A Reliable Algorithm Based on Combination of EMG, ECG and EEG Signals for Sleep Apnea Detection

(*A Reliable Algorithm for Sleep Apnea Detection*)

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ABSTRACT— **Sleep Apnea Syndrome is one of the most common and dangerous causes of sleep disorder that the suspected patients are tested (examined) by recording various types of vital signals during sleep using polysomnography (PSG). Since human body rhythms have a chaotic and non-linear behavior, the nonlinear analysis of body parameters provides the researchers with valuable information about body behavior during the disease and its comparison with the normal state for a more accurate examination of the diseases. The purpose of this is to diagnose apnea events using linear and nonlinear analyses and combining the EMG, ECG and EEG signals in patients with Obstructive Sleep Apnea (OSA). The research data are obtained by the Physionet database including 25 subjects (21 males and 4 females). After performing the pre-processing phase to remove the noise related to EMG, ECG, EEG and artifact signals based on the corresponding algorithms, the healthy and apnea sleep ranges are separated from one another. Linear and nonlinear analyses in MATLAB environment are performed on signals and conditions which are evaluated in healthy sleep and during sleep apnea at different stages of sleep in patients with OSA by multilayer perceptron classifier. The best result of the proposed algorithm obtained by combining the signals and the specificity, sensitivity and accuracy values are 96.87 ± 1.78, 97.14 ± 2.24 and 98.09 ± 2.15 respectively. The results show that the proposed algorithm can help doctors and nurses as a diagnostic tool with more accuracy than the similar techniques.**

Keywords: Sleep Apnea, Feature Extraction, Wavelet Decomposition, MLP* (Multilayer perceptron) *Classifier, Computer Aided Diagnosis

I. INTRODUCTION

Sleep apnea is one of the most common disorders characterized by decreasing or stopping the air stream during sleep. In many countries, this disorder is usually diagnosed in sleep labs by polysomnography (PSG) [1]. Sleep apnea is divided into three types: obstructive, central, and mixed. In Obstructive Sleep Apnea (OSA), despite the patient's struggle to breath, upper respiratory tract parts lie on each other and the air stream coming through the nose is reduced or stopped. Central Sleep Apnea (CSA) is caused by impaired central respiration in the brain. This disorder is observed in people with stroke and brain stem injury. Mixed Sleep Apnea (MSA) is a combination of both objective and central types and is most commonly seen in the elderly [2]. In this study, the goal of the researcher is the OSA diagnosis at various stages. Nowadays, due to the high cost and time-consuming process of recording signals with polysomnography, different biological signals such as EMG, ECG and EEG are used to diagnose sleep apnea in many studies. The Electromyogram (EMG) signal, measured on the skin level, provides vital access to muscle tones in the body. Some diseases, such as OSA, are closely related to the muscle tones and can be diagnosed by EMG [3].

The Electrocardiogram (ECG) signal is a very practical tool for recording the electrical activity of the heart. In OSA, both right and left ventricles are under hemodynamic stress. Systemic blood pressure, pulmonary arterial pressure or both are increased with sleep apnea during sleep. This increase in systemic and pulmonary arterial pressure may continue throughout the day. ECG shows the electrical activity inside the heart and reflects the effects of these hemodynamic changes [4]. Moreover, apnea triggers Electroencephalogram (EEG), and the patients' sleep with OSA syndrome is often interrupted. The number of respiratory interruptions over the night is directly related to the quality of sleep and changes in the brain signal [5]. Therefore, diagnosis of sleep apnea is an important goal in many areas, including medicine, psychiatry and neurology. The automatic analysis of sleep apnea can reduce human errors caused by an intuitive diagnosis. Besides, using the automatic analysis will

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increase the speed and accuracy of diagnosis. The most important step for automatic classification of sleep stages is to extract the proper features. In this paper, obstructive sleep apnea of different individuals is accurately diagnosed according to the EMG, ECG and EEG signals. The time, frequency and time-frequency domain features of the EMG, ECG and EEG signals are used because these signals are non-stationary in their nature and the performance of the proposed diagnostic system increases. Figure 1 shows the time that the disorder has occurred on the EMG, ECG and EEG signals recorded simultaneously by the PSG. The region marked on this figure is according to the information mentioned of the database.

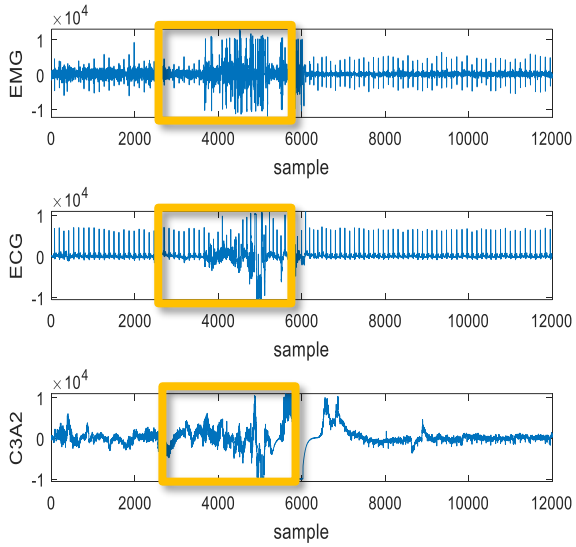

Figure 1. Presetation of the apnea disorder window in EMG, ECG, and EEG signals

In recent years, many researchers have attempted to diagnose this disease by using fewer signals than PSG. Several studies have diagnosed this disease using ECG [6-9], EEG [10-12] and SPo2 [13-14] signals. Other studies have used the combination of two or more signals for diagnosis [15-17]. The abdominal effort signal in the abdominal and chest areas is also used to diagnose apnea incidents that did not have significant results [18-19].

This paper is organized as follows: In the second section (materials and methods), the database is introduced and the proposed method in this paper is devoted to the processing of biological signals. The third section provides the simulation results obtained from the proposed method, and the fourth section presents the discussion and conclusion.

II. Materials and Methods

A. The Database

The data used in this study are from the physionet database [20] which are recorded by Dublin University Hospital [21]. 14 data are recorded from 25 persons, including 4 women and 21 men, using PSG device. In this article, only the persons' electrocardiogram signals (ECG) are used, due to the easiness of recording them and also a direct effect of the patient's conditions in obstructive sleep apnea disorder on this signal. The sampling frequency of the ECG signal is 128 Hz (lead V2). The EEG signal was each sampled at 100 Hz. The submental-EMG signal was electronically high pass filtered, rectified and low-pass filtered after which the resulting EMG envelope expressed in uV rms (root-mean-square) was sampled at 1Hz.

All the patients' specifications are shown in Table 1. The mean and standard deviation in the patients' ages, BMI and AHI respectively are 50±10 (range from 28 to 68 years old), 31.6±4 (range from 25.1 to 42.5 Kg.), and 24.2±20.3 (range from 1.7 to 90.9) [22].

B. Proposed Method

The biological signals recorded by polysomnography are in the time domain. These signals have valuable information. In some cases, in order to find out more about temporal signals, it is necessary to have the frequency domain of the time domain signals. In some cases, the fast-Fourier-transform method does not process the unstable signals properly. The frequency of unstable signals varies over time because in the fast-Fourier-transform, the time resolution is zero. Frequency and time analyses alone cannot provide the frequency and time information of a signal simultaneously; therefore, it is necessary to consider the information obtained from the signal in the time domain and frequency domain at the same time. In order to study the frequency content, the wavelet transform is one of the new and effective tools in engineering which has been able to compensate for the Fourier transformation defects and add the time domain as one of the effective parameters in change level caused by apnea disorder. The discrete wavelet transform is a two-dimensional signal analysis to achieve time and frequency resolution simultaneously and is a very effective way of signal processing. The wavelet transform deals with the level-by-level decomposition of the signal to diagnose the time-frequency properties of the signal compared to other methods.

In this paper, EMG, ECG and EEG signals with specific frequency content are decomposed into signals of different frequency bands using discrete wavelet transform and each of these new signals covers a specific bandwidth of the original signal's frequency content. As a result of this transform (with different signals with different frequency bandwidth), the effect of different frequency contents caused by sleep apnea disorder is studied. This effect is one of the most important factors affecting the behavior of biological signals. Since continuous signals have many quantities inserting them into the wavelet transform formula is difficult and requires sophisticated calculations, the Discrete Wavelet Transform (DWT) defined by formula (1) is used to achieve the loading and coding wavelet transform in MATLAB software [23-24].

$$DWT_{(m.k)} = \frac{1}{a}\sum_{n=0}^{N-1} x(n)\, g(\frac{k-b}{a}) \qquad (1)$$

In this formula, $x(n)$ is the original signal, $a = a_0^m$, $b = b_0^m$ and N is the number of samples in the windowed signal. The $g()$ is called the mother wavelet. m is an indicator of the decomposition level. a and b are the translation and scaling parameters. For example, $a_0 = 3$, DWT can interpret a multi-stage filter banks and run the high and low pass filters on a series of dilations.

Figure 2 shows the signal processing using the DWT method for three levels. The coefficients obtained after the high-pass filter are called the detail coefficients and the coefficients after the low-pass filter are known as approximate coefficients.

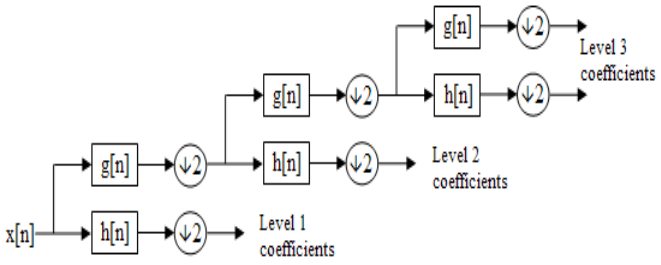

Figure 2. Three level of the discrete wavelet decomposition

Table 1 shows a variety of statistical parameters of the extracted features from the above-mentioned biological signals. The name and mathematical equation of these parameters are listed in this table. *x (n)* is the value of the time series and *N* is the number of data points [25].

TABLE I: INTRODUCTION OF VARIOUS PARAMETERS OF THE RESULTS OF EXTRACTED FEATURES

No	Feature Type	Formula
1	Mean	$M = \frac{\sum_{n=1}^{N} x(n)}{N}$
2	Standard Deviation	$\text{STD}=\sqrt{\frac{\sum_{n=1}^{N}(x(n)-M)^2}{N-1}}$
3	Kurtosis	$\text{KURT}=\sqrt{\frac{\sum_{n=1}^{N}(x(n)-M)^2}{(N-1)STD^4}}$
4	Root Mean Square	$RMS = \sqrt{\frac{\sum_{n=1}^{N} x(n)^2}{N}}$
5	Energy	$En = \sum_{n=1}^{N} x(n)^2$
6	Harmonic Mean	$Harmo = \frac{N}{\sum_{n=1}^{N} \frac{1}{x(n)}}$
7	Skewness	$SKEW = \frac{\sum_{n=1}^{N}(x(n)-M)^3}{STD^3}$
8	Correlation Coefficient	$CC_{x,y} = \frac{cov(x,y)}{\sigma_x \sigma_y}$

Different extracted features have different numerical ranges. In order to prevent the undesirable effect of large amounts of data on the output, they are normalized. The normalization of data is obtained by the following transformation (2).

$$\text{Xnorm} = \left(\frac{X_i - X_{min}}{X_{max} - X_{min}}\right)(X_{Hi} - X_{Low}) + X_{Low} \qquad (2)$$

Where X_i , X_{min} and X_{max} are the actual input data, minimum and maximum input data. X_{Hi} and X_{Low} be the minimum and maximum target value.

Since some of the normalized features are incapable of proper sleep apnea classification, the feature dimensions are reduced by using the principal component analysis (PCA) method. Selecting a few features prevents highlighting the properties and state of a signal and also fails to distinguish between two different signals. Selecting a large number of feature functions confuses the classifier and leads to its failure to distinguish between the two groups of features extracted from the two categories of the signal [26-27].

C. Artificial neural network (ANN)

The behavior of the real nervous system is modeled by the neural networks. These networks have many applications in the field of classification and they can be trained to provide an appropriate response to new samples. Neural network structure consists of the input, processor and output sections. The data are applied to the neural network through the input and then each input is multiplied by a weighted coefficient so that each datum receives a certain value. Finally, the weighted sum of the inputs of each neuron is passed through the activator function and the output of each neuron is generated. By combining a number of neurons and make connections between them, an artificial neural network is created. One of the most widely used networks in the classification of medical signals and images is the multilayer perceptron (MLP) neural network. The MLP neural network is also used to solve the problems of clinical diagnosis, analysis of medical images and signals, prediction of survival in a wide range of medical fields, including oncology, cardiology and hematology, special care, biometrics, dentistry, surgery, etc. This network is a class of feedforward artificial neural network. The network output is compared with the optimal output and the error is calculated. The MLP Neural Network uses the supervised learning method. One of the main challenges in neural networks is to determine the values of the connecting weights between neurons [28-29]. One of the common methods for determining the weights is to use error back propagation method which is used in this paper. Figure 3 illustrates the architecture of the MLP neural network.

The structure of the MLP neural network consists of two hidden layers in which the number of neurons in each layer is considered to reach the minimum mean square error. The selected criteria for the number of hidden neurons in neural network was $(4n^2 + 3) / (n^2 - 8)$ [30]. The *n* is number of input parameters.

The sigmoid activation function is used for MLP neural network's neurons. Artificial neural network inputs included the various features presented in Table 1, which used the time, frequency and time-frequency signals of the EMG, ECG, and EEG biosignals independently and combinedly. Two neurons are also located on network output that shows apnea and non-apnea state. With 10 fold cross validation method, 80% of the data are for training and 20% are for testing the network. The MATLAB software version 2018 is used to design an artificial neural network. The block diagram presented in Figure 4 shows the stages of biological signal processing to diagnose sleep apnea.

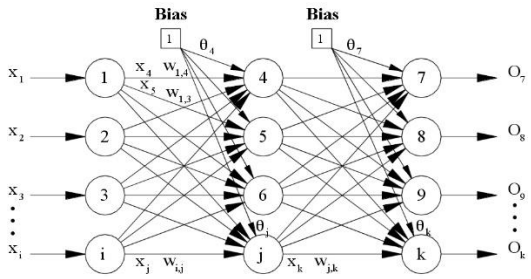

Figure3. A schematic diagram of a Multi-Layer Perceptron

In order to be more successful in signal processing, after recording the biological signals of EMG, ECG and EEG in different stages of sleep, noise is eliminated. In the next stage, according to the incidence of apnea disorder tag in the database, the EMG, ECG and EEG signals are divided into two apnea and non-apnea periods. Then due to the nature of the signals and to increase the classifier efficiency, the time, frequency and time-frequency domain features are extracted. The extracted features are entered the MLP artificial neural network. Finally, using an artificial neural network toolbox and based on the features extracted from each signal, the diagnosis and classification of apnea and non-apnea state are performed. Finally, in order to evaluate the effectiveness of the proposed system, the criteria for specificity, sensitivity, and accuracy are used according to formulas (3), (4) and (5). *TN* is the diagnosis of non-apnea and *TP* is the correct diagnosis of apnea period. *FN* means that the system has falsely announced the apnea period as non-apnea and *FP* means the system has falsely announced the non-apnea period as apnea.

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (3)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (4)$$

$$\text{Accuracy} = \frac{TN+TP}{TN+FP+TP+FN} \quad (5)$$

All of the steps in Figure 4 are performed using the MATLAB software and its various toolboxes.

III. RESULTS

In this phase, 32 samples (80%) are used to train the artificial neural network. After implementing the multilayer perceptron neural network with backpropagation algorithm in MATLAB software and changing the number of layers and neurons of the MLP network and observing the error, the best structure is obtained which is an NN (13-6-6-2) structure with 1500 training cycles. This means that the MLP network has 13 variables for the input layer, 2 variables for the output layer, and 6 neurons for the first and second middle layer (hidden) and the learning process is repeated 1500 times at the training stage. The output variable based on database information has two states defined as apnea or non-apnea. 8 samples (20%) are used for testing the artificial neural network. Specificity, sensitivity and accuracy levels of 96.87%, 97.41%, and 98.9% are obtained respectively by combining EMG, ECG and EEG signals. The different network structures and the results of the test phase are summarized in Fig. 5 and Table 2. The use of EMG, ECG, and EEG signals independently and in binary combination have less significant outcomes than the use of all three biological signals. The network performance does not change significantly by increasing the neurons of the hidden layer for values greater than 6; Therefore, the best structure for the neural network is shown in Table 2 in this paper.

TABLE 2. THE MEAN AND STANDARD DEVIATION OF THE PERFORMANCE OF A NEURAL NETWORK WITH DIFFERENT STRUCTURE

Signal Type	Input	Hidden layer1	Hidden layer1	Training Function	Learning Function	Transfer Function	Specificity (%)	Sensitivity (%)	Accuracy (%)
EMG	8	4	3	trainlm	learngdm	tansig	78.12±6.10	80.45±5.65	82.84±4.64
ECG	9	5	4	trainlm	learngdm	tansig	83.19±4.77	84.21±5.01	86.43±4.21
EEG	10	4	4	traincgf	learngdm	logsig	82.78±4.87	84.65±5.47	86.09±5.76
EMG+ECG	10	6	3	trainlm	learngd	tansig	87.11±3.87	86.66±3.89	87.46±3.67
EMG+EEG	11	6	5	traincgf	learngdm	tansig	86.15±4.21	85.05±4.11	86.33±4.09
ECG+EEG	12	6	5	trainlm	learngdm	logsig	90.72±3.09	91.56±3.34	91.25±3.11
EMG+ECG+EEG	**13**	**6**	**6**	**trainlm**	**learngdm**	**tansig**	**96.87±1.78**	**97.14±2.24**	**98.09±2.15**

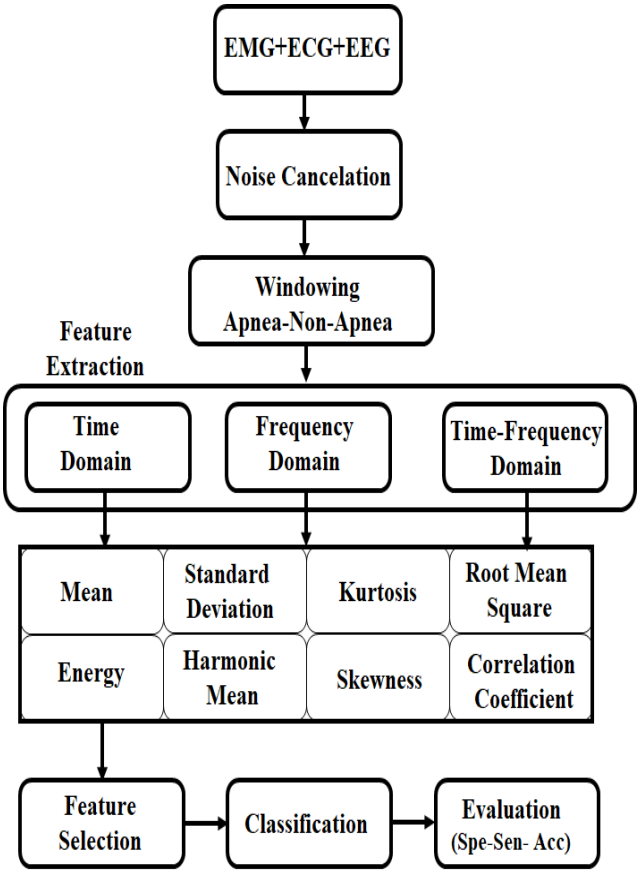

Figure 4. The block diagram for intelligent diagnosis of sleep apnea disorders

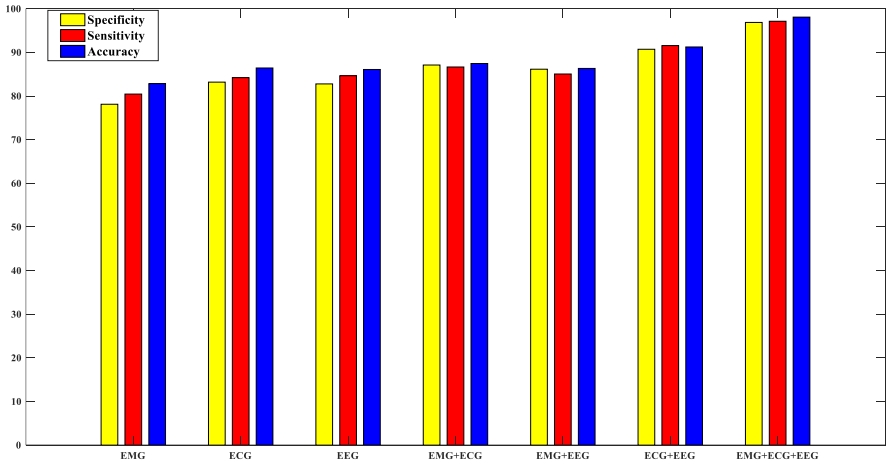

Figure5. Sensitivity, specificity and accuracy evaluated by MLP classifier

IV. Discussion and Conclusion

In this paper, a new, simple, and low-cost method based on an intelligent algorithm is proposed to increase the accuracy of sleep apnea disorder diagnosis to help control and predict this disease. Accordingly, the EMG, ECG, and EEG signals are initially windowed into apnea and non-apnea periods according to the tags in the database. Then, the time, frequency, and time-frequency features are applied on these periods and the

parameters given in Table 1 are extracted based on their partial coefficients. Then the data of 17 patients are randomly used for training and those of 8 other patients are used for the MLP classifier test. Training is used individually and in combination with the MLP inputs. The results of this proposed algorithm are examined with specificity, sensitivity and accuracy indicators and the results are shown in Table 2.

Based on the results presented in Table 2, the proposed algorithm has been able to diagnose this disease with a better performance than other studies in this area. On the other hand, the PCA technique has increased the performance of the algorithm by reducing the input dimension which is important due to the clinical application of this algorithm. Due to the high accuracy, the results of this article can help physicians and nurses to diagnose the disease and because of the use of highly related signals, there is a false alert reduction for hospitals. The comparison between the results of this paper and previous studies indicated the better performance of the proposed method in distinguishing the apnea and non- apnea periods. Table 3 summarizes the research results conducted in this field.

TABLE 3. COMPARING RECENT STUDIED ON OSA DIAGNOSIS

No.	Authors	Signal type - Methods	Results (%)
1	Ebrahimi et al. [31]	EEG - ANN	Acc = 93 Sen = 48 Spe = 94.4
2	Karandiker et al. [32]	ECG - NN ,Regression,Decision Tree & Ensemble Models	Acc = 88.06
3	Huang et al. [33]	EEG – SVM	Acc = 70.92
4	Sanders et al. [34]	EEG – LDA	Acc = 84
5	Zhang et al. [35]	Sparse Deep Belief Net	Acc = 91.31
6	Rachim et al. [36]	ECG – wavelet-PCA	Acc = 94.3
7	Tsinalis et al. [37]	EEG – stacked sparse autoencoders NN	Acc = 78
8	Shi et al. [38]	Multichannel EEG – extreme learning machine	Acc = 81.1
9	Khald et al. [39]	EEG –SVM,KNN,LDA	Acc = 93.13 Sen = 89.06 Spe = 98.61
10	Sharma et al. [40]	ECG - KNN,PNN,SVM ,RBF	Acc = 97.14
11	Janbakhsh et al. [41]	ECG – supervised Machine Learning	Acc = 90.9 Sen = 89.6 Spe = 91.8

In Fig. 6, a comparison is made between the results of various research in this field. Given that most of the research in this field provided the correctness of their proposed algorithm, this comparison is made based on three validity criteria. A comparison of these results shows that the proposed algorithm is capable of achieving high accuracy compared to the related references. As a suggestion, the future studies can increase specificity, sensitivity, and accuracy by reducing the overlap between the features selected by optimization algorithms such as the genetic algorithm and using other artificial intelligence methods. The key novelty of this paper is to detect the sleep disorder from an available signal dataset by using a workable set of features.

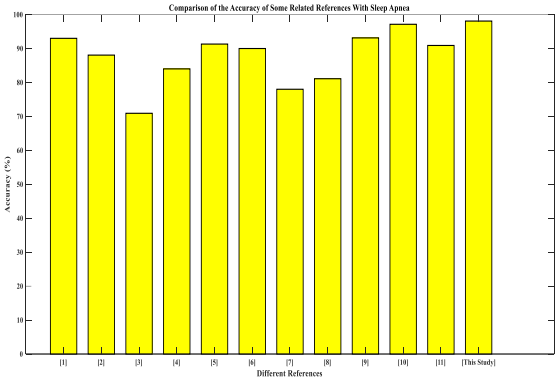

Figure6. Comparison of the Accuracy of Some Related References with Sleep Apnea

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