PERFORMANCE EVALUATION OF SMART OSA DETECTION: ARTIFICIAL INTELLIGENCE AND NEURAL NETWORK WITH ECG

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ABSTRACT : *Sleep-apnea has been related to breathe and sleep associated with respirational illness. The prolonged Sleep apnea (SA) can lead to serious cardiovascular and neurological diseases. The SA has been diagnosed by the patient with Polysomnography (PSG). But there have been many complications and the test has been only possible with the hospitalized patient with one or two nights. There have been much research has been carried out for an alternative for the PSG. One of the most interesting research with a single-lead ECG test by the wearable device. In this paper review the various research for the detection of SA with ECG. Numerous works issued in the widespread journals between 2016 and 2020 are reviewed in this paper to accomplish these requirements. The reviewed articles are compared concerning algorithms' simplicity, the type they belong, and the performance metrics the work assumed that the movement in the application of elementary methods to detect SA is better than the recommendations that custom some artificial-intelligence techniques.*

Keyword: **sleep apnea, ECG, Artificial intelligence, neural network, filter classification, feature extraction**

1. INTRODUCTION

Sleep-apnea has been related to breathe and sleep associated with respirational illness. The prolonged Sleep apnea (SA) can lead to serious cardiovascular and neurological diseases[1]. There have been the various type of SA, one of the most commonly detected SA has Obstructive-SA. The breathing has been often stop-start while sleeping mostly on the night time sleep[2, 3]. The snoring has been one of the common symptoms of OSA[4]. Figure 1 represents the normal breathing and blocked breathing with commonly understandable OSA

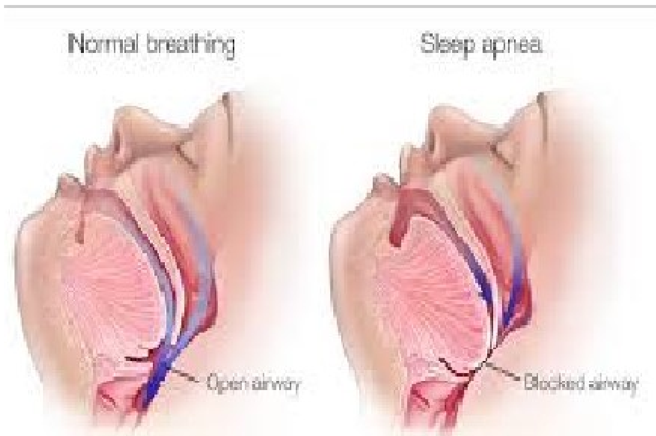

Figure 1 normal and OSA breathing

The prolonged stop-start breath may lead to OSA, the brath has been stoped and start five to 30 times or more on the overnight sleep can lead the OSA, this has been detected only by the following OSA related health issues represented by figure 2 .sleep apnea may increase the risk of heart attack, stroke, type 2 diabetic, etc[5]. many studies determined the OSA can lead most of the work-related accident[6]. The OSA has been diagnosed by a doctor based on the symptoms. the primary test includes the throat, mouth, and nose tissue abnormality. The next step of the test involved overnight monitoring of the breath sequence with the PSG test[7].

Another method of detecting the OSA has a home test involved by single-lead ECG, this method has been taken by the person who has the symptoms of OSA with a smartphone or other device like sensor will detect and store the pattern of breathing, limb movement, blood pressure, and snoring pattern

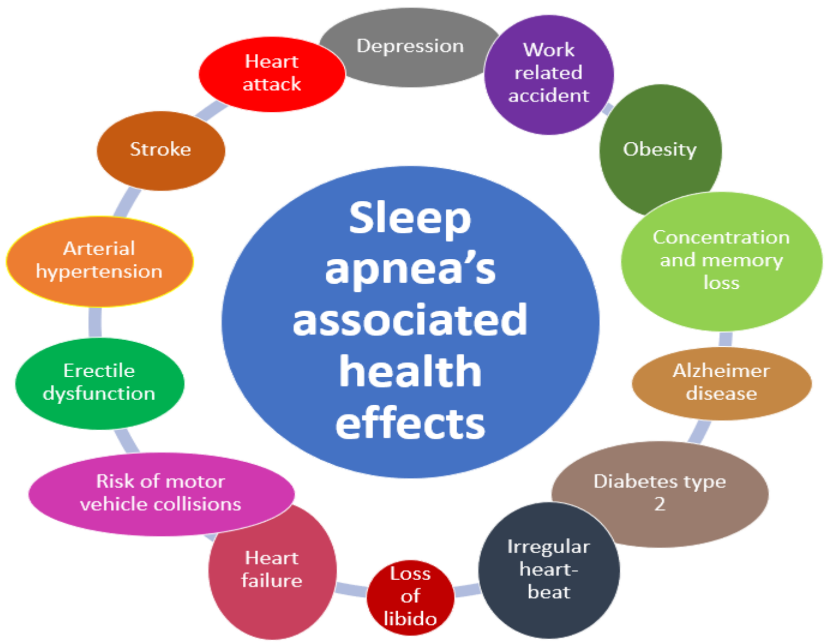

Figure 2 sleep apnea associated health issues

Much research has been carried out towards the smart health environment, the smart health system involved several automatic detections and monitoring health issues like heart rate, blood pressure, etc., towards the automatic detection of OSA using various physiologic signals like EEG, ECG,spo2 etc., in this paper rview various reserch work towards the smart detection of OSA by ECG signals has been carried out. Numerous works issued in the widespread journals between 2016 and 2020 are reviewed in this paper to accomplish these requirements. The reviewed articles are compared concerning algorithms' simplicity, the type they belong, and the performance metrics the work assumed that the movement in the application of elementary methods to detect SA is better than the recommendations that custom some artificial-intelligence techniques.

2. OSA Detection process

The automatic detection of OSA involves several steps, the RAW ECG signals have bee sent to preprocessing steps.

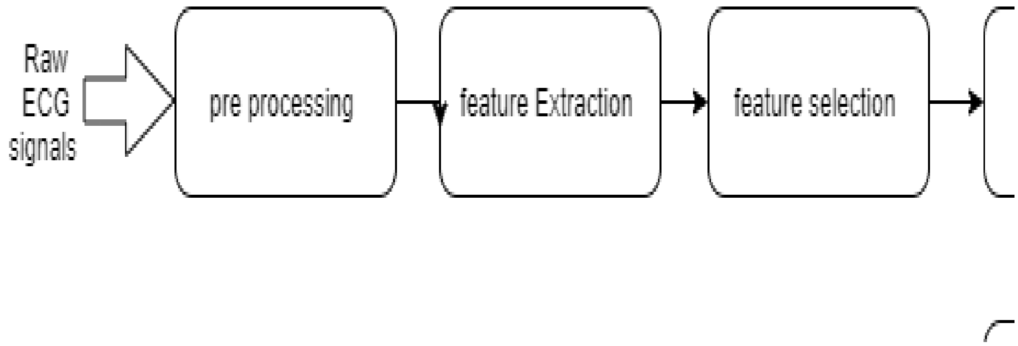

Figure 3 block diagram of OSA detection process

3. ECG preprocessing

The preprocessing the raw ECG has been filtered to remove the various noise in the ECG dataset, the denoised signals have been segmented with various segmentation methods. There have been various research methods involved to filter the ECG signals the following table represents the various techniques. from the table, the pan Tompkins algorithm has been a widely used filtering method to filter the ECG noise. In 1985 the pan and Tompkins experimented with the algorithm for removing the ECG noise an detect the QRS complex in the ECG signals, The algorithm spread over the ECG signals with a series of filtering methods to highlight the main content of ECG and used to remove the backroad noise. The performance has been evaluated with 99. 3% of detection accuracy with the annotated arrhythmia database. There have been other filtering methods has also been used like weight calculating algorithm, low pass filter, high pass filter, the Savitzky–Golay filter, the IIR-Chebyshev Type II bandpass filter, FIR bandpass (0.5–30 Hz) filter, median filters, and biorthogonal antisymmetric wavelet filter bank.

4. Feature Extraction And Selection

feature extraction has been used to select the suitable feature subset from the overall dataset. The main motive of this process is to sect the relevant information and eliminate the irrelevant information from the dataset. The feature extraction has been improving the knowledge about the dataset. The overall computation cast has been reduced and the training process has also been reduced. In the ECG dataset, there has been a few feature selection process that has been implemented for detecting the OSA from the Dataset, table 2 represents the feature selection techniques for various research in ECG-OSA detection.

Table 1. Comparision of different filter technique in the OSA detection process

Author	**Year**	**Method**	**Performance**	**Result and analysis**
Asghar Zarei, Babak Mohammadzadeh	2020	weight calculation algorithm	an accuracy of sensitivity and specificity	accuracy of 97.14%, sensitivity of

As[10]			apnea-hypopnea index (AHI)	95.65%, and specificity of 100%
Şule Yücelbaş Cüneyt Yücelbaş Gülay Tezel Seral Özşen Serkan Küççüktürk Şebnem Yosunkaya[11]	2020	Pan-Tompkins algorithm lowpass and high-pass filter,	average accuracy rate TP FP Matthews Correlation Coefficient precision	Success rates of 97.20±2.15% and 90.18±8.11% with the SBFS algorithm were obtained.
Himali Singh A, Rajesh Kumar Tripathy B, Ram Bilas Pachori[17]	2016	Pan Tompkins' algorithm	sensitivity and specificity,accuracy	Sensitivity 62.87% specificity 81.53%, Accuracy 94.3%
Pinho, A., Pombo, N., Silva, B. M. C., Bousson, K., & Garcia, N[16]	2019	the Savitzky–Golay filter	accuracy sensitivity and specificity	accuracy was 82.12%, with a sensitivity and specificity of 88.41% and 72.29%
Bozkurt, F., Uçar, M. K., Bozkurt, M. R., & Bilgin, C[12]	2020	the IIR-Chebyshev Type II bandpass filter	detection of apnea accuracy sensitivity and specificity	detection of apnea, 82.11% accuracy 3 features 85.12% accuracy 13 features. sensitivity and specificity for the 3 properties are 0.82 and 0.82,
Erdenebayar, U., Kim, Y. J., Park, J.-U., Joo, E.-Y., & Lee, K.-J.[18]	2019	FIR bandpass (0.5–30 Hz) filter	Accuracy Recal	D CNN and GRU models were the best-performing of the accuracy was 99.0% and recall was 99.0%.
Janbakhshi, P., & Shamsollahi, M. B.[14]	2018	median filters approach Pan–Tompkins algorithm	accuracy, sensitivity and specificity	accuracy, sensitivity and specificity of 90.9%, 89.6% and 91.8%,
Manish Sharmaa,∗ , Mitesh Ravala , U. Rajendra Acharyab,C,[8]	2019	two-band filter bank .	accuracy, sensitivity and specificity	highest average accuracy (AVAC), average sensitivity (AVSE), average specificity (AVSP) and F1-score of 90.87%, 92.43% 88.33%

				and 92.61%
Manish Sharmaa,∗ , Shreyansh Agarwala , U. Rajendra Acharya[9]	2018	biorthogonal antisymmetric wavelet filter bank	average classification accuracy, sensitivity, specificity and F-score of	average classification accuracy, sensitivity, specificity and F-score of 90.11%, 90.87% 88.88% and 0.92, respectively.
Kunyang Li , Weifeng Pan, Qing Jiang Guanzheng Liu[15]	2018	Pan-Tompkins algorithm	Accuracy Sensitivity Specificity	Sen: 88.9% Spe: 82.1% Acc: 84.7%

Table 2. Comparison of feature selection / extraction methods

Author	Year	Method	Performance	Result and analysis
Asghar Zarei, Babak Mohammadzadeh As[10]	2020	Sequential forward feature selection (SFFS)	an accuracy of sensitivity and specificity apnea-hypopnea index (AHI)	accuracy of 97.14%, the sensitivity of 95.65%, and specificity of 100%
Şule Yücelbaşcüneyt Yücelbaş Gülay Tezel Seral Özşen Serkan Küççüktürk Şebnem Yosunkaya[11]	2020	sequential backward feature selection	average accuracy rate TP FP Matthews Correlation Coefficient precision	Success rates of 97.20±2.15% and 90.18±8.11% with the SBFS algorithm were obtained.
Himali Singh A, Rajesh Kumar Tripathy B, Ram Bilas Pachori[17]	2016	Hilbert transform separation algorithm	sensitivity and specificity accuracy	Sensitivity 62.87% specificity 81.53%, Accuracy 94.3%
Pinho, A., Pombo, N., Silva, B. M. C., Bousson, K., & Garcia, N[16]	2019	Discriminant Relevance (DR) method	accuracy sensitivity and specificity	accuracy was 82.12%, with a sensitivity and specificity of 88.41% and 72.29%
Bozkurt, F., Uçar, M. K., Bozkurt, M. R., & Bilgin, C[12]	2020	Fisher feature selection	detection of apnea accuracy sensitivity and specificity	detection of apnea, 82.11% accuracy 3 features 85.12% accuracy 13 features.

				sensitivity and specificity for the 3 properties are 0.82 and 0.82,

5. Classification

The classification has been the most important part of the machine learning process, the wide variety of information has been classified. In OSA detection the classification takes place in the apnea segment and non-apnea segment. In this, all the relevant information has been segmented into sub Catagories. The following table 3 represents the various OSA detection methods with highlighted classification methods, the most widely used classification method is the Support Vector Machine.

Table 3. Comparison of a various classification method

Author	**Year**	**Method**	**Performance**	**Result and analysis**
Asghar Zarei, Babak Mohammadzadeh As[10]	2020	Pre-segment classification	an accuracy of sensitivity and specificity apnea-hypopnea index (AHI)	accuracy of 97.14%, sensitivity of 95.65%, and specificity of 100%
Şule Yücelbaş Cüneyt Yücelbaş Gülay Tezel Seral Özşen Serkan Küççüktürk Şebnem Yosunkaya[11]	2020	Support Vector Machine	average accuracy rate TP FP Matthews Correlation Coefficient precision	Success rates of 97.20±2.15% and 90.18±8.11% with the SBFS algorithm were obtained.
Himali Singh A, Rajesh Kumar Tripathy B, Ram Bilas Pachori[17]	2016	support vector machine	sensitivity and specificity accuracy	Sensitivity 62.87% specificity 81.53%, Accuracy 94.3%
Pinho, A., Pombo, N., Silva, B. M. C., Bousson, K., & Garcia, N[16]	2019	Support Vector Machine	accuracy sensitivity and specificity	accuracy was 82.12%, with a sensitivity and specificity of 88.41% and 72.29%
Bozkurt, F., Uçar, M. K., Bozkurt, M. R., & Bilgin, C[12]	2020	Ensemble classifier	detection of apnea accuracy sensitivity and specificity	detection of apnea, 82.11% accuracy 3 features 85.12% accuracy 13 features. sensitivity and specificity for the 3 properties are 0.82 and 0.82,

Janbakhshi, P., & Shamsollahi, M. B[14].	2018	Linear and Quadratic Discriminant (LD and QD) models,	accuracy, sensitivity and specificity	accuracy, sensitivity and specificity of 90.9%, 89.6% and 91.8%,
Manish Sharmaa,∗ , Mitesh Ravala , U. Rajendra Acharyab,C,[8]	2019	Support Vector Machine	accuracy, sensitivity and specificity	highest average accuracy (AVAC), average sensitivity (AVSE), average specificity (AVSP) and F1-score of 90.87%, 92.43% 88.33% and 92.61%
Kunyang Li , Weifeng Pan , Qing Jiang, Guanzheng Liu[15]	2018	Support Vector Machine	Accuracy Sensitivity Specificity	Sen: 88.9% Spe: 82.1% Acc: 84.7%

6. Artificial Intelligence And Neural Network

Artificial neural networks (ANN) have been an important part of machine learning. The human learning system has been adapted to a machine with the stimulation functionality of the brain. The many smart technologies have adapted Artificial intelligence with a neural network. the automatic detection of OSA has been adapted to various types of Nural network and integrated artificial intelligence.

Table 4. various AI and NN towards automatic OSA detection

Author	**Year**	**Method**	**Performance**	**Result and analysis**
Şule Yücelbaş Cüneyt Yücelbaş Gülay Tezel Seral Özşen Serkan Küççüktürk Şebnem Yosunkaya[11]	2020	ANN-SVM	average accuracy rate TP FP Matthews Correlation Coefficient precision	Success rates of 97.20±2.15% and 90.18±8.11% with the SBFS algorithm were obtained.
Himali Singh A, Rajesh Kumar Tripathy B, Ram Bilas Pachori[17]	2016	stacked autoencoder based deep neural network (SAE-DNN),	sensitivity and specificity accuracy	Sensitivity 62.87% specificity 81.53%, Accuracy 94.3%
Pinho, A., Pombo, N., Silva, B. M. C.,	2019	Artificial Neural Networks (ANN) and Support Vector Machine	accuracy sensitivity and specificity	accuracy was 82.12%, with a sensitivity and

Bousson, K., & Garcia, N[16]				specificity of 88.41% and 72.29%
Erdenebayar, U., Kim, Y. J., Park, J.-U., Joo, E.-Y., & Lee, K.-J.[18]	2019	DNN, 1D CNN, 2D CNN,	Accuracy Recal	D CNN and GRU models were the best-performing of the accuracy was 99.0% and recall was 99.0%.
Janbakhshi, P., & Shamsollahi, M. B[14].	2018	Artificial Neural Network (ANN),	accuracy, sensitivity and specificity	accuracy, sensitivity, and specificity of 90.9%, 89.6%, and 91.8%,
Kunyang L, Weifeng Pan, Qing Jiang,Guanzheng Liu[15].	2018	deep neural network and Hidden Markov model (HMM)	Accuracy Sensitivity Specificity	Sen: 88.9% Spe: 82.1% Acc: 84.7%

From the above table, there has been plenty of neural networks that have been adapted like CNN, DNN, 2D CNN, ANN.

7. Discussion

The automatic OSA detection has been involved in many processes, preprocessing, feature extraction/ selection, and classification . from the above tables each step has been reviewed with various authors. the preprocessing has been used various filtering for removing ECG noise, the review resulted in the Pan-Tompkins algorithm plays a vital role in ECG denoise process it also highlights the QRS ECG components. the feature extraction has been done by various methods for reducing the training and learning time, it also makes the accuracy for OSA detecting. the3 process of automatic OSA detection involves classification, the support vector machine plays a key role in the classification technique. the overall process has been trained and tested by artificial intelligent and neural network using table there has been plenty of neural networks has been adapted like CNN, DNN, 2D CNN, ANN.

8. Conclusion

In this study, various research work towards the smart detection of OSA by ECG signals has been carried out. Numerous works issued in the widespread journals between 2016 and 2020 are reviewed in this paper to accomplish these requirements. The reviewed articles are compared concerning algorithms' simplicity, the type they belong, and the performance metrics the work assumed that the movement in the application of elementary methods to detect SA is better than the recommendations that custom some artificial-intelligence techniques. finally concluded that the pan-Tomkins algorithm, the feature selection, and SVM individually works with high accuracy. The deep leaning plays an important role in OSA detection.

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