A Survey on Detection and Prediction Methods for Sleep Apnea

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Abstract. Sleep disorders are common health issues that can affect the multiple aspects of life. Sleep apnea (SA) is the most common sleep disorder, and it is described as a reduction or cessation of airflow to the lungs during sleep. This disorder is usually diagnosed and tested using polysomnography (PSG) in a special laboratory. However, this method is costly, inconvenient, time consuming, often causes anxiety for the patient, and the equipment cannot be moved from the lab. There are several methods suggested to address these shortcomings, including testing and analysis at the patient's home and the sleep laboratory, by using sensors to detect physiological signals that can be automatically analyzed based on specific algorithms. The purpose of this study was to explore the previous works related to SA in such a way that highlights the methods of detection or diagnoses that use different sensors. The researcher aimed to adopt algorithms and make a comparison between those works to explain the accuracy, sensitivity, and specificity of SA detection and prediction. This review was conducted to provide information for those researchers who want to implement algorithms for detection and prediction of sleep apnea event (SAE). Limitations and challenges are also discussed.

Keywords: Accuracy, detection, polysomnography, prediction, sensors, sleep apnea

1. Introduction

Sleep apnea (SA) is a prevalent sleep disorder. SA refers to the cessation of airflow to the lungs for at least 10 s. It affects approximately of 4% of men and 2% of women in the general U.S. population, according to Young and Coworkers [1]. Generally, SA is initiated when a decrease in blood oxygenation level (SpO2) at a minimum of 4% causes an individual wake up to take a deep breath, and then return to sleep again. The symptoms of SA are loud snoring, excessive daytime sleepiness, nocturnal choking or gasping, insomnia, and failure to concentrate, which might cause accidents. There are three types of SA: obstructive sleep apnea (OSA), which is the most popular form of the disease, central sleep apnea (CSA), and mixed sleep apnea (MSA). The first type is caused by the relaxation of the tongue or upper airway muscles during sleeping that blocks the airway, making breathing impossible. The second type happens when the brain fails to send neural signals to the muscles necessary for breathing. The third type is comprised of symptoms from the first and second combined. This illness, accompanied by asphyxia and arousal, leads to high blood pressure, increasing heart rate (HR), compromised immune system, cardiovascular disease, type 2 diabetes mellitus, stroke, and memory
impairment, as well as depression, growth and worsening of the condition if left untreated due to heart failure. In [2], OSA affects human health and sometimes leads to death. Polysomnography (PSG) is the gold standard method for diagnosis of SA. The PSG test is the process of monitoring the patient’s vital signs overnight, which is carried out by several sensors and electrodes attached to the patient’s body to collect bio signals. The PSG data includes SpO2, HR, nasal airflow, electroencephalogram (EEG), electrocardiogram (ECG), electrooculogram (EOG), electromyogram (EMG), and thoracic-abdominal movements. This procedure has many limitations such as (i) it requires a special laboratory for testing, (ii) a large amount of connected wires, (iii) requires a tube for the nasal airflow, (iv) restricts patients’ movement during sleep, (v) generates stress for patient that can affect the actual OSA result, (vi) requires a sleep expert to read the data and connection of sensors, and (vii) PSG is expensive and time consuming.

Many studies have tried alternative methods to simplify the techniques for screening and diagnosis. One of the methods for detection is called home SA testing, and is smaller, lower cost, and can be performed in the comfort of the patient’s home. Usually, they use an SpO2 signal to help sense apnea. Various methods have been projected based on SpO2 [3-8], while the others are based on HR and ECG signals [1, 8], and tracheal sound [9, 10]. Other authors have achieved detection with combining two HR sensors with SpO2[10-13], and using EEG analysis to give more details about sleep stages and OSA events [14, 15]. Moreover, different approaches have been used to detect OSA, such as [16], which adopted EOG. However, these studies also used some PSG signals. However, they were not sufficient to recognise sleep stage or apnea event duration. There have been several studies conducted for the detection of OSA, but a fewer have been conducted to predict sleep apnea event (SAE). Therefore, these limitations and challenges motivated us to propose a system that can combine the three sensors (HR, SpO2, and flex) to detect and predict apnea events using the artificial neural network (ANN), and transmit the sensor data to the monitoring unit, calling it a sleep apnea monitoring unit (SAMU), which is wirelessly based on Bluetooth technology.

The contributions of the paper can be summarised as follows:
1. The potential for using sensors and technologies in SA was investigated, and a technology with suitable power consumption was identified.
2. The taxonomy of the SA method was examined to determine the best detection method that is more suitable for such application.
3. The existing solutions, limitations, and challenges of applying sensors in SA were reviewed and compared.

2. Related works
The following related previous works are classified based on the sensor types used for SA detection:

2.1. Related work based on SpO2
In [3], the authors proposed a system that uses only an SpO2 sensor signal. They analysed this signal based on the relationship between oxygen saturation and apnea events. The signals were processed by a field programmable gate array (the Avnet Spartan-6 LX9 Micro Board), and thereafter were sent via two transmitters (i.e., WiFi and Bluetooth). The SAE was detected based on a logistic regression algorithm. Smartphone-based WiFi and a personal-computer-based Bluetooth were employed to monitor the SAE. Both of these methods have a graphical user interface, which makes them easy to use and monitor. This system was tested using 70 volunteers with a SpO2 signal collected from the hospital of the Universidad de Gran Canaria. The performance of algorithm was achieved at 87.5%, 79.5%, and 90.8% average accuracy, sensitivity, and specificity, respectively. This work utilised only SpO2 signal for the detection of OSA, and it is not recommended by the American Academy of Sleep Medicine (AASM) [17].

In [4], the authors investigated the overnight oximetry method of diagnosing moderate and moderate-to-severe OSA in patients. After statistical analysis and feature selection, the model of the classifier has been built based on a support vector machine (SVM). The authors recruited 699 suspected OSA patients to
be examined by PSG and overnight oximetry at the Sleep Centre of China Medical University Hospital. The designed model provided 90.42-90.55% accuracy in diagnosing severe OSA patients, 89.36-89.87% of sensitivity, and 91.08-93.05% of specificity. The performance of diagnosing moderate to severe OSA patients includes the accuracy of 87.33-87.77%, a sensitivity of 87.71-88.53%, and a specificity of 86.38-86.56%. From the obtained results, the authors found that the diagnosis of severe OSA patients is more accurate than moderate to severe diagnosis in OSA patients. They concluded that the overnight oximeter can be used for detecting severe OSA in patients as in-home oximetry test for detecting severe OSA patients. However, the performance of the diagnoses performance can take another signal into consideration, such as HR, to improve the detection of SA.

Gutiérrez-Tobal et al. [5] focused on determining OSA severity in children by using oximetry. The single channel of SpO2 data was recorded from 176 kids. The severity was divided into three groups according to the apnea hypopnoea index (AHI): AHI < 1 e/h, 1 ≤ AHI < 5 e/h, and AHI ≥ 5 e/h. Spectral analysis was applied to the SpO2 signal for feature extraction. The feature extracted was employed as inputs for ANN. The ANN includes one input layer (i.e., SpO2), five hidden layers, and three output layers as categories. The combination of spectral analysis data and the reduction of oxygen desaturation index adopts a multilayer perceptron network (MLP) to detect and classify the OSA event. The detection accuracy with two common cut offs (i.e., AHI = 1 e/h and AHI = 5 e/h) was 84.7% and 85.8%, respectively. As a result, the information contained SpO2 that could be helpful in the detection of OSA severity in paediatric patients. However, this method requires more data for training the neural network to give the best result.

In [6], the authors analysed a single channel of a nocturnal SpO2 signal to identify sleep apnea-hypopnoea syndrome (SAHS). The system could evaluate the degree severity of the disease (non-SAHS, mild-SAHS, moderate-SAHS, and severe SAHS). The decision tree (DT), SVM, and probabilistic neural network (PNN) were used as classifiers for the system. The extract features in the time and frequency domains of the SpO2 signal were used as inputs to this classifier to detect the SAE. The authors collected data from 115 patients with suspected OSA from the University Hospital Puerta del Mar in Cadiz (Spain), and conducted a full night of monitoring SpO2 signals. An overall accuracy of 82.6% was achieved in the classification of four classes. The proposed method could be beneficial to the in-home health care diagnosis of SAHS, and to reduce the costs of an over-night test and lists of patients waiting in sleep laboratories. However, SA detection based on SpO2 gives insufficient accuracy. Therefore, to improve the SA detection accuracy, a combination between more than one sensors is necessary to achieve higher detection accuracy.

In [7], the authors proposed a novel method of automatic estimation of the AHI based on nocturnal SpO2 recording. A set of 240 signals of SpO2 was used for study, and the data were divided into training (96 signals) and testing (144 signals) for validation to produce an optimal model. The authors extracted 14 features in the time and frequency domain to quantify the effect of SAHS, and performed multiple linear regression (MLR) and MLP. The MLP network achieved high performance with a correct decision rate of 93.06%, whereas the MLR model achieved 88.89% accuracy. The proposed method based on MLP can be used with an accurate and cost-effective procedure for the detection of SAHS in the absence of PSG. The suggested method can automatically estimate the severity of OSA. However, in this particular study, the severity of OSA of PSG was estimated manually. In some cases, apnea and hypopnoea occur during sleep, and may not be accompanied by desaturation events.

Oliver et al. [8] presented a health gear monitoring system working in real-time. The system provides the monitoring, visualising, and analysing of physiological signals. The authors developed a wearable medical engineering system that monitors and diagnoses through various medical non-invasive sensors connected to the patient’s body. These sensors transmit their data via Bluetooth technology to the cell phone for monitoring purposes. The monitoring system includes a pulse oximeter to monitor the blood oxygenation level during sleep. Through a friendly phone user interface and the general packet radio service (GPRS), the device can automatically send physiological data to the doctor. Automatic apnea detection was done by two methods: the time domain adopted a multi-threshold analysis, and the frequency domain used a spectral analysis. The results of OSA-detection events revealed that the system
accuracy was 100% reliable in 20 volunteers, 80% male, and between 25–65 years old. Incorporating other sensors in health gear, such as galvanic skin response, ECG, and other sensors, can deliver high detection accuracy.

2.2. Related works based on HR
In [18] the authors show a new heterogeneous recurrence model for distinguishing the HR variability for the detection of OSA. Cheng et al. [18] integrated classification models with heterogeneous recurrence analysis to identify healthy subjects and OSA patients. Experimental results show an average accurate performance rate of 85%, and a sensitivity of 83%, and specificity of 82% in 35 patients, according to the database available on PhysioNet (http://physionet.org). Thus, they proved that the tool for OSA detection from a single lead of ECG was an effective method. However, the proposed method was only highlighted on the cardiac disorder for identification of apnea, and did not take other signals into consideration, such as SpO2, breathing rate, and chest volume.

The proposed detection of OSA based on single lead of ECG was recorded in [1]. The proposed method depended on the Kernel density classifier concept. The features were extracted from a segmented R-R interval, which is obtained from ECG signal. These features are fed into the classifier to identify apnea events. To validate the suggested approach, data were collected from 35 subjects obtained from the PhysioNet (http://physionet.org) database. In addition, 25 new ECG recordings from St. Vincent’s University Hospital at University College Dublin’s Sleep Apnea Database were used for further verification. The accuracy, sensitivity, and specificity were achieved with mean of 82.07%, 83.23%, 80.24% based on the proposed classifier, respectively. The introduced method showed good performance that could be used in home-based screenings or diagnoses of OSA. The poor quality of ECG signal measurement, which, in turn, affects R-R interval, were extracted and therefore reflected in the diagnosis of SA.

In [19] the authors proposed an algorithm that can automatically estimate the AHI by using a disposable health patch sensor that detects HR variability, respiratory signals, posture, and movements. The data of the sensor was investigated in 53 volunteers. The sensor was installed on the chest of the patients, who also underwent an overnight PSG study. The extracted data were transmitted wirelessly via Bluetooth technology to Smartphone. Linear SVM was used as a classifier for the detection of the presence or absence of an apnea or hypopnoea event. The predicted AHI accuracy was 89.4%, and the accuracy of the classifier for control to mild apnea (AHI < 15) and moderate to severe apnea (AHI ≥ 15) were 85.0%, 82.9% respectively. The results revealed that using an overnight wireless patch sensor provided an accurate estimation of AHI for SA syndrome.

2.3. Related works based on a combination of SpO2 and HR
In [20], the suggested method for detection of SAE and sleep analysis was based on only two parameters: SpO2 and EEG. The instrument classifier was based on ANN for detecting the apnea event. The idea of ANN was implemented in MATLAB using a neural network toolbox based on the Levenberg-Marquardt algorithm. The ANN was trained for data collection from 8 patients at the University Hospital of Lord's Transfiguration sleep laboratory. Their methods were divided into three parts: recognition of apnea event, determination of the sleep stage, and determination of the AHI. The proposed method has an accuracy performance rate of 100% for identification events. Home SA testing is very efficient, and can be used in lieu of PSG, which is often uncomfortable for the patient, time consuming, and requires a special laboratory. Limitations of this study included that the results of the network were incorrect only in the instance of change and were always delayed by one sample.

Haoyu et al. [11] formulated and assessed an automated and convenient SA detector, with traditional diagnosis methods based on PSG. However, the method based on PSG was inconsistent with new developments in health care, which focus on wellness and prevention. Therefore, the authors addressed this problem by proposing a home health care system including minimal invasive devices, provider lower cost diagnosis, and higher accessibility, for which they utilised the SpO2 sensor and the HR. The proposed analysis process was a combination of measuring of oxygen saturation in the blood and
monitoring HR variability with apnea events. The measured data were then sent to the cloud-based system to detect and inform the remote patient of his critical status. Three well-known techniques were used in the server to classify the data: ANN, SVM, and k-nearest neighbour (KNN). The data were monitored by both PC and mobile phone. The data were collected from 10 apnea patient volunteers from St. Vincents University Hospital at University College Dublin. The results revealed that the proposed algorithm was achieved at 98.54%, 97.05%, and 98.95% for an average accuracy, specificity, and sensitivity, respectively. The limitation of this system was that the SA detection only depended on the SpO2 sensor, whereas the measurements were achieved for HAR and SpO2 sensors.

In [12], the authors designed a framework to assess the severity level of OSA. They evaluated the AHI using features only obtained during wakefulness, such as blood pressure (BP), HR, and SpO2. The framework was divided into two layers. The first layer classified the patients by OSA severity. The second layer estimated the AHI within a classified group. The classified groups were composed of healthy versus moderate (HvM), healthy versus severe (HvS), and moderate versus severe (MvS) models. The HvM and HvS models used SVM classifiers, and the MvS model used a DT classifier. The authors collected the data from 24 subjects. The performance of the framework was compared with the AHI of PSG scores as the benchmark. They found that the classification of the correct group had an accuracy of 99.6%, and an AHI estimation with an error of 4.5 events per hour. The proposed framework is reliable in determining the severity of OSA from a daytime screening. This method of detection was effective during the initial stages of the disease. However, it was ineffective in patients suffering from cardiovascular disease.

In [13], the authors’ proposed detection method was based on a phone oximeter, which is a portable device integrating pulse oximetry (i.e. SpO2 with HR variability) with a Smartphone to detect OSA events. They suggested a combination of SpO2 and pulse rate variability and process in order to provide more details of sleep and to identify events. The classification of OSA events is performed in the time domain by using central tendency measure (CTM), and in the frequency domain by adopting power spectral density (PSD). The results showed that when the SpO2 decreases, the HR and sympathetic activity increase at SAE. Data were collected from 160 children using a standard PSG. Ten discriminant features were extracted from CTM and PSD to improve the accuracy of the system from 74.5% to 78.9%. The area under the curve of OSA also increased from 81% to 87%. The study was limited to OSA and did not take other kinds of SA into account.

In [21], the authors introduced continuous positive airway pressure (CPAP) as the standard method therapy for OSA. Most of the patients did not feel comfortable with this treatment because it is not easy to deliver air through the nasal passage during sleep. The proposed system analysis adopted a complicated multiple heterogeneous signal, including ECG, heart sound, respiration, and SpO2, which were all gathered from a wearable wireless multisensory suite. The authors introduced a Dirichlet process-based mixture Gaussian process (DPMG) model to predict OSA events and adopted SVM for the classification of OSA. The multisensory component was part of a sleepwear shirt that transmitted data from sensors using Bluetooth technology to a host computer. The data were collected from six healthy male subjects and two subjects with suspected SA from the Apnea-ECG, PhysioNet (http://physionet.org), and COMMSENS lab databases. The classification OSA for multisensory suit performed at 88% accuracy. However, the prediction accuracy 1 min ahead of the event was about 83%, and 77% for 3 min ahead. This accurate detection and prediction of OSA events can help to auto adjust the pressure and flow of air in CPAP. However, this method of SA detection is costly because it requires 12 leads attached to the patient’s body for detecting ECG signal.

In [22], the authors investigated the methods and applications in the prediction of SAE by using ANN. The system depended on three sensors for the prediction of HR variability, SpO2, and chest volume. The proposed system used three neural network techniques called Elman, radial basis function (RBF), and feed-forward backpropagation (FFBP) in order to forecast the SAE, and relied on data collected from five patients. According to the aforementioned methods, the SAE can be predicted before 30, 60, 90, and 120 s. As a result, the best performance was obtained based on the FFBP neural network with an average area-under-curve (AUC) statistic equal to 88.62%. The results presented in this work were
obtained from a fixed model of neural networks. However, the dynamic neural network requires investigation to achieve the best results.

2.4. Related works based on microphone

Fang et al. [23] proposed a novel method for respiratory rate (RR) detection with high computational speed based on characteristic moment waveform (CMW). For this study, a wireless microphone device was fixed near the nose to collect breathing sound signals. The processing device included a Smartphone with an android system. To validate the efficiency of the proposed method, the experiment was conducted on one OSA subject and five healthy subjects for the detection of the sleep RR method. Their system can detect the breathing cycle with a success rate of up to 98.40%. In addition, the authors evaluated a section of OSA by detecting sleep RR value and time duration and segmentation of breathing. The proposed method showed high interference rejection and accuracy for apnea event extraction. One limitation of this study was that the microphone fixed near the nose that might become detached during sleep movement.

Kalkbrenner et al. [9] designed a comfortable system for monitoring sleep patients based on tracheal sound and patient movement. The apnea event detection uses a special signal processing method for both channels of signals mentioned. The microphone, located on the neck, recorded the breathing sound data of 10 volunteers. In addition, the data from the accelerometer and gyroscope were used to detect the patient movement, sleep position, and angular velocity of the body. These data were collected and sent via Bluetooth technology to the laptop for monitoring and analysis. The results revealed that the sensitivity and specificity were 92.8% and 99.7%, respectively. This method is reliable and noninvasive for the detection of apnea. However, the tracheal sounds of obese patients cannot be recorded by microphone due to the fat present around the neck.

Yadollahi et al. [10] developed the method of automatic detection and monitoring for OSA. The proposed method required two channels of biomedical signals of SpO2 and breath sound (detected from trachea by a small microphone on the neck). The breath sound signal was divided according to the energy of the signal to sound and silence. The sounds were classified as breath, snore, and noise segment according to the amplitude and duration of the sound signal. The snore and SpO2 signals were combined to find the threshold of apnea and hypopnoea events. The proposed system was tested on 66 patients, all recorded simultaneously, during a full night of PSG study. The proposed system produced sensitivity and specificity ratings of more than 91% for OSA patients. The results revealed that the quality of sound (detected by a microphone) for patients with high body mass indexes (BMI) was low because of the amount of fat and tissue around the neck.

2.5. Related work based on EEG

Zhou et al. [14] discovered a novel and simple method of apnea detection and measurement of the nonlinear characteristics of the EEG signal. In this study, the apnea detection depended on the non-linear behaviour of EEG signals. They used two techniques for analysis of EEG signals called detrended fluctuation analysis and scaling exponents. Consequently, SVM was considered to classify apnea patients. Two groups of six healthy subjects and six apnea subjects were compared during sleep, where the data set of EEG was collected from the PhysioNet database. DFA with SVM was used to obtain high recognition rates corresponding with 95.1%, 93.2%, and 98.6%, for accuracy, sensitivity, and specificity, respectively. However, only the obstructive factor of SA was studied in this system. This method may be considered uncomfortable due to the number of electrodes attached to the head.

In [15] the authors proposed method of detecting OSA based on the EEG signal. The EEG signal was filtered by infinite impulse response and a Butterworth filter, divided into delta, theta, alpha, beta, and gamma, depending on frequency. SVM, ANN, linear discriminant analysis (LDA), and Naive Bayes (NB) were employed as classifiers. The extracted feature from each frequency band was fed into classification to detect the occurrence of OSA. Data were collected from 16 subjects found on PhysioNet. The result form the proposed method revealed the best accuracy, with an SVM of 97.14%,
as compared with the other classifier. The methods that depend on EEG signals are complex because they use different filters to extract sub-bands utilised for detection.

2.6. Related work based on other methods

Hung [24] proposed method for the detection of CSA using signals from an accelerometer sensor. The sensor was strapped onto a flexible belt above the heart on the patient's chest and powered with a data acquisition board connected to a computer. The ANN-based MLP algorithm was used for identification of CSA. The MLP was fed by features extracted from the accelerometer sensor about respiration and HR for different features in time and frequency domain. To validate the proposed approach, the author used data from 30 male and female volunteers. The results revealed that the performance of the system with a classification accuracy of up to 84% was achieved. The presented system is suitable for CSA detection. However, this method of detection can give inaccurate results with excessive body movement or if a patient sleeps on his front as opposed to his back. In addition, the sensors might be uncomfortable for patients due to the belt strap around the chest.

Islam et al. [25] investigated a method for the detection of OSA by using a deep learning technique through depth maps of human facial scans. Facial depth maps were captured from 3D scans by Artec Eva through Artec Studio. After converting the facial depth map to reduce unwanted variations, a 2D image was created using MeshLab software. A small sample of 69 volunteers was collected from Genesis Sleep Care. Therefore, three techniques for transfer learning were utilised: Visual Graphics Group (VGG) face recognition, pose-aware models-AlexNet (PAMs-AlexNet), and PAMs-VGG19. The proposed system for the prediction of OSA is based on end-to-end deep learning, which was built in MATLAB. The best performance of VGG Face was found with an accuracy of 68.75% (validation) and 67.42% (test). The limitation of their study was the very small number of participants, which hindered the validation and testing of the deep learning technique. This system also includes costly components for image processing and the accuracy of detection is relatively low.

Kopaczka et al. [26] presented a novel apnea detection system based on a thermal infrared thermography. The authors implemented two techniques for face tracking. The techniques were used to track, learn about, and detect TLD (i.e., track, learn, detect). Active appearance models (AAM) that allow adaptation to the region of interest (ROI) included position of head movement for detection of apnea event, and respiratory rate. The operation of two techniques of ROI focused on the nostrils for monitoring signals. They implemented the following four different methods for detecting an apnea event: gradient sum, variance analysis, spectral analysis, and wavelet transform. The results disclosed 100% sensitivity. The AAM tracking technique was accurate, and the spectral analysis proved to be a more robust mechanism for the detection of the event than others have adopted in their work. However, all these algorithms cannot run in real-time, and the head must be kept still throughout the process.

In [27], the authors proposed a new approach to the detection of apnea events that depended on the raw signal from nasal airflow using a convolutional neural network (CNN). They used two methods in the classification of an apnea event: CNN and SVM. The algorithms used for training the neural network were the back propagation algorithm and Adam optimizer. Data from 100 patients were used in this study. The main advantages of using CNN and SVM are the capability to learn information featured automatically from high dimensional data without the need for signal processing and feature engineering. The experimental results revealed a good performance of CNN over the SVM in their system with an accuracy and F1-score of about 75%. However, the disadvantages of the proposed system include the potential detachment of the airflow sensor from a set position due to the patient moving during sleep, and the patient might also breathe from mouth instead of the nose.

In [16], the authors proposed a method to investigate two stages (sleep and wake stages) for the detection of SAHS. The method was based on the EOG signal. The ANN was used as a classifier for the detection of the stages. For training ANN use back propagation algorithm. There were several features extracted in the time and frequency domain as an input to ANN. The data were collected from seven healthy subjects, and nine subjects with MSA and SAHS from the Belgian Sleep Hospital. The results from the proposed method revealed an accuracy of 91.3%, a sensitivity of 84.5%, and a specificity of 91.5%. One
limitation in this method is that the EOG signals are affected by different signals from head movement, eyeball rotation, and EEG signal.

The review of different SA studies is summarised in Table 1. The table presents the significant parameters that must be taken into consideration when a sleep system is designed, such as diagnoses methods, wireless technology, sensors, adopted algorithm, accuracy, sensitivity, and specificity.

**Table 1.** Comparison of previous studies related to the SA system.

| Author/year | No. of Volunteer | Diagnoses Method | Wireless Technology | Sensor | Method/Algorithm | Acc (%) | Sen (%) | Spe (%) |
|-------------|------------------|------------------|---------------------|--------|------------------|---------|---------|---------|
| Mendonça et al. [3]/2018 | 70 | OSA | Wi-Fi Bluetooth | SpO2 | LR | 87.5 | 79.5 | 90.8 |
| Hang et al. [4]/2015 | 699 | OSA | Wire connection | SpO2 | SVM (Severe) | 90.55 | 89.87 | 93.05 |
| | | | | | SVM (Moderate to severe) | 87.77 | 88.53 | 86.56 |
| Gutiérrez-Tobal et al. [5]/2015 | 176 | OSA | Wire connection | SpO2 | MLP(AHI=1) | 84.7 | N/A | N/A |
| | | | | | MLP(AHI=5) | 85.8 | N/A | N/A |
| Sánchez-Morillo et al. [6]/2014 | 115 | SAHS | Wire connection | SpO2 | DT | N/A | 90.6 | N/A |
| | | | | | PNN | N/A | 94.6 | N/A |
| | | | | | SVM | N/A | 76.7 | N/A |
| Marcos et al. [7]/2011 | 240 | OSA | Bluetooth connection | SpO2 | ANN (MLP) | 93.06 | N/A | N/A |
| | | | | | MLR | 88.89 | N/A | N/A |
| Oliver et al. [8]/2007 | 20 | OSA | -Bluetooth -GPRS | SpO2 | Spectral analysis | 100 | N/A | N/A |
| Mostafa et al. [28]/2017 | 25 | OSA | Wire connection | SpO2 | ANN | 85 | 60 | 92 |
| Pathinarupothi et al. [29]/2017 | 7 | OSA | Wire connection | SpO2 | ANN | 96 | N/A | N/A |
| Hwang et al. [30]/2017 | 92 | OSA | Wire connection | SpO2 | Signal processing | 91 | 83 | 89 |
| Mostafa et al. [31]/2017 | 8 | OSA | Wire connection | SpO2 | ANN | 98 | 97 | 99 |
| Abedi et al. [32]/2017 | 54 | OSA | Wire connection | SpO2 | SVM | 99.5 | 90.2 | 96 |
| Morillo & Gross. [33]/2013 | 115 | OSA | Wire connection | SpO2 | ANN | 92.42 | 95.92 | 93.91 |
| Crespo et al. [34]/2017 | 50 | OSA | Wire connection | SpO2 | LR | 84.5 | 83 | 83.5 |
| Almazaydeh et al. [35]/2012 | 93 | OSA | Wire connection | SpO2 | MLP | 87.5 | 100 | 93.3 |
| Cheng et al. [18]/2016 | 35 | OSA | Wire connection | ECG signal | Heterogeneous recurrence | 85 | 83 | 82 |
| Chen et al. [1]/2015 | 60 | OSA | Wire connection | ECG signal | Kernel density | 82.07 | 83.23 | 80.24 |
| Hassan et al. [36]/2015 | 35 | OSA | Wire connection | ECG signal | ANN | 84 | N/A | N/A |
| Hassan et al. [37]/2016 | 35 | OSA | Wire connection | ECG signal | SVM | 87 | 82 | 91 |
| Hassan et al. [38]/2017 | 35 | OSA | Wire connection | ECG signal | SVM | 89 | 88 | 91 |
| Selvaraj et al. [19]/2014 | 53 | OSA | predict | Bluetooth | -HR -Resp -Acce | SVM | 89.4 | N/A | N/A |
| Selvaraj et al. [19]/2014 | 53 | OSA | predict | Bluetooth | -HR -Resp -Acce | SVM | 89.4 | N/A | N/A |
| Ferdula et al. [20]/2019 | 8 | OSA | Wire connection | SpO2 -HR | ANN | 100 | N/A | N/A |
| Haoyu et al. [11]/2019 | 10 | OSA | Wi-Fi | SpO2 | SVM | 98.54 | 97.05 | 98.95 |
| Authors               | Year | OSA Severity Level | Measurement                  | Method         | Accuracy (HR) | Sensitivity (HR) | Specificity (HR) |
|----------------------|------|--------------------|-------------------------------|----------------|---------------|-----------------|-----------------|
| Samy et al. [12] /2016 | 24   | OSA severity level | Wire connection -BP -HR -SpO2 | SVM(HvM)        | 96.36         | 97.21           | 96.87           |
|                      |      |                    |                               | SVM(HvS)       | 99.40         | 100             | 99.5            |
|                      |      |                    |                               | DT(MvS)        | 71.10         | 100             | 99.4            |
| Garde et al. [13] /2015 | 160  | OSA                | Wire connection HR            | CTM & PSD      | 74.50         | 75.5            | 74.1            |
| Garde et al. [13] /2015 | 160  | OSA                | Wire connection -SpO2 -HR     | DPMG 1-min     | 83.00         | N/A             | N/A             |
|                      |      |                    |                               | DPMG 3-min     | 77.00         | N/A             | N/A             |
| Le et al. [21] /2013  | 8    | OSA predictio n    | Bluetooth -ECG signal -SpO2  | SVM            | 88.00         | N/A             | N/A             |
|                      |      |                    |                               |                |               |                 |                 |
| Maali et al. [22] /2013 | 5    | OSA predictio n 120 S | Wire connection -SpO2 -HR -Chest volume | ANN(Elman) | N/A           | N/A             | N/A             |
|                      |      |                    |                               | Anna(RBF)      | N/A           | N/A             | N/A             |
|                      |      |                    |                               | Ann(FFBP)      | N/A           | N/A             | N/A             |
| Fang et al. [23] /2018 | 6    | OSA                | Bluetooth -ECG signal -SpO2  | SVM            | 98.40         | N/A             | N/A             |
|                      |      |                    |                               |                |               |                 |                 |
| Kalkbrenner et al. [9] /2018 | 10  | OSA                | Bluetooth -ECG signal -Microp -Acce and gyr | Signal processing | N/A         | 92.8            | 99.7            |
| Yadollahi et al. [9] /2010 | 66  | OSA                | Wire connection -SpO2 -HR -Microp -Chest volume | Signal processing | N/A         | 91.0            | 91.0            |
| Zhou et al. [14] /2015 | 12   | OSA                | Wire connection EEG signal    | SVM            | 95.10         | 93.2            | 98.6            |
| Almuhammadi et al. [15] /2015 | 16 | OSA                | Wire connection EEG signal    | SVM            | 97.14         | 97.01           | 97.26           |
|                      |      |                    |                               | ANN            | 94.60         | 93.1            | 96.3            |
|                      |      |                    |                               | LDA            | 89.29         | 83.82           | 94.44           |
|                      |      |                    |                               | NB             | 92.38         | 86.45           | 98.54           |
| Hung. [24] /2018     | 30   | CSA                | Wire connection Acce          | MLP            | 84.00         | N/A             | N/A             |
| Islam et al. [25] /2018 | 69  | OSA                | Wire connection 3D scans by Artec | SVM            | 67.42         | N/A             | N/A             |
|                      |      |                    |                               | PAMs-VGG19     | 57.14         | N/A             | N/A             |
|                      |      |                    |                               | PAMs-AlexNet   | 59.37         | N/A             | N/A             |
| Kopaczka et al. [26] /2017 | N/A | OSA                | Wire connection Thermal infrared thermography | Gradient Sum | N/A           | 100             | N/A             |
|                      |      |                    |                               | Variance Analysis | N/A       | 96.6            | N/A             |
|                      |      |                    |                               | Spectral Analysis | N/A       | 100             | N/A             |
|                      |      |                    |                               | Wavelet Transform | N/A       | 96.6            | N/A             |
| Haidar et al. [27] /2017 | 100 | SAHS               | Wire connection Nasal airflow | CNN            | 76.13         | N/A             | N/A             |
|                      |      |                    |                               | SVM            | 73.22         | N/A             | N/A             |
| Malaekah et al. [16] /2014 | 16 | SAHS               | Wire connection EOG signal    | ANN            | 91.30         | 84.5            | 91.5            |

Acc: accuracy; Sen: sensitivity; Spe: specificity; Resp: respiratory; Acce: Accelerometer; Microp: microphone; gyr: gyroscope
Figure 1: Accuracy comparison among the previous work.

3. Proposed System

The PSG full night test is considered the ideal method for the detection of SA. However, this test has numerous of limitations for patients, as was highlighted in the introduction. Therefore, these limitations are good motivators for researchers to address SA diagnosis. The purpose of this study was to find a low-cost and convenient method for in-home sleep monitoring. The SAE can be detected and predicted by using artificial techniques, such as ANN, which is proposed in Figure 2. Adopting ANN is a good solution for the detection of SAE, because ANN has the ability to navigate a huge amount of dimensional data without manual intervention, possesses learning capabilities, features flexible modelling, offers fast implementation, has fewer detection errors, and is easy to be used [39].

The proposed method can detect SAE using CSA and OSA types, give an alarm for prediction, and run in real-time monitoring. The two types were selected because the OSA is more common than other forms of the disorder, and CSA was highlighted in previous studies, which gave us the motivation to explore its features. The proposed system can be used for adult subjects. Using a combination of three sensors (i.e. SpO2, HR, and flex) is efficient in obtaining accurate results and reducing inaccurate predictions. This method is equipped with Bluetooth wireless protocol for sending data from the sensors to a personal computer for processing without restricting the patient’s movement during sleep. These sensors are small hand low in weight, flexible, easy to set up, and capable of a faster diagnosis and long-term monitoring due to their low power consumption. Figure 2 shows a block diagram of the proposed method. Based on this design, we expect the model to provide accurate diagnoses, enable real-time application, prevent degradation of the patient’s case due to the prediction of ANN, and feature low-power consumption and a long-term monitoring system because it uses low power components. It is also an easy-to-use, wearable, comfortable, efficient, and cost-effective system.

Figure 2. Block diagram of proposed SAE detection and prediction method.
4. Limitations and Challenges of SA

The PSG study is currently considered the standard technique for the detection of SA, as it is a more common and effective diagnostic test. The PSG method still open for discussion due to its numerous limitations. Implementation of the PSG test requires an SA-suspected subject to stay in the sleep centre for one or two nights with special equipment [40]. It is time consuming, complex, expensive, requires a special lab and expert, equipment that cannot be transferred from one place to another, and there is often limited availability at outpatient sleep centres [27]. These drawbacks lead to several challenges when the SA is implemented. Therefore, designers must take the ideal features into consideration when developing a detection method, such as being easy to use, offering detection and prediction services, cost efficiency, convenient for patient movement during sleep due data being transmitted wirelessly and not restricted by wire connection, producing high measurements of accuracy and diagnoses, being a portable, small, and low-power consumption device to be used with the Internet of Things and at home. Most previous works featured authors’ discussions and highlights of their detection method. Our proposed method is focused on the detection and prediction of SA, taking care to identify the most accurate and energy-efficient method.

5. Maturity evaluation

There are several studies that have featured an evaluation of the utility of SpO2 to identify OSA [3-8]. However, AASM did not accept the adoption of SpO2 only for the detection of SAE [17] because sometimes, SAE occurs without a notable change in blood oxygenation level, and therefore must be detected by another sensor. There is another method that depends on the tracheal sound [9, 10], but such a method cannot be used on obese patients. The EEG, ECG, EOG signals cannot send data from electrodes wirelessly [1, 8, 14-16]. The imaging system must be placed on the face, and the patient cannot move [26]. Several studies combine data with two or three sensors for more precise detection. There are many researchers who have discussed the detection of OSA, and a few of them have recognised a prediction method for OSA events. In addition, the CSA method have rarely been considered in previous works. Our proposed method highlights OSA and CSA detection and prediction using a low-power wireless technology.

6. Conclusions

This review featured many tools and strategies reported in previous articles on the diagnosis of SA. The presented solutions and strategies were still insufficient compared with the gold standard of a full laboratory PSG. There are relatively few studies with a small number of volunteer patients who participated in research on other methods of SA diagnoses instead of PSG. Different methods focused on using SpO2, HR, breathing sounds, airflow, EEG, ECG, EOG, and imaging systems for the in-home observation of SA. Overnight SpO2 with HR variability is a suitable approach for detecting sleep disorders. Pulse oximetry is cost-effective and presents high accuracy, sensitivity, and specificity. The previous works were introduced to explore the performance metrics of SA, such as sensitivity and specificity. Therefore, the impact of previous research can prompt us to present a new method that can overcome the gaps in these works, such as accuracy. Figure 2 depicts where the detection and predication accuracy can be improved based on our proposed method. In addition, the adopted wireless technologies, algorithms, sensor types, and diagnosis methods were gathered from previous studies. The future work will be focused on (i) prediction of CSA events and (ii) the extraction of the frequency (0.2-0.35) Hz of respiratory rate from Photoplethysmography HR signals for the detection of SA.

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