

B. EEG SIGNALS-BASED

A precise DL-based automated approach for classifying sleep phases in patients who are suspected of having OSA was developed by Korkalainen et al. [68]. They used EEG and EOG signals from a large clinical dataset of patients with potential OSA and a database of healthy individuals made available to the general public.

Their automation has produced encouraging outcomes for sleep staging with a single channel. A single-channel approach could facilitate cost-effective, straightforward, and precise sleep staging. with an accuracy range of 84.5 to 76.5% in OSA diagnostics. Mahmud et al. proposed an SA event diagnosis technique from a variation of Sub-frame features using EEG-based data and DCNN [105]. This study uses an algorithm for Fully Convolutional (FCNN) DL architecture to identify apnea episodes. This study develops a system for categorizing online apnea events automatically. To determine whether the entire frame has apnea, a dense classifier is trained to look at each local feature obtained from

TABLE 4. Brief summary of studies using EEG signals.

Author, Year	Objectives	Classifier/Technology	Results
S. Taran *et al.* [54], 2019	To investigate Hermite Coefficient-based features for apnea event identification via an adaptive decomposition of EEG signals	Extreme ML and LS SVM	The presented scheme outperformed cutting-edge methods with 99.53% accuracy, 99.47% sensitivity and 99.58% specificity
T. Mahmud *et al.* [55], 2021	To use EEG signals and a CNN-BiLSTM network to detect apnea frames in the subject-independent test scenario	Automatically Hybrid CNN-BiLSTM	Their model's highest accuracy was 93.22%, and its specificity was 93.79% when utilizing the variational mode decomposition approach
T. Mahmud *et al.* [105], 2020	To identify apnea episodes from EEG subframe-based feature variation, a fully convolutional deep learning method is developed	FCNN	The FCNN model achieved the highest accuracy of 80.2% using a sub-frame-based approach
R. Gupta *et al.* [40], 2020	To distinguish apneic and non-apneic patients using 5 sub-band features collected from EEG data	Ensemble Decision Tree	Their ensemble bagging method achieved the highest accuracy (95.10%), sensitivity (93.2%), and specificity (96.8%)
Henri *et al.* [68], 2019	To use deep learning with EEG inputs to identify sleep stages and detect OSA severity	CNN, LSTM	Single-channel input yielded the highest 83.9% accuracy in a public dataset and 83.8% in the clinical dataset
V. Thorey *et al.* [70], 2019	Comparing AI and humans for the screening of SA	State-of-the-art deep learning method	The average accuracy and F1 scores are 75% and 0.55 for sleep experts and 81% and 0.57 for automatic detection of sleep apnea severity
V Vimala *et al.* [56], 2019	Using two filters for EEG signals to distinguish sleep apnea sufferers from healthy subjects	SVM, KNN, ANN	They retrieved entropy, variance, etc., from frequency subbands. SVM with 99% accuracy performed best among SVM, KNN, and ANN
A. Bhattacharjee *et al.* [57], 2018	To introduce a novel approach for SA detection that uses a Rician modelling approach to analyze feature variation in multi-band EEG signals	KNN	Using KNN the best result is obtained with a sensitivity, specificity, and accuracy of 98.28%, 83.76%, and 91.0%, respectively
A. Onargan *et al.* [71], 2021	To predict SA using EEG signals based on the EMD method	SVM, LR, DT, Naive Bayes, KNN and Ensemble classifier	The accuracy values obtained for the dataset of 2 varied from 47.5% to 71.9%, while for the dataset of 3, they ranged from 33.8% to 63.1%
M.M. Moussa *et al.* [72], 2022	Detection of OSA and Depression using explainable computer-supported detection methodology	Explainable AI, SVM	The best event for the detection purpose while deep sleep gives an accuracy along F1-Score of 98.36% and 98.82%, respectively

a subframe. Traditional techniques analyze the global features of the frame. This paper's sub-frame-based methodology can assist in better retaining the local variation patterns. Finally, an innovative post-processing method is used to increase accuracy greatly.

An automatic apnea frame detection method for the cross-subject evaluation using a hybrid CNN-BiLSTM network from EEG signals was proposed by Mahmud et al. [55]. In the subject-independent cross-validation scheme, three publicly available datasets used by the model give average accuracy of 93.25%, 93.22%, and 89.41%.

Gupta et al. [40] proposed an effective approach where the EEG signal was filtered and classified based on subbands to detect sleep apnea syndrome. When compared to recently published publications, the suggested strategy gives superior outcomes. The suggested approach provides a maximum accuracy of 95.10%. The recommended method is a great strategy for automatically detecting SA that could be widely applied in clinical settings because here, the subject-independent accuracy and subject-specific accuracy are calculated.

A study on SA detection utilizing Artificial Bee colonies to enhance Hermite Basis Functions specifically for EEG signals was proposed by Taran and Bajaj [54]. In this study, an adaptive decomposition technique is introduced for identifying apnea events by analyzing EEG signals. The decomposition parameters for the proposed partitioning are chosen by comparing ETs. The performance metrics of the recommended approach are 99.47% sensitivity, 99.58% specificity, and 99.53% accuracy.

Thorey et al. proposed cutting-edge DL methods to detect SA and compared the output from an AI model and a sleep expert [70]. The automatic approach provides an accuracy of 81% with an F1-score of 0.57, which is more accurate than prediction accuracy by a sleep expert. Moreover, the average accuracy and F1 scores are 75% and 0.55, respectively, for sleep experts detecting sleep apnea severity. Vimala et al. [56] suggested a model where EEG signals are decomposed into

5 bands to classify OSA. The authors used two filters to fit the EEG data and split the data into different frequency sub-bands passed to ML models to classify sleep apnea. They extracted features like entropy, variance etc., for processing in several algorithms. They used SVM, KNN and ANN, compared the performance, and obtained the best performance for SVM with an accuracy of 99%

Bhattacharjee et al. [57] proposed a novel method for detecting SA by analyzing the variation of features in multi-band EEG signals using a Rician modelling approach. The method is tested on a dataset of 50 subjects and accurately identifies SA. Onargan et al. proposed a work employing EEG signals and ML algorithms to predict SA, achieving high accuracy in identifying patients with the disorder [71]. Moussa et al. [72] proposed a model to classify OSA and depression patients having OSA. The result shows that among 118 patients, 40 are with OSA and depression, and 40 are not with depression but suffering from OSA.

Table 4 summarizes the studies covered within this section where the objectives, results and classifiers or technologies are used for detection or classification purpose.

C. RESPIRATORY SIGNALS BASED

In Elmoaqet et al., a single-channel respiratory signal was used to identify apneic occurrences using deep RNN models automatically [114]. Nasal pressure signals consistently produced the best detection results when the framework was evaluated across three distinct respiration signals: oronasal thermal airflow, nasal pressure, and abdominal area respiratory inductance plethysmography sensors. In particular, the nasal pressure signal with a deep BiLSTM model yielded 90.3%sensitivity, 83.7% specificity, and 92.4% AUC.

In a separate study by the same author [115] a probabilistic approach was introduced using a Gaussian mixture probability model to detect sleep apnea. This model analyzes the posterior probabilities of events based on single oronasal airflow records obtained through an oronasal thermal sensor. The framework achieved an overall performance summary of 88.5% sensitivity, 82.5% specificity, and an AUC of 86.7%.

Kim et al. [116] proposed a new algorithm for detecting sleep apnea using a single-channel oronasal airflow signal. The algorithm dynamically adjusts thresholds to characterize baseline changes and identifies apneic events by analyzing respiration amplitudes and intervals. This approach achieved 80.0% sensitivity, 88.7% specificity, and an AUC of 0.844.

D. INTERNET OF THINGS (IOT)-BASED

Table 5 highlights the works on the Internet of Things (IoT), mentioning the study purpose and the outcomes of the research as well as the technologies used.

In this table, John et. al. [106] proposes a unique method for detecting apnea using ECG data employing wearable technology. The authors primarily created a 1D CNN to reduce complexity and used network pruning techniques and binarization. This reduced the number of feature extraction stages. An accuracy of 99.56% was achieved because they could develop models that were particular to each patient.

Yacchirema et al. [107] built an IoT-based monitoring system and predictive analysis for services like remote monitoring, in-the-moment warning notifications, information visualization, and data processing. They employed a three-layered architecture with integrated cloud and fog computing and used an IoT gateway to enable compatibility between various networks and communication protocols. They additionally used an analyzer built on big data to extract and process the real-time data obtained from open data sources and cloud technology. A GUI has also been developed to help medical professionals monitor patients easily.

John et al. [39] using a 1D-CNN model, put forward a framework for integrating multisensor and multimodal data using a data-driven approach. The authors performed a complexity analysis for their fusion model and used pruning techniques to cut down on computational costs. They achieved an accuracy of 99.72% by focusing on detecting sleep apnea without resampling the signals.

Dhruba et al. [83] proposed the study to track and alert patients about their health status. Using a microcontroller and different sensors including a pulse sensor, galvanic skin response (GRS) sensor, ECG sensors, etc., the authors created a sleep surveillance system utilizing IoT that reads multiple parameters, including heart rate, SpO2, ECG, sound intensity level, etc.

Cay and Mankodiya [48] proposed the Smart Mattress, a wireless sleep monitoring system that uses textile pressure sensors to track breathing rates and sleeping patterns in real-time in the bed. To show updates, the author connected an embedded system via Bluetooth. The biggest problem they face is connecting the sensors to the electronics, and they also have a hard time getting the sensors to be repeatable and linear.

Anu et al. [82] suggested a three-tier architecture of a framework for OSA observation based on IOT and DL that enables both OSA identification and therapy. The authors created a monitoring system using IoT and numerous sensors, such as a temperature sensor, a heart or pulse rate sensor, and an ECG sensor to collect data. Messages are sent to users based on the parameter threshold values. These data are then fed into a CNN model for feature extraction before being fed into a deep-learning model for data preparation. These technological advances enabled the writers to reach an accuracy of 97%.

A methodology for detecting sleep apnea utilizing IoT technology and an SVM classifier is presented in the study proposed by Ma et. al. [37]. They used SpO2 signals divided into per-minute intervals and preprocessed the Matlab data fed into SVM architecture. IoT was used to build a connection between ML and smartphone, finally achieving 94.1% specificity with a sensitivity of 87.6% and an accuracy rate of 90.2%

TABLE 5. Findings involving internet of things (IoT).

Author, Year	Objectives	Classifier/Technology	Results
A. John *et al.* [106], 2021	To develop a patient-specific OSA detection model using ECG signals from wearable devices and CNN architecture	CNN	The proposed approach using 1D CNN and IoT obtained a maximum accuracy of 99.56%
DC Yacchirema *et al.* [107], 2018	To design an IoT-Big-based monitoring and notification system and big-data analyzer with a graphical user interface	ANN	The 3 layered design performed well in latency and usability tests, supporting its usage by health professionals
G. Cay *et al.* [48], 2020	To create an IoT-enabled wireless fabric mattress covering utilizing textile pressure sensors allowing mattress supervision	Embedded Algorithm	The 3 milestones are to create a mattress cover and create an embedded algorithm for OSA detection and IoT based app for monitoring
A. John *et al.* [39], 2021	To create a 1D-CNN-based framework for multisensor and multimodal data fusion using data like ECG, SpO2 etc.	1D CNN	The fusion model produced 99.72% accuracy and 98.98% sensitivity while considering complexity reduction
VM Anu *et al.* [82], 2022	To create a system that uses IoT for user notification and CNN and Deep Learning techniques for OSA detection	CNN, DL	The maximum accuracy as well as F1-score were 97% and 98%, sequentially. The model's UI evaluation proves its usability
D Yacchirema *et al.* [117], 2018	To use smart city data to identify and treat sleep apnea and provide the elderly with a less polluted environment	Fog computing, big data	Their system sends real-time messages to health workers concerning OSA, tracks patient behaviour, and reads smart data to provide a healthy place to live
A. R. Dhruba *et al.* [83], 2021	To use health sensors to monitor SpO2, ECG, GRS etc for identifying and notifying about sleep apnea in real time	IoT	This study included 5 factors and galvanic skin response, which had never been used before and obtained better results
B. Ma *et al.* [37], 2020	To detect SA based on IoT architecture using SpO2 features in ML algorithms via smartphones	IoT, SVM, Adaboost, DBM	SVM performed best with 90.2% accuracy and 87.6% sensitivity
A. Channa *et al.* [84], 2020	To detect sleeping posture using pressure mats employing IoT to evade supine sleeping position, which may cause OSA	IoT, KNN	Their model was experimented and obtained the best results using KNN
L. Haoyu *et al.* [85], 2019	To identify SA utilizing HRV and SpO2 signals input into ML algorithms and construct IoMT-based real-time monitoring system	IoT, KNN, ANN, SVM	SVM had the highest accuracy (98.54%) and found that SpO2 and combining HRV characteristics boosted accuracy

Channa et. al. [84] discovered that supine sleepers are more likely to experience breathing problems. In order to address this challenge, the authors developed a sleep position tracking system utilizing pressure mats based on IoT technology. They used supervised ML models to identify sleeping posture and obtained the best results with the KNN algorithm yielding a 71.1% accuracy rate. In the study by Haoyu et al. [85], the authors developed an IoMT-based monitoring system utilizing SpO2 connecting with HRV signals. At first, heart rate was collected using a SpO2 sensor and SpO2 signals to detect OSA, and cloud architecture was used for real-time data analysis and alerts about patients' condition. Combined features were classified using SVM, KNN, and ANN, and the best result was obtained using SVM.

E. PULSE-OXIMETRY (SPO2) SIGNALS-BASED

Mostafa et al. proposed a study [104] utilizing SpO2 signals only to recognize OSA events. This approach is developed to automatically select the structure and optimize hyperparameters of a one-dimensional CNN. The optimal model obtained 94% average accuracy, specificity and sensitivity of 96% and 92% sequentially. Sharma et al. [41] suggested an algorithm that offers a reliable and sensitive method for detecting sleep apnea events utilizing a pulse oximeter sensor and gives high sensitivity for different types of apnea.

Deviaene et al. [97] presented a work for automatic diagnosis of SA. The model suggests that an algorithm based on simple SpO2 desaturation characteristics outperforms more complex techniques in detecting apneic occurrences and detecting SAHS patients. Vaquerizo-Villar et al. [43] proposed a study where the objective is to create a CNN model and assess how effective deep learning is at enhancing the evaluative accuracy of oximetry in identifying pediatric OSA through automated ways.

Mostafa et al. presented a study [118] that successfully optimized sleep apnea detection and demonstrated that the combination of ANN with GA yielded good accuracy. Most of the selected features by GA were time-frequency signals, indicating that apnea events contain crucial information in this domain. This approach outperformed previous works and can be tested on databases and classifiers.

Sharma et al. [42] suggests a wavelet decomposition-based approach for individuals aged 60 and above that makes use of respiratory signals and pulse-oximetry (SpO2). With the aid of big datasets, they classified apneic and healthy participants using two algorithms: RUSBoosted Tree and

TABLE 6. Summary of studies utilizing pulse-oximetry (SpO2) signals.

Author, year	Objectives	Classifier/Technology	Results
S.S. Mostafa *et al.* [104], 2020	To create and evaluate a model CNN hyper-parameters optimization algorithm for detecting OSA	CNN	Average accuracy, sensitivity, and specificity for the best model were 94%, 92%, and 96%, respectively
P. Sharma *et al.* [41], 2022	To diagnose sleep apnea based on DL using Pulse rate and SpO2	CNN	The sensitivity of the model is 93.4% for OSA, for CSA it is 90.5% and 89.1% for recognising low oxygen-associated hypopnea
M. Deviaene *et al.* [97], 2018	To automatically detect respiratory episodes using SpO2 readings by detecting and classifying apneic-induced desaturations	Random Forest (RF)	Throughout the various test sets, an average desaturation categorization accuracy of 82.8% was obtained
F. Vaquerizo-Villar *et al.* [43], 2021	To design a CNN architecture and analyse deep learning's capacity to improve oximetry's automated paediatric OSA detection	CNN	The proposed model performed better than other state-of-the-art studies
SS Mostafa *et al.* [118], 2017	To utilize an ANN classifier to determine the superior blood SpO2 features subset for detecting sleep apnea	ANN, Genetic Algorithm	ANN achieved an impressive accuracy rate of 97.7%, utilizing only seven selected features determined by the Genetic algorithm
M Sharma *et al.* [42], 2022	To design an autonomous method based on wavelet to detect OSA in older people using SpO2 and respiratory signals	GentleBoost, RusBoosted Tree	They obtained max accuracy of 89.30% using cross-validation in a balanced dataset
CR Wu *et al.* [119], 2020	To compare the PSQ and PO questionnaires for detecting OSA severity in terms of specificity and sensitivity	Questionnaire data	The PSQ had the topmost sensitivity to diagnose moderate neonatology SA, and PO had the maximum specificity for recognizing paediatrics without mild SA
M Sharma *et al.* [76], 2022	Compose SpO2 signals into several sub-bands using the best duration-bandwidth focused wavelet transform.	DT, Ensemble algorithm	The highest performance was observed for the DT algorithm for both databases with a precision rate of 95.97% and 89.21%
J Jim´enez-García *et al.* [44], 2022	To categorize OSA using airflow and SpO2 data with DL algorithms	CNN	They employed the AHI level to categorise binary data with 94.44% accuracy for four accuracy levels: severe, mild, moderate, or normal
A Leino *et al.* [77], 2021	To determine OSA severity in stroke or TIA patients using SpO2 data solely	CNN	Using CNN based on respiratory episodes and SpO2 signals, they achieved 88.3% accuracy for SpO2 data
R. Lazazzera *et al.* [78], 2020	To diagnose apnea-hypopnea events utilizing photoplethysmography (PPG) and SpO2 signal	Fine Gaussian SVM	One-minute apnea and hypopnea detection were 75.1% accurate. Central (83.7%) and obstructive (82.7%) apnea were classified with good accuracy (92.6%)
H. Yoon *et al.* [45], 2020	To estimate apneic events utilizing only SpO2 dynamics	Regression model	The algorithm detected minute-by-minute apneic segments with 87.58% average accuracy and 0.6327 as Cohen's kappa coefficient

GentleBoost. For an unbalanced dataset, the RUSBoosted algorithm outperformed all others with 89.39% accuracy.

In another study of the same author [76], a study is proposed to diagnose OSA utilizing SpO2 signals. The authors worked with optimal duration-frequency concentrated (ODFC) wavelet filter bank (WFB) and SpO2 signals in this paper. They extracted the Shannon entropy attributes from the sub-bands and fed those to ML algorithms like DT, ensemble algorithm etc. The highest CAC was obtained for the SAE dataset with 95.97% accuracy.

A CNN-based model is proposed by J Jiménez-García et al. to diagnose OSA for neonatology. The authors combined airflow (AF) and pulse-oximetry (SpO2) signals to evaluate their suggested model. They also estimated the total AHI using these two signals together. Their model is unique because it combines these two types of signals for OSA identification in children. With the help of AHI standards and the CHAT dataset, they achieved accuracy within 84.64% to 94.44% [44].

Leino et al. [77] created a model using CNN architecture to determine the severity of OSA in individuals who had recent strokes or transient ischemic episodes (TIA). Only signals from pulse oximetry (SpO2) were used for this study's diagnosis. This was done so that the results could be referred to various types of evaluations to validate the discovery of OSA. Their model obtained a 90.9% sensitivity rate along with an accuracy of 88.3%. Lazazzera et al. [78] presented a study exploring how PPG and SpO2 data can identify and categorize SA and hypopnea. In this research, the authors studied how the previous occurrences of sleep apnea can be identified by studying the change in respiratory and SpO2 data. Their approach obtained 87.5%

accuracy on average using polysomnographic data containing 15 recordings.

Yoon et al. [45] proposed a study that demonstrates the potential for accurately detecting apneic events in sleep apnea patients using only SpO2 dynamics without the need for additional data sources. Using the regression method, they utilized per-min segments of SpO2 data to detect OSA. Their model achieved an accuracy rate of 87.58%.

Table 6 includes some recent studies utilising SpO2 signals that include the objective, classifiers or technology, and a description of the results.

F. SMARTPHONE OR DEVICE APPLICATION-BASED

Lyon et al. [80] proposed a paper where the effectiveness of a sonar-based non-contact sensing system as a screening tool for Sleep Disordered Breathing (SDB) is evaluated. A subject in bed can have their breathing and motions monitored using a smartphone placed on a nightstand with a personalized tray app. To recognize stages of sleep and find SDB patterns, this app uses cutting-edge proprietary algorithms. The model shows how well Drive technology works when compared with PSG, consistently and accurately detecting clinically notable SDB and calculating the AHI. The drive is a technology that can be easily adopted at scale for population monitoring and screening because it doesn't require any specialized hardware besides the ubiquitous smartphone.

Without external sensors, Jeon et al. [47]. described a process for real-time SA detection using a wearable smart device. The model proposes a system capable of forecasting SA at any instant. A wearable device was used to monitor the breathing, heart rate, 3-ACC signals and SpO2 in patients with SA. Patients' breathing and SpO2 levels are monitored to determine how severe their sleep apnea is. The heart or pulse rate and 3-ACC data are measured using machine learning techniques like GNB, ANN, and KNN to see if sleep apnea correlates with the measurement. The study here includes 5 apneic patients and 3 healthy volunteers, both tracked for 7 days. The dataset for apnea used in this study consists of data sets evaluated by SpO2 and respiration. When the three algorithms are compared, this model provides the highest accuracy for KNN with an accuracy of approximately 95%.

A fully integrated hardware set for ML-based SA detection in Neo-natal Intensive Care Units (NICU) is represented by Hassan et al. [79]. It is suggested to use an ML-based compact feedforward architecture for hardware system design. This system benefits from the proposed model's accuracy rate of over 85%. This machine learning-based wearable biomedical device will offer a substantial improvement compared to existing approaches for identifying SA in newborns in NICUs. The customary, hefty, high-power equipment used in NICUs and ICUs will be replaced in the future by ML models that are extremely accurate and use low-power methods. The automatic alarm guide of this technology would also reduce the heavy workloads of doctors and caregivers during long shifts.

Hoppenbrouwer et al. [46] proposed a study that revealed how to screen individuals for OSA utilizing multivariate random forest (RF) models that use SpO2 and airflow inputs and a new nasal pulse oximeter. The airflow signal performs better when screening adults for OSA when using AHI 5 and AHI 10 as the detection cutoff, with AUC values of 89.0% and 80.0%, respectively, compared to 78.0% and 77.0% with SpO2 analysis. Including airflow signals in the analysis enhances the potential of using nasal pulse-oximetry for improved screening of OSA at home, surpassing the capabilities of traditional finger pulse-oximetry.

Castillo-Escario et al. [81] propose a mHealth system, utilizing the integrated microphone of a smartphone to capture and analyze breathing signals overnight, aiming to conduct OSA screening [81]. They mainly developed an algorithm to detect silent events, classify them into apnea & hypopnea, and compare their performance with other commercial portable devices. Their developed device detected apnea with an accuracy of 89%, whereas hypopnea was detected with an accuracy of 61%. Due to a lack of mouth airflow data, they misidentified oral breathing as apneas at some point.

A study is presented by Ferrer-Lluis et al. [49] to detect the sleeping posture angle of people with OSA. They studied the effectiveness of smartphones to be used as a sleep position tracker. In this paper, the authors mainly detected the sleep position of the patients by using triaxial accelerometry from smartphones and compared it with the traditional sleep postures attained by video-authenticated PSG records to obtain high-resolution sleeping positions. Their developed algorithm obtained an accuracy of 95.6% to identify the sleeping position inclination of OSA patients.

Table 7 summarizes the works discussed in this section, including the study purpose, result analysis and classifiers utilized.

G. BASED ON WEARABLE OR PORTABLE DEVICES

The studies included in this section are summarised in Table 8, highlighting the objectives, classifiers or technology used and results.

Azimi et al. [86] proposed a study for recognizing CSA utilizing Pressure-sensitive mats (PSM). Here, a BiLSTM network and a Time-based Convolutional Network (TCN) are two deep learning techniques used to detect CSA events automatically. The top-performing BiLSTM model attains an accuracy rate of 95.1%. For the experiment, 9 elderly patients worked as volunteers for testing and training purposes. A device for detecting OSA is developed by Yüzer et al. The authors designed an OSA screening and detection method using an accelerator sensor in this paper [50]. The sensor continuously records the patient's diaphragm, which is then utilized to detect the subject's sleeping posture. Their device also sends alert notifications to users regarding their sleeping position. Their system measures crucial sleep apnea characteristics with a maximum breathless time of 42 sec.

TABLE 7. Works relating to smartphones or other smart gadgets.

Author, year	Objectives	Classifier/Technology	Results
Y. Jeon *et al.* [47], 2020	To diagnose sleep apnea using a smart watch excluding external sensors relying only on 3-ACC signals and pulse rate	KNN	KNN algorithm performed best with 95% accuracy in 640 μs, enabling wearable device real-time detection.
O. Hassan *et al.* [79], 2020	To develop an ML-based hardware system to detect sleep apnea for infants in NICU	FNN	The model performed well with an accuracy rate of more than 85% with minimal loss.
G. Lyon *et al.* [80], 2019	To evaluate the contactless sonar-based SDB screening drive technology and AHI calculation.	LR	Their SDB screening method outperformed others with 96% accuracy, 94% sensitivity, and 97% specificity.
X. L. Hoppenbrouwer *et al.* [46], 2019	To determine if an airflow signal is more effective than SpO2 signal evaluation in screening elders for OSA.	RF	Screening adults for OSA with 89% AUC and for airflow scrutiny, 80% rate is more effective.
Y Castillo Escario *et al.* [81], 2019	A smartphone microphone is used to acquire nocturnal breathing acoustic signals for OSA screening and classification and compare performance with commercial equipment.	Self-made functions in MATLAB	The device detected apnea with an accuracy of 89%, whereas hypopnea was detected with an accuracy of 61%.
Lluis *et al.* [49], 2021	This work proposes a higher-resolution sleeping posture detector utilising a smartphone's tri-axial accelerometry.	Custom computation method in MATLAB	They primarily created an algorithm with an accuracy of 95.6% to identify the sleeping position inclination of OSA patients.

TABLE 8. Researches related to wearable or portable devices.

Author, Year	Objectives	Classifier/Technology	Results
H. Azimi *et al.* [86], 2020	To detect Central sleep apnea using Pressure-sensitive mats (PSM), implementing deep learning methods	TCM, BiLSTM, SVM	Using a BiLSTM network, the model achieves an accuracy of 95.1%.
Yüzer *et al.* [50], 2020	To implement an SA detection device that alerts patients/ This study suggested employing an acceleration sensor for sleep apnea assessment, recognition, alerting, and patient position detection.	Accelerator Sensor	Their system measures crucial sleep apnea characteristics with a maximum breathless time of 42 sec.
F Baty *et al.* [87], 2020	To analyse SA intensity using a transportable ECG belt in SAS suspects.	KNN, SVM, LDA	The ECG belt produced data similar to patched ECGs and might be utilized to detect sleep apnea incidences, notably during follow-up.
A Manoni *et al.* [88], 2020	To develop an unobtrusive wireless wearable device, designated MORFEA, for the home pre-screening of SRBD.	Power Spectral Density (PSD), Pulse Wave Amplitude (PWA) features	The wearable gadget with a 9-hour battery backup can detect sleep apnea with 88.6% sensitivity, differentiate between OSA and CSA and identify user sleeping posture.
E Zancanella *et al.* [51], 2022	To compare home unaided type-II transportable polysomnography for OSAS diagnosis with sleep lab polysomnography using the same equipment.	EEG sensors, sleep pattern, respiratory episodes, and oxyhemoglobin concentration	They found that the same lab equipment used by technicians may be utilised unaided at home with the same precision.
M. Baboli *et al.* [89], 2019	To develop a non-contact sleep apnea detection system using radar, achieving high accuracy, which uses continuous wavelet quadrature Doppler Radar	PRMS (Physiological radar monitoring system)	The study achieved an accuracy of 92% in distinguishing apnea-hypopnea events with a sensitivity of 86% and a specificity of 91%.
G Surrel *et al.* [120], 2018	To produce an energy-efficient, patient-specific online OSA detection method that screens for 46 days on a single charge.	SVM, RF	Their model achieved an accuracy of 88.2% with 84.7% F1 score using SVM implementing single channel ECG signal for monitoring SA.
T. Van Steenkiste *et al.* [90], 2020	To detect an automated event, this research proposes a portable device and a two-phase LSTM deep learning algorithm that uses bioimpedance of the chest	LSTM	The specificity, sensitivity, AUC, and accuracy were recorded to be 76.2%, 58.4%, 46.9%, and 72.8%, respectively.

Baty et al. [87] analysed the intensity of SA. In this work, the authors developed an ECG chest belt and recorded signals using both the ECG belt and patched ECG during PSG recordings. They used recordings from 241 patients to assess their devices. The study found that the ECG belt produced signals similar to those obtained from patched

TABLE 9. Additional studies based on different sensors and signals.

Author, Year	Objectives	Classifier/Technology	Results
M.S. Adha *et al.* [38], 2021	To identify OSA from thoracic and abdominal movement based Signals	A dual (respiratory inductance plethysmography) RIP-based automatic apnea detection (RAAD) system	By using the developed method, it was capable of identifying OSA with accuracy (99.83 ± 0.71%)
H. B. Kwon *et al.* [110], 2021	To utilize a DL model and IR-UWB radar, a unique method for real-time Apnea event identification.	Hybrid CNN BiLSTM	The suggested approach has an accuracy of 93.0%, a sensitivity of 78.1%, a specificity of 95.6%, and a Cohen's kappa value of 72.8%.
P. Weng *et al.* [121], 2022	To detect OSA using Emma-fApEn from HRV	Random Forest (RF)	In the study, RF gives the maximum accuracy of 96.67% and 91.67% in moderate OSA and acute OSA diagnosis
T. Van Steenkiste *et al.* [122], 2018	To introduce a technique that utilizes state-of-the-earth deep learning models to extract characteristics and identify sleep apnea occurrences within respiratory signals automatically using the LSTM neural network	State-of-the-art deep learning method, LSTM	The paper presents an automatic technique for detecting SA through LSTM neural networks, which were trained on respiratory signals, resulting in an accuracy of over 90%.
G. Ye *et al.* [123], 2021	To introduce a new network called FENet can extract features from RRI signals and produce continuous detection results with downsampled and discontinuous RRI signals.	FENet	The FENet model showed promising results in detecting OSA using frequency bands of RR-interval signals, outperforming previous methods giving an accuracy of 99.22% using the PAE dataset.
C. Wang *et al.* [99], 2019	To introduce a new system for detecting sleep apnea using an AI mattress with UWB technology.	KNN	After comparing several classifiers, KNN gives the best sensitivity as 71.5 %± 6.8%
D Padovano *et al.* [100], 2022	To aid in the advancement of SA detection techniques that are more precise and dependable, which could improve diagnosis and treatment for individuals with sleep apnea with ML using HRV.	BAG, SVM, KNN, TREE, ADA	The study found that more diverse databases are needed, instead of traditional ML models trained using popular datasets and external validation is essential for reliable assessment.
Xin-Xue Lin *et al.* [124], 2022	To detect OSA through the RAPIDEST framework, which utilizes AI and works by analyzing sleep stage sequences	CNN	The RAPIDEST framework gives an accuracy of 82.9%, 80%, and 69.15% for Sleep EDF, UCD, and WSC datasets, respectively.
L. Tang *et al.* [102], 2021	To use 2D temporal dependency analysis in conjunction with time series of RR segments to detect SA and ANS complexity.	SVM, KNN, GNB, DT	CgSampEn2D accurately measured ANS complexity in patients with OSA with 93.3% accuracy.
R.K. Tripathy *et al.* [125], 2020	To diagnose sleep apnea automatically utilizing bivariate CP signals	SVM, RF	Using the 10-fold cross-validation approach, the average sensitivity and specificity are 82.27% and 78.67%, respectively.
Yuliya Zhivolupov *et al.* [126], 2019	To detect Cheyne-Stokes breathing, and also determine sleep apnea and hypopnea episodes at the same time, all within a singular framework using the suggested algorithm.	LR	The average sensitivity and specificity are 79.22% and 95.57%, respectively using this model.

ECGs and could be utilized for evaluating the severity of SA, particularly in follow-up assessments.

The authors developed a wearable device, MORFEA with 9h lasting battery backup which can detect sleep apnea, distinguish between OSA and CSA, and identify the sleeping position of the patient in the study proposed by Manoni et al. [88]. The wearable gadget can detect sleep apnea with 88.6% sensitivity and identify the user's sleeping posture. Baboli et al. [89] proposes a wireless SA recognition system employing continuous-wave quadrature Doppler radar. The system achieves high accuracy and specificity, making it a promising alternative to traditional polysomnography for sleep disorder diagnosis.

In another study, Surrel et al. [120] developed a patient-specific online OSA detection technique that is energy efficient and gives a battery backup of continuous monitoring for 46 days and shows great accuracy as well using single channel ECG signal. Van Steenkiste et al. [90] introduced a novel technique for identifying sleep apnea and hypopnea events via a portable device that measures bio-impedance of the chest [90]. This method uses deep learning algorithms to analyze the data and accurately detect these events. Zancanella et al. [51] experimented with the performance accuracy of SA for home diagnosis using Type 2 portable polysomnography, which can record 11 polygraph signs and compared the results with laboratory testing accuracy.

H. ADDITIONAL STUDIES ON DIFFERENT TYPES OF SIGNALS AND SENSORS

Adha and Igasaki [38] suggested a study where a 3-stage breathing effort quantification method for detecting OSA has been developed based on signals from the thorax and abdomen. It gives a high accuracy of 99.83 ± 0.71%. Kwon et al. [110] showed a model with hybrid CNN-LSTM for the live AH diagnosis collecting the data from IR-UWB radar.

Uddin et al. presented a study saying that patients with obstructive Sleep Apnea (OSA), the most prevalent sleep disorder, suffers from inadequate at-home monitoring [127]. Doppler radar is emerging as a promising solution as the previous radar-based systems faced challenges in accurately distinguishing apnea and hypopnea. This study introduces a heart rate variability (HRV) method claiming a 97% accuracy in discerning various OSA events, surpassing previous methodologies. Martín-Montero et al. [128] proposed a study that examines heart rate variability (HRV) in pediatric obstructive sleep apnea (OSA), integrating sleep stages and apneic events. NREMS showed significant HRV changes with increasing apneic events, less pronounced in REMS. Specific HRV parameters distinguished sleep stages and events, aiding OSA assessment.

The suggested study gives an accuracy, specificity, Cohens's kappa and sensitivity of 93.0%, 95.6%, 72.8% and 78.1% respectively. A work where the HRV nonlinear analysis technique Emma-fApEn was proposed for the identification of OSA is presented by Weng et al. [121]. Van Steenkiste et al. proposed a new approach for detecting SA utilizing LSTM networks on raw respiratory signals [122]. The study tested the accuracy of the proposed method using data from the SHHS and found that it outperformed traditional machine learning methods. This method holds promise in enhancing the precision and effectiveness of SA diagnosis, which can lead to better treatment outcomes.

Ye et al. [123] introduce a new method called the FENet, which is capable of retrieving features or characteristics from various frequency ranges of theRR-intervals (RRI) as input. FENet can generate uninterrupted detection outcomes even with non-continuous and downsampled RRI signals. Another study introduces a new sleep apnea detection technique that uses an ultra-wideband (UWB) artificial intelligence mattress [99]. The method demonstrated high accuracy in detecting sleep apnea events and provides a non-invasive approach to sleep monitoring.

Padovano et al. [100] presented an article that discusses the limitations of using HRV and ML for SA recognition and emphasizes the necessity of larger and more diverse databases for reliable clinical use. Lin et al. [124] suggested a new AI framework called RAPIDEST that utilizes the sequence of sleep stages to identify and detect OSA [124]. A novelty score to measure the atypicality of the sleep stage sequence was introduced in this study.

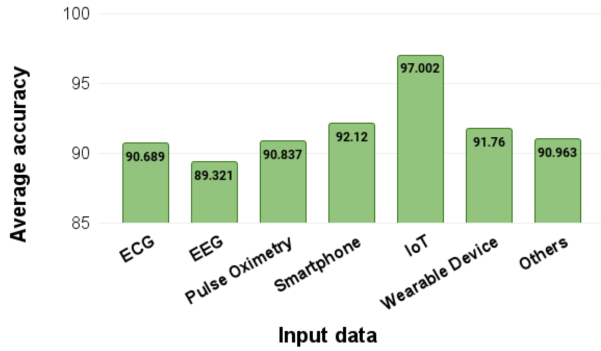


FIGURE 8. **Average Accuracy using different input.**

Tang and Liu [102] proposed a study based on heart-rate variability utilizing ECG signals [102]. The authors suggested a method for the analysis of time dependency complexity. They introduced the CgSampEn2D model, where the conversion of a single scale to a multi-scale series of time is done, then converted to GASF image files, and at last, the complexity of the images is studied. This method was evaluated through simulation while optimizing the testing parameters. This model obtained 93.3% accuracy for OSA screening.

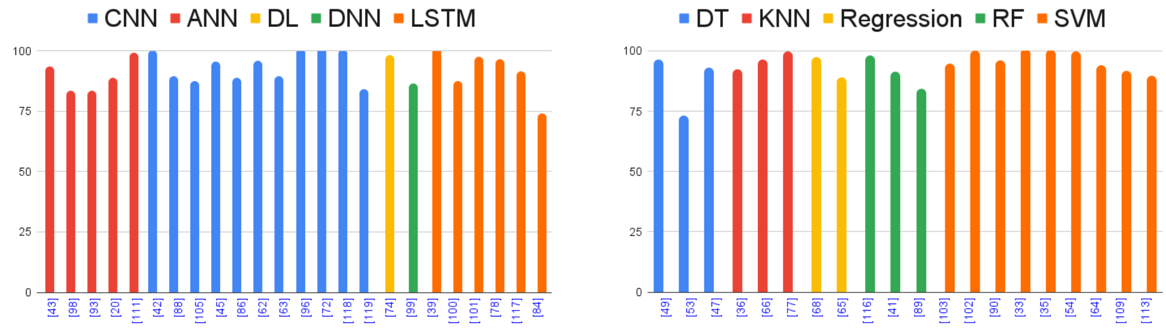
Tripathy et al. [125] proposed a study that suggests an autonomous approach to identify SA utilizing CP signals through a combination of bivariate fast and adaptive EMD, along with cross-time-frequency analysis. They aimed to detect SA using bivariate CP signals that obtained an average sensitivity of 82.27% along with 78.67% specificity.

Zhivolupova et al. [126] presents an algorithm that aims to detect Cheyne-Stokes breathing and determine sleep apnea and hypopnea episodes together within a single framework.

V. DISCUSSION

Diverse methodologies have been employed to attempt and detect SA. In this paper, some of the effective sleep apnea detection techniques, which can be further studied for implementation as a parallel procedure of polysomnography or HSAT are summed up briefly. This study places significant emphasis on the procedure of collecting and utilizing data, as well as the methodologies employed for detecting or categorising SA. The paper also highlights the performance evaluations of the proposed models, underscoring their significance in the research.

Many researchers also reviewed SA detection strategies [96], [129], [130], [131]. In [129], the authors highlighted the focus on utilizing ML techniques, specifically with ECG data, to detect SA. Here, the authors carefully examined the chosen works and went into detail about the performance indicators; however, the focus was only on ECG signals. In the comprehensive study of [96], the reviewers compared and contrasted ML methodologies and DL approaches, but preprocessing steps were elaborated for ECG signals only. In [130], a systematic review was



(a) Overall accuracy based DL models (b) Overall accuracy based ML models

FIGURE 9. A comparative analysis of accuracy performance of different ML and DL classifiers.

conducted on SA detection using DL approaches only. The authors analysed SA detection approaches in [131], but there is a lack of information about preprocessing techniques or feature extraction processes. However, only current studies were included in this review, along with ML and DL techniques, various detection categories, and a thorough examination of the generic SA detection strategy.

The performance, approaches, and strategies related to SA detection are outlined in this study, emphasising various ways based on sensors, signals, or technology. According to recent statistics, the greater focus is given to detecting SA categories implementing ECG signals using DL algorithms [29], [33], [34], [64], [94], [98], [108], [109]. Most of the researchers implemented CNN architecture or modified algorithms like DCNN [34], SCNN [64], CNN-LSTM [109] or CNN-DRNN [96] combination. Apart from ECG signals, authors implementing EEG signal or SpO2, AF signals or IoT technology also used DL approaches like CNN [39], [68], [82], [106], ANN [32], [35], [62], [107], ANN-MLP combination [21], [36], FCNN [105]. Table 3 - 9 shows that DL algorithms are often utilised for SA detection because they are more suited for precise and patient-specific feature extractions. However, the works based on IoT technology have superior average accuracy, as illustrated in Fig. 8. Few authors also implemented ML algorithms like SVM, KNN, DT, RF etc. but yielded the best accuracy for SVM [37], [56], [85], [98], [111]. Fig. 9 represents some of the accuracies found using different DL and shallow ML-based classifiers within the studied papers. Table 3 summarizes the works where ECG signals are used for SA detection. Their typical working method involves extracting HRV characteristics, R-R intervals [35], [59], [94], [111] or statistical data [60], or time-dependent features [21], [113], which are then fed into ML or DL algorithms for classification. Few authors also used wavelet transform techniques [62], [64].

Table 4 lists the studies employing EEG signals for SA identification. Generally, EEG signals are decomposed into sub-bands of different frequencies or EMD (Empirical Mode Decomposition), which are then used for extracting features and then put into ML [40], [54], [56], [57], [71], [72] or DL algorithms [55], [68], [105]. Works employing the Internet of Things are included in Table 5. Most studies in this category follow a standard methodology in which the authors develop a real-time monitoring and warning system for SA that also benefits healthcare professionals. Here, fog computing offers better protection for instantaneous sensitive data and operates more quickly owing to its short latency. A few authors have also used machine learning [37], [84], [85] or deep learning [39], [82], [106] methods in addition to cloud computing. Even though a few authors utilised data they generated themselves [82], [83], the accuracy seems greater due to their population being too small. In light of this, it is rather uncertain if their system will function with more data. A few trending works with a combination of oxygen saturation, chest movement or airflow signals are summarized in Table 6. Since SpO2 readings and AF signals may precisely identify apnea episodes, this combination has recently gained prominence and shows promising outcomes.

The average model accuracy for the categories included in this review work is highlighted in Fig. 8. A few IoT-based studies used simulated models instead of actual ones, which would have provided greater accuracy [48]. However, ECG-related studies produced inconsistent findings, resulting in an average accuracy of about 91% on average. In Table 7 and 8, works utilizing smartphones, wearable devices like ECG belt [87], smartwatch [47] or portable devices [88], [89], [90] are listed out. Some of the works detected sleeping posture [49] or some detected SA intensity [87] or some detected or classified SA utilizing different sensors like accelerometer [50] or EEG sensors [51]. Still, most of them worked with self-generated or private data. Some additional studies are also included in Table 9. Here, different works are presented where authors used thoracic and abdominal movement [38], radar-based model [110], AI mattress [99], HRV features [100] or a single algorithm to detect multiple diseases [126]. These works also utilized ML or DL algorithms for classification, such as CNN, LSTM, KNN, SVM, and GNB.

VI. CONCLUSION

In this research, we thoroughly analysed the models, data, and performance of existing approaches for various data sources. It has been discovered that approaches for identifying OSA that use classifiers like CNN, SVM, and ANN generally perform better than other methods. Other methods may encompass techniques such as logistic regression, decision trees, and k-nearest neighbors, which typically rely on handcrafted features and simplistic models. In contrast, contemporary approaches like CNN, SVM, and ANN leverage more sophisticated architectures and automated feature learning, allowing them to capture intricate patterns and relationships within the data. Wearable devices are also anticipated to be crucial in diagnosing SA and aiding doctors in providing care. The studies based on wearable technology mostly utilized IoT, Big Data, and Cloud computing technologies.

The utilization of classifier-based models facilitates precise feature extraction and selection, offering a more refined preprocessing approach compared to manual signal scoring conducted by laboratory experts. This automated methodology enhances the accuracy and efficiency of data preprocessing, ensuring that relevant signal characteristics are systematically extracted and optimized for subsequent analysis. By leveraging ML and DL based approaches, researchers can streamline the preprocessing workflow, minimizing subjective biases inherent in manual scoring processes. Consequently, this automated preprocessing strategy surpasses conventional manual scoring methods, demonstrating superior efficacy in signal preprocessing for obstructive sleep apnea detection.

A comprehensive analysis of existing studies reveals that using Convolutional Neural Network (CNN) in conjunction with other models improves accuracy. Additionally, SVM and ANN algorithms provide notable accuracy. Most studies used the easily accessible ECG dataset from the Physionet bank to develop their algorithms. The University College Dublin (UCD) database is also commonly used. IoT-based efforts, however, put a strong emphasis on notification or treatment systems in addition to detection. Wearable devices as well as pulse oximetry, are useful today for identifying SA. Several authors also used hybrid models in the study. Numerous studies have shown that when multiple features are offered, different classifiers solve the same problem differently depending on the significance of the individual features to the system performance. In brief, this review emphasizes the critical role of precise sleep apnea detection techniques in enhancing patient health and scientific inquiry. Future research should focus on integrating advanced sensor technologies, developing more robust hybrid models, and improving the interpretability of machine learning algorithms. By prioritizing these areas, researchers can enhance diagnosis accuracy and ultimately improve the quality of life for individuals suffering from this pervasive sleep condition.

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ROKSANA AKTER RAISA received the B.Sc. degree in information and communication engineering (ICE) from Bangladesh University of Professionals (BUP), in 2023. She has published one conference paper in Springer. Her research interests include machine learning, deep learning, artificial intelligence, bio-medical image processing, signal processing, and natural language processing.

AYESHA SIDDIKA RODELA received the B.Sc. degree in information and communication engineering (ICE) from Bangladesh University of Professionals (BUP), in 2023. Her research interests include machine learning, deep learning, artificial intelligence, bio medical image processing, signal processing, and natural language processing.

MOHAMMAD ABU YOUSUF received the B.Sc.(Engineering) degree in computer science and engineering from the Shahjalal University of Science and Technology, Sylhet, Bangladesh, in 1999, the Master of Engineering degree in biomedical engineering from Kyung Hee University, South Korea, in 2009, and the Ph.D. degree in science and engineering from Saitama University, Japan, in 2013. In 2003, he joined as a Lecturer with the Department of Computer Science and Engineering, Mawlana Bhashani Science and Technology University, Tangail, Bangladesh. In 2014, he moved to the Institute of Information Technology, Jahangirnagar University, Savar, Dhaka, Bangladesh. He is currently a Professor with the Institute of Information Technology, Jahangirnagar University. He has published more than 100 research papers in different international journals and conferences. His research interests include bio medical image processing, human-robot interaction, computer vision and natural language processing.

AKM AZAD received the Ph.D. degree in computational systems biology and biostatistics from Monash University, Australia, in 2017. He did his a first Postdoctoral Fellowship with the Faculty of IT, Monash University. He was a Postdoctoral Research Associate with the AI Laboratory, School of BABS, UNSW Sydney, contributing/leading multiple bioinformatics, and computational biology projects. Recently, he has joined the University of Technology Sydney, as a Research Fellow for developing cutting-edge methodologies and tools for online inference of phylogenetic trees from COVID-19 sequences. His research interests include AI/ML/DL, Bayesian statistics, MCMC, Bayesian networks, bioinformatics, and computational biology.

SALEM A. ALYAMI (Member, IEEE) received the Ph.D. degree in bio-statistics from Monash University, Australia, in 2017. Since 2017, he has been an Associate Professor with the School of Mathematics and Statistics, Faculty of Science, Imam Mohammad Ibn Saud Islamic University (IMSIU), Riyadh, Saudi Arabia, contributing/leading several grants in biostatistics projects. Recently, he has appointed as the Dean of the Deanship of Scientific Research with IMSIU. His research interests include Bayesian networks, neural networks, Bayesian statistics, MCMC methods, and applications of statistics in biology and medicine.

PIETRO LIÒ received the M.A. degree from the University of Cambridge, the Ph.D. degree in complex systems and non-linear dynamics from the Department of Engineering, School of Informatics, University of Firenze, Italy, and the Ph.D. degree in (theoretical) genetics from the University of Pavia, Italy. He is currently a Full Professor of computational biology with the Computer Laboratory, University of Cambridge, and a member of the Artificial Intelligence Group. His research interests include bioinformatics, computational biology modeling, and machine learning to integrate various types of data (molecular and clinical, drugs, social, and lifestyle) across different spatial and temporal scales of biological complexity to address personalized and precision medicine.

MD ZAHIDUL ISLAM is currently a Professor of Computer Science and the Associate Dean Research of the Faculty of Business, Justice and Behavioural Sciences (FOBJBS), Charles Sturt University (CSU). His main research interests include data mining, with a particular focus on its applications in heath, agriculture, and cyber security.

GANNA POGREBNA received the Ph.D. degree in economics and social sciences. She studied economics with the University of Missouri Kansas City, U.S., and the University of Innsbruck, Austria. He is currently the Executive Director of Artificial Intelligence and Cyber Futures Institute, Charles Sturt University. Before coming to Australia, he was with Columbia University, New York, NY, USA, the University of Bonn, Germany, Humboldt-Universitt zu Berlin, Germany, the University of Innsbruck, the University of Warwick, U.K., and the University of Birmingham, U.K. Blending behavioral science, AI, computer science, data analytics, engineering, and business model innovation, he helps cities, businesses, charities, and individuals to better understand why they make decisions and how they can optimize their behavior to achieve higher profit, better social outcomes, and flourish and bolster their wellbeing.

MOHAMMAD ALI MONI received the Ph.D. degree in artificial intelligence and digital health data science from the University of Cambridge, U.K. He worked in world top universities, including Oxford University, Cambridge University, Sydney University, UNSW Sydney, and The University of Queensland. He is currently a Professor of artificial intelligence and data science. He continued to focus on the same teaching and research areas during the last 15 years and has led and managed significant research programs, such as using big health data to develop machine learning, deep learning and translational data science models, and software tools to aid diagnosis and prediction of disease outcomes, particularly for hard-to-manage complex and chronic diseases. He has published over 300 top-tier journal articles and received more than 23000 citations with H-index 65. His research interests include developing statistical models, machine learning and deep learning algorithms, software tools utilizing multimodal data, especially medical images, neuroimaging, EEG, ECG, bioinformatics, and secondary usage of routinely collected data for different conditions.