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PAPER

AI-Enhanced Biosignal Analysis for Obstructive Sleep Apnea Detection: A Comprehensive Review

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ABSTRACT

Obstructive sleep apnea (OSA) detection using single-lead electrocardiograms (ECGs) has advanced significantly with the integration of artificial intelligence (AI). This review explores how AI enhances feature extraction and machine learning algorithms to improve OSA detection. The RR interval in electrocardiographic data is particularly valued for its ease of identification and low error rate. We review a range of machine learning and deep learning techniques employed in OSA detection. This review offers insights into developing single-lead ECG-based OSA detection systems by analyzing database availability, feature extraction methods, and machine learning approaches.

KEYWORDS

obstructive sleep apnea (OSA), bio signal-based detection, artificial intelligence (AI), electrocardiogram (ECG)

1 INTRODUCTION

The international classification of sleep disorders (ICSD) meticulously categorizes more than sixty distinct sleep disorders, with sleep apnea emerging as one of the most prevalent conditions that significantly disrupt normal breathing during sleep. This disorder manifests predominantly in two primary forms: obstructive sleep apnea (OSA) and central sleep apnea (CSA). OSA, the more prevalent type, primarily arises from anatomical obstructions, resulting in breathing challenges during sleep. These obstructions, commonly associated with relaxed throat muscles or structural issues in the upper airway, lead to the hallmark symptom of snoring in affected individuals. The disruptions in breathing, characterized by partial or complete blockages of the upper airway, cause intermittent pauses in breathing, leading to oxygen deprivation and sleep disturbances [1].

Untreated OSA significantly increases the risk of cardiovascular and neurological problems. It raises stroke risks due to irregular breathing patterns (low oxygen) and contributes to hypertension (strain on the heart). OSA can worsen heart failure and

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lead to excessive daytime sleepiness, impacting daily life and increasing accident risks—notably, memory and cognitive function decline in individuals with untreated OSA. Early diagnosis and treatment are crucial to mitigate these health risks [2].

Acknowledging the profound impact of OSA on overall health and well-being, the early identification of this condition becomes imperative to mitigate its potential long-term consequences. Polysomnography (PSG), often acknowledged as the gold standard in diagnosing sleep disorders such as OSA, plays a pivotal role in objectively assessing and quantifying the severity of this condition [3]. PSG involves an extensive monitoring process conducted in a controlled sleep laboratory setting. During this diagnostic procedure, a multitude of physiological parameters are meticulously recorded. These include brain wave activity, eye movement, muscle tone, heart rate, respiratory effort, airflow, and blood oxygen levels, providing comprehensive insights into an individual's sleep patterns and identifying any irregularities or disruptions. PSG allows clinicians to accurately assess the frequency and severity of breathing disturbances characteristic of OSA, thereby aiding in its diagnosis and guiding appropriate treatment strategies [3].

One of PSG's limitations is its cumbersome nature, requiring patients to spend a night in a specialized sleep laboratory environment under the close supervision of trained technicians. This necessitates considerable time commitments, inconveniencing patients and potentially disrupting their natural sleep patterns. The setup's complexity, involving an array of sensors and wires attached to the patient's body, often leads to discomfort and unease, affecting the overall sleep experience and potentially compromising the accuracy of recorded data. These factors collectively increase the overall cost and limit the accessibility of PSG, making it less feasible for routine diagnostic use in sleep clinics or broader community healthcare settings [4].

Research efforts have extensively focused on simpler diagnostics for OSA. One uses single-lead electrocardiography (ECG) to enhance patient comfort during diagnostic procedures [3]. The ECG waveform exhibits distinctive patterns corresponding to different phases of the cardiac cycle, enabling the identification of irregularities in heart rate, rhythm, and conduction. Its ability to precisely capture these electrical signals facilitates the detection of subtle cardiac abnormalities or variations, which can indicate the presence of sleep-related disorders such as OSA. By employing ECG as a diagnostic tool for OSA, researchers aim to minimize patient discomfort associated with conventional diagnostic methods, such as PSG, while ensuring accurate and reliable diagnostic outcomes [3].

In OSA detection using ECG, substantial research has been dedicated to leveraging machine learning techniques for analyzing ECG data, aiming to enhance the accuracy and efficiency of diagnostic processes. Many studies have delved into diverse methodologies utilizing ECG signals for OSA detection, showcasing the evolving landscape of machine learning applications in this field. Laiali (2012) extensively explored the application of support vector machine (SVM) techniques for OSA detection through ECG signals [5]. Hassan and Haque (2016) focused on tailored signal processing methods for OSA detection using ECG, integrating spectral features to extract relevant information for diagnostic purposes [6]. Further enhancing diagnostic capabilities, OSA detection was investigated by integrating heart rate variability (HRV) and ECG-derived respiration (EDR) signals, employing SVM methodologies [7].

Advancements continued, adopting convolutional neural networks (CNN) and long short-term memory (LSTM) networks to detect OSA from ECG signals, demonstrating the effectiveness of deep learning approaches in signal analysis for sleep disorder detection [8]. Building upon this progress, we expanded the scope by incorporating additional physiological data, such as HRV and oxygen saturation (SpO2) signals, into CNN and LSTM methodologies for OSA identification, showcasing the integration of multiple signals for improved diagnostic accuracy [9].

These diverse studies illustrate the broad application of machine learning techniques in ECG signal processing for OSA detection. Such advancements highlight the evolving landscape of technology in sleep disorder diagnosis and emphasize the potential for developing more accurate, patient-friendly, and efficient diagnostic tools for identifying and managing sleep-related conditions.

2 INNOVATIONS AND BREAKTHROUGHS

Numerous scholarly reviews have explored the application of diverse deep networks. These reviews delve into the necessity of pre-processing or feature extraction and a comprehensive analysis of the merits and drawbacks of various network types [10]. Additionally, it examined the effectiveness of different algorithms and methodologies employing signals from multiple source sensors for OSA detection [4]. Discussed detecting sleep apnea through heart rate and explored treatment methods [11]. Showcased the effectiveness of various devices in diagnosing sleep apnea [12]. Reviewed diagnosis support systems based on ECG for OSA [13]. Reviewed classification methods for detecting adult sleep apnea based on respiratory and oximetry signals [14]. Provided an overview of OSA, covering its pathophysiology, detection methods, physiological signals associated with OSA, and different preprocessing, feature extraction, feature selection, and classification techniques employed for its detection and classification [15]. Systematically reviewed the literature on systems utilizing classification models to detect and predict apnea events in diagnosing sleep apnea syndrome [16].

Existing reviews have delved into various aspects of OSA detection; however, a comprehensive one still needs to be discovered. This paper aims to spotlight specific research gaps and opportunities that demand an in-depth investigation to drive progress in OSA detection. The aspects include database, feature extraction, algorithms, and performances.

Comprehensive database analysis: Current reviews touch upon public databases relevant to OSA detection. However, there is a need for a more exhaustive analysis. This necessitates a thorough evaluation of these databases, encompassing an assessment of their strengths, limitations, and the array of bio signals they offer for OSA research.

In-depth feature extraction techniques: While existing reviews provide insights into feature extraction methods from bio signals associated with OSA; a deeper exploration is required. Understanding the efficacy of various techniques and their impact on detection accuracy is crucial for a comprehensive understanding of OSA detection methodologies.

Comprehensive algorithmic comparison: Previous reviews discuss algorithms used in OSA detection, yet an extensive comparative analysis needs to be done. Considering algorithms' strengths, weaknesses, and applicability across diverse bio signals, such an analysis is essential for advancing OSA detection methodologies.

Evaluation of performance metrics: While existing reviews showcase performances of OSA detection methods, a consolidated analysis of performance metrics used across studies is absent. A detailed examination of the consistency and significance of these metrics in evaluating detection systems is pivotal for better understanding the efficacy of OSA detection methods.

3 METHODS

This review employed a comprehensive literature search strategy to identify relevant studies published between 1984 and 2022. The percentage of journals indexed in both Scopus and WoS is 73%, the percentage indexed only in Scopus is 18%, and the rate of other indexers is 9%. We utilized a combination of keywords, including "sleep apnea and algorithm," "sleep apnea and ECG," "sleep apnea and algorithm performance," "apnea and respiratory analysis," "RR interval ECG and apnea," and "sleep apnea and polysomnography."

After applying rigorous selection criteria, the search yielded many articles, including relevance to the specific research, prioritization of high-impact factor journals, comprehensive data, and frequent citations. In addition, the selected papers promise effective diagnostic tools. Our selection prioritized studies that presented diverse solutions and achieved promising results using similar methodologies. Figure 1 depicts the distribution of the selected articles across publication years, categorized by the keywords above.

This review paper focuses on OSA detection techniques. The following section will provide a brief overview of OSA and its diagnosis using PSG to ensure readers possess a foundational understanding. Additionally, we will explore publicly available databases relevant to OSA research. The subsequent section will delve into the various techniques employed for OSA detection. This section will detail the bio signals used, including SpO2, ECG, respiratory effort, and snoring. We will then focus on ECG analysis, exploring commonly used ECG components and RR interval features for identifying OSA. Finally, the review will analyze different classification methods employed in OSA detection, aiding readers in comprehending their effectiveness.

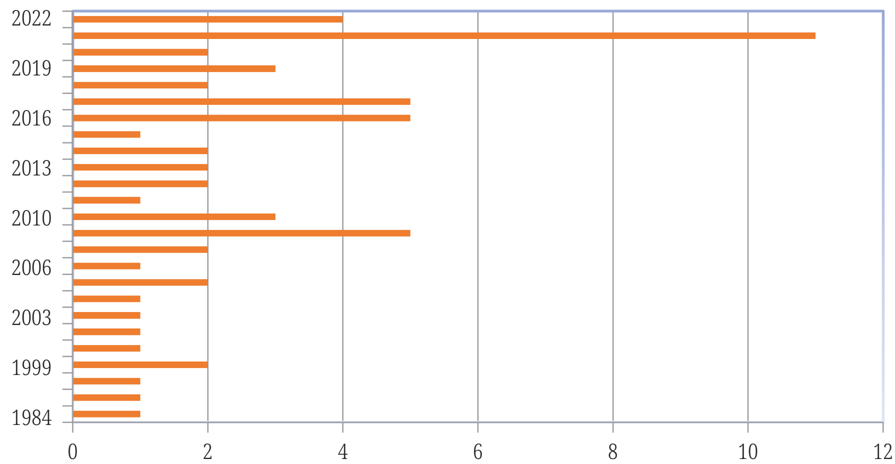

Fig. 1. The distribution of the selected papers by year

Figure 1 shows the distribution of the selected papers by year. According to it 73% are indexed in both Scopus and WoS, 18% are indexed only in Scopus, and 9% are other indexers

4 OVERVIEW OF OSA

Obstructive sleep apnea is a prevalent sleep disorder characterized by recurrent episodes of complete or partial breathing cessation lasting at least 10 seconds [1].

These episodes occur due to the transient collapse of the upper airway (pharynx) during sleep, leading to temporary interruptions in breathing. This airway closure disrupts airflow, preventing adequate ventilation and hindering patients from entering the restorative rapid eye movement (REM) sleep stage. The struggle to breathe also elevates blood pressure, stressing the heart. Consequently, individuals with OSA often experience distinct patterns of snoring and disrupted breathing. (see Figure 2 for a visual representation of airway obstruction in OSA patients [1]). The severity of OSA is measured using the apnea hypopnea index (AHI), which categorizes OSA into three stages based on the number of breathing events per hour: low (AHI 5-15), moderate (AHI 15-30), and severe (AHI ≥ 30) [1].

Several factors contribute to OSA development. Obesity is a significant risk factor strongly correlated with body mass index (BMI) and OSA frequency. Studies show that a 10% reduction in BMI can lead to a 26% decrease in AHI, highlighting the impact of weight management on OSA severity [17]. Conversely, weight gain can worsen OSA. This is because excess fat deposits around the pharynx constrict the upper airway.

Craniofacial abnormalities can also contribute to OSA. These include irregularities in the jaw (mandible) and upper jaw (maxilla) that compromise the airway. For example, a recessed jaw (mandible) can lead to a narrowed palatal arch, displacing surrounding tissues and constricting the airway. Similarly, a posteriorly positioned upper jaw can reduce the size of the respiratory passage [17].

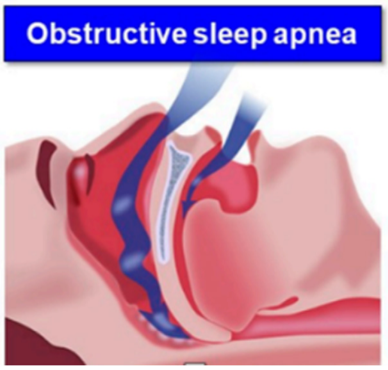

Fig. 2. Airway obstruction in OSA patients [18]

5 POLYSOMNOGRAPHY: STANDARD OSA STUDY

Polysomnography stands as a pivotal diagnostic test for sleep disorders. Its primary objective is to uncover any underlying irregularities in a patient's sleep patterns, aiding in an accurate diagnosis. This meticulously designed test captures a spectrum of physiological parameters, including electrical cardiac activities, brainwave dynamics, respiratory patterns, and leg and eye movements during sleep. While individuals with a low likelihood of OSA may be evaluated based on symptomatic and historical considerations, patients displaying moderate to severe OSA indicators are typically recommended for PSG assessment [19].

During a PSG evaluation, the patient's body is outfitted with an array of sensors strategically placed on the head, chest, temples, and legs. This multi-sensor configuration enables the simultaneous collection of data from various devices. The ensemble of devices encompasses electroencephalography (EEG) for monitoring brainwave activities, ECG for capturing electrical cardiac events, electromyography

(EMG) for tracking muscle and leg movements, electrooculography (EOG) for detecting eye movements, and a nasal airflow sensor. An illustrative representation of the PSG procedure is presented in Figure 3, depicting sensor inputs on the left and corresponding outputs on the right.

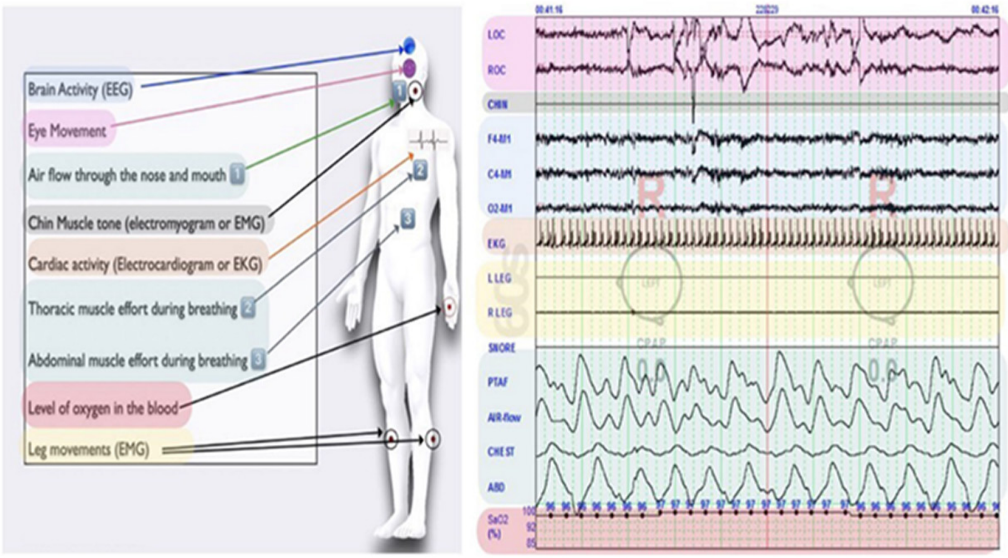

Fig. 3. Polysomnography examination [20]

6 POLYSOMNOGRAPHY: STANDARD OSA STUDY DATABASES FOR OSA DETECTION METHODOLOGIES

Data essential for experimentation and the design of OSA detection systems can be procured from data repositories dedicated to OSA detection research. Among the frequently tapped resources are the Stanford Sleep Disorders Clinic [21], exploration Fonctionnelle Cardio-Respiratory, Laboratoire de Physiologie [22], Philipps-University, Marburg, Germany [23], Pediatric Sleep Clinic [24], Apnea-ECG dataset [7], [25]–[31], Sleep Center of Samsung Medical Center (Seoul, Korea) [32], University College Dublin Sleep Apnea Database/St. Vincent's University Hospital [31], the Sleep Unit of Dr. Negrín collected in Gran Canaria University Hospital [33], and Beijing Tongren [34]. These pivotal databases are meticulously cataloged in Table 1.

Table 1. Databases for OSA detection

Database	Number of Patients	Access	Bio Signal
Stanford Sleep Disorders Clinic [21]	400 Patients (16 Female and 384 Male)	Accessible	ECG signal
d'Exploration Fonctionnelle CardioRespiratoire, Laboratoire de Physiologie [23]	91 patients (20 female and 71 male).	Inaccessible	ECG signal
Philipps-University, Marburg, Germany [23]	32 patients (7 Female and 25 Male),	Inaccessible	ECG signal
Pediatric sleep clinic [24]	50 patients	Accessible	ECG and EDR signals
Apnea-ECG dataset [7], used in [19], used in [20]	35 patients	Accessible (physionet.org)	ECG and SpO2 signals

(Continued)

Table 1. Databases for OSA detection *(Continued)*

Database	Number of Patients	Access	Bio Signal
University College Dublin Sleep Apnea Database/St. Vincent's University Hospital [31]	25 patients (4 Female and 21 Male)	Accessible	ECG signal
Sleep Center of Samsung Medical Center (Seoul, Korea) [9], used in [32]	82 Patients (19 Female and 63 Male)	Accessible	ECG, SpO2, respiratory and snoring signals
Sleep Unit of Dr. Negrín was collected in Gran Canaria University Hospital [6], used in [25]	70 patients (19 Female and 51 Male)	Inaccessible	ECG signal
Beijing Tongren [7], used in [27], used in [34]	148 Patients (34 Female and 114 Male)	Inaccessible	ECG signal
Apnea-ECG dataset [22], used in [23], used in [35]	70 patients	Accessible (physionet.org)	ECG and SpO2 signals

Table 1 provides a comprehensive overview of available databases, enumerating patient counts and accessibility particulars. These databases encompass direct access options, allowing immediate download of patient data from online sources and indirect access routes. Databases that can be accessed directly include the sleep center of Samsung medical center [32], pediatric sleep clinic [24], Stanford sleep disorders Clinic [21], and University College Dublin Sleep Apnea Database/St. Vincent's University Hospital [31]. On the other hand, databases such as d'Exploration Fonctionnelle CardioRespiratoire, Laboratoire de Physiologie [22], Sleep Unit of Dr. Negrín collected in Gran Canaria University Hospital [33], and Beijing Tongren [34] require an indirect access approach. For instance, the Apnea-ECG dataset [7], [25]–[31], [35], which is accessible directly, is outlined in Figure 4, while the direct accessibility of St. Vincent's University Hospital database [31].

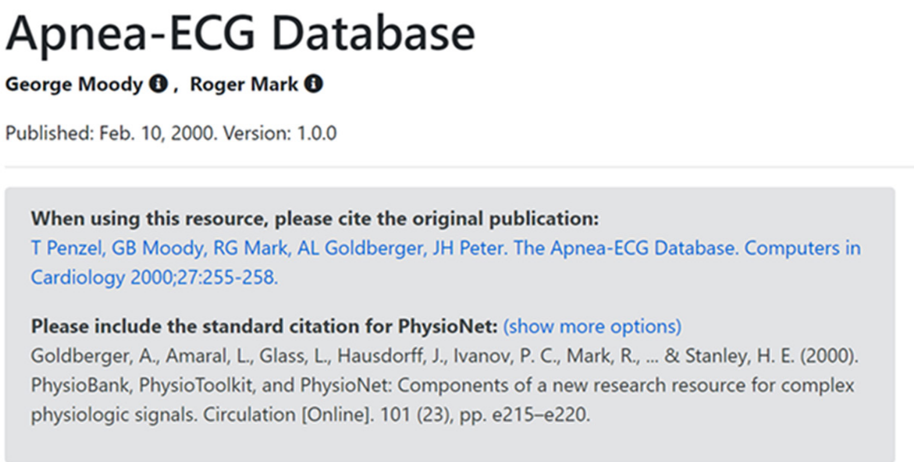

Fig. 4. Database of apnea-electrocardiography dataset [36]

A notable discrepancy arises in patient counts across these databases, with the Stanford Sleep Disorders Clinic [21] boasting the highest count at 400 patients and the University College Dublin Sleep Apnea Database/St. Vincent's University Hospital [33] registered the lowest count at 25 patients. Gender distribution exhibits marked disparities across databases, with the Stanford Sleep Disorders Clinic [21] database recording the most significant gender difference, with 384 males and 16 females.

Several databases further categorize patients based on OSA severity levels. For instance, the apnea-ECG dataset [22–25] and the pediatric sleep clinic [25] classify patients into severe, moderate, and mild apnea categories based on the duration of apnea episodes during sleep. Notably, patient data stratification into testing and training subsets is observed in specific databases such as d'Exploration Fonctionnelle Cardio-Respiratory, Laboratoire de Physiologie [22], and pediatric sleep clinic [24]. For example, the pediatric sleep clinic's dataset is partitioned into 25 training patients (11 normal, 14 with OSA) and 25 testing patients (11 normal, 14 with OSA) [24].

The apnea-ECG dataset emerges as a prevalent choice for research endeavors, featuring two distinct versions—an initial 35-patient dataset [19–21] and a subsequent iteration with 70 patients [22–25]. The former includes records coded a01 to a20, b01 to b05, and c01 to c10, while the latter encompasses records a01 to a20, b01 to b05, and c01 to c10, along with additional test records coded x01 to x35. Each ECG record within these datasets is obtained via PSG and spans 401 to 587 minutes. These ECG signals maintain a 100 Hz frequency and 12-bit resolution, with each minute labeled as A (apnea episode) or N (normal episode), corresponding to the presence or absence of apnea in OSA patients.

7 PREVIOUS STUDIES IN OSA DETECTION

The OSA detection techniques have been studied. In general, the various methods used can be seen in Figure 5. As seen in Figure 5, which illustrates OSA detection studies, the first stage includes multiple types of signals used, the second involves ECG components, the third comprises various features, and the final is classification.

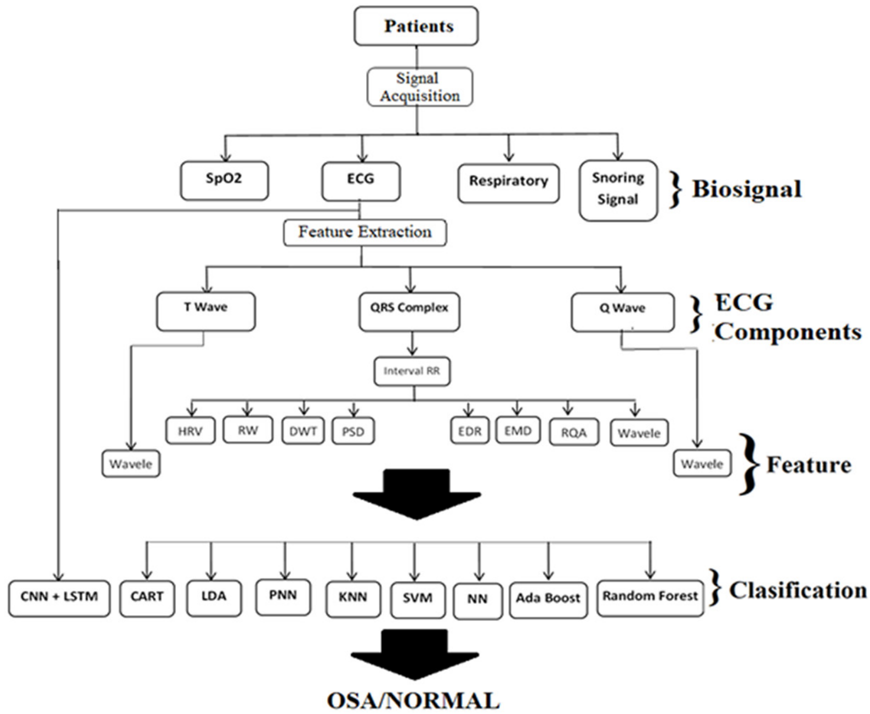

Fig. 5. Studies for developing OSA detection

7.1 Bio signal

As depicted in Figure 5, various types of biomedical signals used for OSA detection are diverse. These include the ECG, SpO2, respiratory signals, and snoring. ECG is a tool for detecting cardiac electrical activity [37]. It serves as a means to identify cardiac electrical activity [37]. The examination of OSA using ECG is based on its association with cardiovascular diseases and atrial fibrillation (AF) [38].

SpO2 measures hemoglobin oxygen saturation through pulse oximetry [39]. The examination of OSA using SpO2 is rooted in the fact that OSA events can disrupt the respiratory system, leading to decreased oxygen saturation levels among OSA patients [40].

Respiration is the process that involves cellular energy acquisition through the oxidation of organic substances [41]. The examination of OSA using respiratory signals is based on the understanding that OSA is a respiratory disorder causing breath cessation during sleep, leading to cognitive impairment in affected individuals [42].

Lastly, snoring signals capture vibrations in the upper airway during sleep [43]. The examination of OSA using snoring signals is based on the fact that snoring is a loud breathing sound resulting from the passage of air through narrowed airways due to OSA, leading to tissue vibrations [42]. Visual representations of ECG, SpO2, EDR, respiration, and snoring signals are explained in Figure 6.

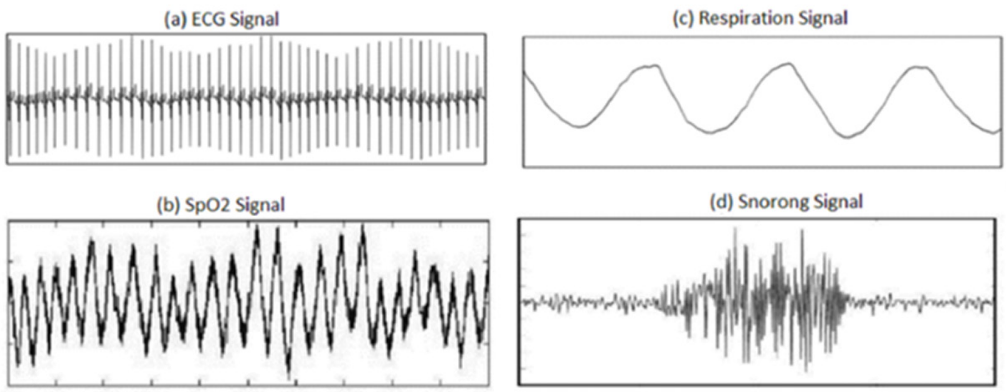

Fig. 6. (a) Electrocardiography signal [19], [25]; (b) SpO2 signal [19], [25]; (c) Respiratory signal [32]; and (d) Snoring signal [32]

7.2 Electrocardiogram components

The ECG signal is a commonly chosen method for detecting OSA. Within the ECG signal, several components are utilized, including the T-wave [26], the Q-wave [6], and the QRS complex [27], [34], [44], as identified in a broad spectrum of studies. The QRS complex, derived from the RR interval, provides distinct features for each RR interval. The T-wave is a waveform that appears during ventricular repolarization, while the Q-wave represents the first negative deflection within the QRS complex. The QRS complex is a key ECG structure associated with ventricular depolarization.

OSA is known to cause frequent sleep disruptions with significant implications for cardiovascular health. Ventricular abnormalities can be detected by analyzing the morphology of the QRS complex and are considered an important risk factor for (AF) [45].

7.3 Features

Figure 5 illustrates the significant features commonly analyzed about the RR interval. These features include HRV, power spectral density (PSD), R wave duration (RWD), discrete wavelet transform (DWT), wavelet transformations, EDR, empirical mode decomposition (EMD), and recurrence quantification analysis (RQA).

Heart rate variability refers to the interval between successive R wave peaks and prominent amplitude waves. HRV analysis, established by National Instruments in 2009, can manifest in frequency and time domain analyses. Frequency domain analysis focuses on frequency, while time domain analysis centers on temporal aspects [46]. Extensive research has been conducted in recent years on the detection of OSA using HRV features [9], [22], [28–30], [47], [48].

R wave duration signifies the temporal interval between adjacent points on an R wave crest. This metric consistently underpins various QRS types, and its quantification as a time function involves dedicated computer programs that analyze data from diverse experimental setups [49]. Researched OSA detection using RWD features [25]. DWT characterizes signals through simultaneous representation in time and frequency domains. Notable advantages of DWT include ease of implementation and computational efficiency [50]. Researched OSA detection using DWT features classified with various machine-learning techniques [48].

Power spectral density is a method for estimating the spectral density function of time series data. PSD exploration delves into uncovering concealed periodicities that might elude detection in the time domain [51]. In recent years, there have been several studies on OSA detection using PSD features [26], [28], [29]. Wavelet transformation involves the conversion of signals into diverse basis wavelets, adjusting shifts, and scaling to derive wavelet coefficients across multiple resolutions [52]. EDR, an acronym for extracting respiratory information from ECG signals, employs a feature-based approach. This method evaluates various parameters, such as the upper slope of the complex QRS, the angle around the R wave, features relevant to frequency, features associated with slope, and features related to baseline wandering, to deduce respiratory patterns [53]. Research focused on detecting OSA using EDR features [24].

Empirical mode decomposition employs scale separation to divide a time series into intrinsic mode functions (IMFs) and residues. The scale corresponds to the period between consecutive local minima or maxima [54]. Researched OSA detection using CWT and EDM features classified with SCNN [55]. RQA finds utility in processing short-duration and non-stationary data, offering insights into dynamic system patterns and structures. RQA's independence from stringent assumptions and constraints permits analysis without data filtering, linear detrending, or distribution matching [56]. Researched OSA detection using RQA features classified with NN and SVM algorithms [30].

7.4 Classification

As illustrated in Figure 5, a diverse range of classification methods is utilized to detect OSA. These techniques include classification and regression tree (CART), support vector machine (SVM), linear discriminant analysis (LDA), probabilistic neural network (PNN), K-nearest neighbor (KNN), neural network (NN), AdaBoost, and random forest (RF). Studies exploring OSA detection through deep learning classification have notably increased in recent years, particularly emphasizing utilizing direct ECG signal data. In this context, a frequently employed deep learning technique is the CNN [9], [55]. CNN, commonly used for image data, is sometimes integrated with LSTM components [9]. LSTM, a recurrent neural network (RNN) subtype, introduces memory cells capable of retaining information over extended intervals.

Classification and regression tree is an exploratory methodology illuminating the interplay between the response variable and independent variables encompassing nominal, ordinal, and continuous attributes [57]. Researched OSA detection using CART classification, achieving a performance of 90% sensitivity [22].

Linear discriminant analysis, a staple in pattern recognition, statistics, and machine learning, serves to discern linear combinations of features, facilitating the separation of diverse events or objects [58]. Research for the detection of OSA using LDA classification has been conducted extensively in recent years [6], [34], [44], [46–48]. Employing supervised training, the PNN operates within the NN paradigm [59].

A neural network, a cornerstone of AI, emulates the neural mechanisms of the human brain [60]. Research on OSA detection using various machine learning techniques, with the best performance achieved using NN classification, resulting in an accuracy of 84.6%, sensitivity of 94.2%, and specificity of 64% [46].

K-nearest neighbor leverages sample training to classify new objects, with the categorization of test samples rooted in the KNN categories. This approach yields the predicted value for new test samples within the KNN algorithm [8]. Research for the detection of OSA using KNN classification has been widely conducted in recent years [6], [46]–[48], [61].

Operating on the tenet of structural risk minimization (SRM), SVM endeavors to ascertain the optimal hyperplane, thereby separating two classes within the input space. SVM, a potent machine learning tool, trains using training datasets and extends this knowledge to predictions for novel data points [62]. Research for the detection of OSA using SVM classification has been widely conducted in recent years [7], [29–31], [34], [46–48], [61]. Researched OSA detection using SVM with an RBF (Radial Basis Function) kernel, achieving high performance with an accuracy of 84.6%, sensitivity of 94.2%, and specificity of 64% [31].

Prominent within the realm of supervised methods for classification model development in data mining, AdaBoost stands as a recurrent choice [63]. Hassan, A.R. conducted research on OSA detection using various machine learning techniques, with the best performance achieved using AdaBoost classification, resulting in an accuracy of 87.3% [6].

Pooling multiple robust decision trees into a cohesive model gives rise to the RF paradigm. Each decision tree, woven into the fabric of the RF, derives from a random vector value uniformly distributed across all constituent trees [64]. Research for the detection of OSA using RF classification has been widely conducted in recent years [6], [48], [61]. Conducted research on OSA detection using various machine learning techniques, with the best performance achieved using RF classification, resulting in an accuracy of 96.6%, sensitivity of 93.8%, and specificity of 98.4% [61].

Among the preeminent deep learning techniques, CNNs shine, demanding meticulous layer-wise training. While CNN shares a foundational structure with the multilayer perceptron (MLP), its distinction lies in its multidimensional traversal—CNN neurons navigate across two dimensions, contrasting with the unidimensional traversal of MLP neurons [65]. Research for the detection of OSA using CNN classification has been widely conducted in recent years [32], [40], [55], [66], [67]. Researched OSA detection using CNN and LSTM and achieved high performance with an accuracy of 96.1%, sensitivity of 96.1%, and specificity of 96.2% [67].

8 PERFORMANCE OF OSA DETECTION

Numerous studies have explored distinct features, often employing diverse classifications to gauge feature performance. Table 2 comprehensively compiles varied features, classifications, and corresponding performance metrics across different investigations. Various approaches have been pursued with the aim of OSA detection. The evaluation results reported for these algorithms are presented in Table 2. This table is divided into three categories: features, classification, and performance, corresponding to the analyzed approaches. In Table 2, the most frequently used feature is the RR interval, while the commonly employed classification methods include LDA, SVM, KNN, and convolutional neural networks.

Table 2. Features, classification methods, and performance in OSA detection

Feature	Data Number	Classification	Performances		
			Sen (%)	Spe (%)	Accu (%)
RR interval and QRS complex [1]	400	CVHR	–	–	–
HRV [35]	91	CART	90.0	–	–
Q wave [6]	70	AdaBoost	81.9	90.7	87.3
QRS complex [15]	70	Wavelet decomposition	90	100	93.3
HRV [9]	70	SVM	94.2	95.4	94.8
HRV [10]	70	NN and SVM	83.5	86.4	85.3
ECG, SpO2, respiratory and snoring signals [5]	70	CNN	96.0	96.0	96.0
QRS complex [7]	125	FNN, LDA, SVM, Complex Tree, RUSBoosted Trees, and LR	98.6	93.9	97.8
HRV [22]	91	LDA, KNN, SVM, and RF	–	–	89.6
RR Interval [23]	70	LDA and QD	100	100	100
RR interval and EDR [24]	32	QD	93.8	98.4	96.6
RR interval and SpO2 [25]	70	RF	95.9	98.4	97.5
HRV, respiratory, and SpO2 [26]	70	SVM	91.8	98.0	95.0
ECG signal (PSD and RPS) [29]	70	SVM	94.8	95.4	94.8
RR Interval [31]	90	SVM	98.9	92.8	97.4
ECG Signal [32]	82	CNN	96.0	96.0	96.0
RR Interval [34]	148	FNN	98.6	93.9	97.8
SpO2 [40]	32	ANN	96.5	98.5	97.7
RR Interval [46]	70	LDA, KNN, NN, and SVM	94.2	64.0	84.6
ECG Signal [47]	35	SVM	92.4	88.3	90.8
ECG Signal [48]	70	LDA, KNN, RF, and SVM	85.1	92.4	89.6
RR interval and SpO2 [68]	70	LDA	91.0	76.0	87.0
HRV, respiratory, and SpO2 [69]	100	SVM	100	90.2	95.0
HRV and EDR [70]	70	SVM, LD, PNN, and KNN	100	100	100

Notes: CVHR = Cyclical Variation of Heart Rate, KNN = K-Nearest Neighbor, CART = Classification and Regression Tree, QD = Quadratic Discriminant, NN = Neural Network, SVM = Support Vector Machine, PSD = Power Spectral Density, ANN = Artificial Neural Network, RF = Random Forest, FNN = Feed-forward Neural Network, PNN = Probabilistic Neural Network, FT = Fourier Transform, RPS = Reconstructed Phase Space, LR = Logistic Regression, LDA = Linear Discriminant Analysis, CNN = Convolutional Neural Network, LSTM = Long Short-Term Memory, SCNN = Scalogram Convolutional Neural Network, RWD = R Wave Duration, EMD = Empirical Mode Decomposition, CWT = Continuous Wavelet Transform, Accu = accuracy, Sen = Sensitivities, Spe = specificity.

Distinct filtering methodologies are employed across studies, encompassing low-pass filters [25] and bandpass filters [34]. Amidst this diversity of features, a dichotomy emerges between segmented and non-segmented data. Segmentation practices vary, with intervals spanning 1 minute [40], 3 minutes [33], 5 minutes [28], 10 minutes [28], 15 minutes [24], and 20 minutes [68]. Following segmentation and normalization, several studies opt for data partitioning into training and testing subsets, with some embracing cross-validation approaches [6].

The assessment of system performance serves as a litmus test for its efficacy in discerning cases of OSA. Across many investigations, three metrics have emerged as the most frequently employed yardsticks: specificity, sensitivity, and accuracy. Specificity quantifies the system's adeptness at correctly identifying negative results. Sensitivity gauges the system's precision in recognizing positive outcomes. Accuracy encapsulates the system's overall competency in correctly identifying positive and negative instances. While some studies focused solely on ECG bio signals, others harnessed a composite of multiple bio signal types. For example, OSA detection employing a CNN classifier with a fusion of ECG, SpO2, respiratory, and snoring signals yielded an accuracy (Acu.) of 96.0%, sensitivity (Sen.) of 96.0%, and specificity (Spe.) of 96.0% [33]. Similarly, OSA detection via a CNN classifier combining SpO2 and HRV bio signals yielded an Acu. of 94%, Sen. of 92%, and Spe. of 96% [33]. These findings underscore the influence of concurrent utilization of diverse bio signal types on OSA detection performance.

Pertinent to prior investigations, optimal performance benchmarks were achieved, exemplified by an Acu. of 97.8%, Sen. of 98.6%, and Spe. of 93.9% [34] through FNN classification. This study harnessed intricate QRS detection features subjected to Pan Tompkins extraction and bandpass filtering, culminating in classification through FNN, LDA, SVM, Complex Tree, RUS-boosted Trees, and LR techniques [34]. Conversely, certain studies reported less favorable outcomes, with an Acu. of 72.9%, Sen. of 72.1%, and Spe. of 73.3% [28]. In this instance, HRV features were segmented over 10-minute intervals and subsequently subjected to Pan Tompkins extraction, bandpass filtering, and classification employing PSD and sample entropy parameters [28]. Notably, certain studies eschewed comprehensive result elucidation, opting to focus solely on accuracy [7], [24], and [71], sensitivity only [22], or a combination of sensitivity and specificity [1]. Similarly, several investigations omitted explicit mention of their performance outcomes [21], [25], and [26].

9 DISCUSSION

Finding effective methods for detecting OSA remains a primary focus in the current healthcare landscape. Various research endeavors have explored diverse approaches to overcome the challenges associated with OSA detection. A notable aspect of these investigations is the utilization of the Apnea-ECG database [7], [25]–[31], a resource that has proven instrumental in these studies.

Several key factors underscore the repeated incorporation of this dataset in research. Firstly, its accessibility ensures that researchers can readily obtain and utilize the data for their investigations. Additionally, the clarity of the presented data within the Apnea-ECG database facilitates a comprehensive understanding of the intricacies involved in OSA detection studies. Lastly, the user-friendly attributes of the dataset contribute to the ease with which researchers can manipulate and interpret the information, further emphasizing its significance in advancing the understanding and methodologies related to OSA detection in healthcare.

An essential point in this paper is emphasizing the superiority of ECG signals as the leading choice for detecting OSA in various studies. ECG signals, which measure the heart's electrical activity, are very useful as they perform better than combining complex signals from multiple sources. This preference for ECG signals indicates their effectiveness when used separately, exceeding the results of combining several bio signals. This paper concludes that the reliability and precision offered by the ECG signal make it a superior choice for OSA detection.

The paper discusses the critical role of selecting features in shaping the uniqueness and effectiveness of various studies, thereby producing a diverse range of performance outcomes. The features mentioned, namely HRV, PSD, EDR, EMD, and RQA, consistently emerge as preferred choices in multiple studies focused on OSA detection. Among these, the RR interval, representing the time between consecutive heartbeats, is highlighted as a cornerstone feature due to its efficacy in pinpointing significant points relevant to OSA.

The paper suggests that the altered cycle of RR intervals observed in individuals with OSA underscores the utility of this feature in achieving accurate OSA detection. By emphasizing the importance of these selected features, the paper implies that their incorporation into study methodologies contributes significantly to the precision and reliability of OSA detection methods, thereby advancing the understanding and diagnosis of this sleep disorder.

In many research projects, effectively filtering data is crucial. The focus is mainly on low-pass filters [55] and bandpass filters [34]. These filters are essential for improving data quality and refining collected information for accurate analysis. Low-pass filters help remove high-frequency noise in the data, while bandpass filters isolate and retain specific frequency ranges of interest. Incorporating filtering techniques is vital in research studies because it reduces inherent noise in collected data and improves the overall signal quality.

Various segmentation strategies are used in the field, but a common practice involves employing one-minute segmentation intervals [40]. This temporal division is crucial for capturing detailed snapshots of OSA and normal signals. The choice of 1-minute intervals strikes a balance between granularity and pattern discernibility. Breaking down the data into these manageable segments allows researchers to capture subtle signal variations effectively, leading to a more comprehensive understanding of normal and OSA-related patterns. The duration chosen for segmentation significantly influences pattern identification and consequently impacts the performance of OSA detection. This strategic approach to segmentation highlights the thoughtful considerations involved in optimizing temporal divisions for effective pattern recognition and accurate detection of sleep disorders.

In OSA detection research, a consistently preferred method is the SVM, renowned for its effectiveness in pattern recognition. The popularity of SVM in this context can be attributed to its alignment with the principles of statistical learning theory. This methodology optimizes learning biases using linear functions and algorithms rooted in optimization theory.

Support vector machines excels at discerning complex patterns within datasets, making them well-suited for detecting OSA. The decision to utilize SVM in OSA detection reflects a strategic choice to leverage its robust capabilities in pattern recognition, aligning with the theoretical foundations of statistical learning to enhance the accuracy and efficiency of classification algorithms in sleep disorder research.

Evaluating the system's performance is crucial in determining its effectiveness in identifying OSA. Elevated specificity highlights the system's proficiency in recognizing common patterns, emphasizing its capability to identify non-OSA instances accurately. Conversely, reduced specificity values suggest challenges in precisely identifying normal patterns. On the other hand, heightened sensitivity underscores the system's adeptness in pinpointing OSA-related patterns, showcasing its ability to accurately detect instances of sleep disorders.

Studies have shown that a significant portion of the features for OSA detection can be derived from RR intervals, which include elements such as HRV, respiration waveform decomposition (RWD), DWT, wavelets, and other critical attributes. These features, extracted from single-lead ECG data, have proven instrumental in accurately identifying OSA. Machine learning techniques, particularly deep learning, have been extensively explored to optimize the detection process. Advanced algorithms leverage these features to enhance detection accuracy and reliability, underscoring the potential of single-lead ECG in OSA diagnosis.

The highest performance levels achieved in this domain highlight the remarkable capabilities of single-lead ECG systems. An impressive accuracy of 100% with both sensitivity and specificity at 100% has been reported. This significant achievement was made possible through LD and QD classification, which utilized RR intervals [23]. This combination of sophisticated signal processing and advanced machine learning algorithms demonstrates the potential for single-lead ECG systems to become a cornerstone in OSA detection. As research continues to evolve, integrating these methods promises to enhance the early detection and management of OSA, paving the way for improved patient outcomes and more effective healthcare solutions.

AI-Enhanced Biosignal Analysis is used to streamline processes, improve decision-making, and automate operations [72]. It offers increased efficiency through automation, accelerating big data processing [73]. Other methods, such as adaptive with approach-based neural approximation, are also important in intelligent techniques.

However, there are notable limitations to this approach. While single-lead ECGs provide valuable data, they may need more comprehensive information than multi-lead ECGs, potentially leading to less accurate OSA detection. The performance of AI algorithms heavily depends on the quality and diversity of the training data; thus, limited or non-representative datasets can affect model generalizability and accuracy. Additionally, although AI techniques have shown promise, their effectiveness can be constrained by computational resources and the need for extensive tuning and validation. Integrating AI-based systems into clinical practice also presents challenges, requiring rigorous validation to ensure reliability and safety. Despite these limitations, the integration of AI in single-lead ECG-based OSA detection represents a significant advancement with the potential to enhance early detection and management of obstructive sleep apnea.

The future holds promise for further exploration in OSA detection, potentially surpassing the benchmarks set by previous studies. As research advances, the goal remains to develop even more robust methodologies that could shed new light on OSA detection and management.

10 LIMITATION

This review has a temporal scope, covering research published between 1984 and 2022. Consequently, relevant studies or advancements outside this time range should be included, potentially overlooking significant contributions made before or after these years. Additionally, while this review provides an overview of AI techniques applied to bio-signal analysis for OSA detection, it needs to delve into these

AI systems' detailed methodologies and underlying algorithms. Readers seeking in-depth technical explanations and specific algorithmic details may need to consult the original research papers or specialized technical resources.

11 AUTHORS' CONTRIBUTIONS

Aida Noor Indrawati comprehensively searched for the input features relevant to OSA detection. Nuryani Nuryani played a pivotal role in shaping the overall design of the review. Wiharto contributed expertise in machine learning analysis for OSA detection. Diah Kurnia Mirawati provided valuable medical insights into obstructive sleep apnea.

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