Obstructive Sleep Apnea Detection using Discrete Wavelet Transform-based Statistical Features

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Abstract

Motivation and Objective: Obstructive sleep apnea (OSA) is a sleep disorder identified in nearly 10% of middle-aged people, which deteriorates the normal functioning of human organs, notably that of the heart. Furthermore, untreated OSA is associated with increased hypertension, diabetes, stroke, and cardiovascular diseases, thereby increasing the mortality risk. Therefore, early identification of sleep apnea is of significant interest.

Method: In this paper, an automated approach for OSA diagnosis using a single-lead electrocardiogram (ECG) has been reported. Three sets of features, namely moments of power spectrum density (PSD), waveform complexity measures, and higher-order moments, are extracted from the one-minute segmented ECG subbands obtained from discrete wavelet transform (DWT). Later, correlation-based feature selection with particle swarm optimization (PSO) search strategy is employed for getting an optimum feature vector. This process retained 18 significant features from initially 32 features computed. Finally, the acquired feature set is fed to different classifiers including, linear discriminant analysis, nearest neighbors, support vector machine, and random forest to perform per segment classification.

Results: Experiments on the publicly available physionet single-lead ECG dataset show that the proposed approach using the random forest classifier effectively discriminates normal and OSA ECG signals. Specifically, our

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method achieved an accuracy of 89% and 90%, with 50-50 hold-out validation and 10-fold cross-validation, respectively. Besides, in both these validation scenarios, our method obtained 96% of the area under ROC. Importantly, our proposed approach provided better performance results than most of the existing methodologies.

Keywords:
Sleep apnea, Single lead ECG, Energy and statistical features, PSO, Random Forest

1. Introduction

A sound sleep is a positive indication of an individual well-being [1]. Nowadays, global technical advancements are influencing our daily routine resulting in an ever-increasing competitive environment, thereby disturbing the natural circadian cycle [2]. This disturbance may result in excessive daytime sleepiness, irritability, and mood swings. Prolonged disturbances in sleep cycles produce chronic sleep disorders, leading to acute conditions such as cardiac arrest and hypertension [3]. On the other hand, sleep disorders may also occur due to inherent physiological problems and environmental changes.

Obstructive sleep apnea (OSA) is a type of sleep disorder that causes abnormal and periodic breath interruptions during sleep due to partial or complete collapsing of the upper airway. Here, airflow may be absent for a minimum of 10 seconds and may occur so many times overnight without individual awareness. OSA can be dangerous because it is associated with increased hypertension, stroke, and perioperative risk [4, 5]. The often symptoms of OSA are excessive daytime sleepiness, tiredness, and loud snoring while sleeping. According to [6], globally, 3 -7 % in men and 2-4% in women are suffering from OSA. Therefore, to reduce the risks mentioned earlier associated with OSA, proper, and timely diagnosis is needed.

Polysomnography (PSG) is a widely used diagnostic tool to study sleep disorders [7]. The test will be conducted in the sleep lab (type I PSG) while the patient is made to sleep with many electrodes placed on various body parts to record multiple physiological signals (electrocardiogram (ECG), electroencephalogram (EEG), electrooculogram (EOG), blood pressure, blood oxygen level, and snoring sounds). Generally, the clinicians visually monitor this data to understand the patient's sleep quality with the help

of computer-based systems [7]. Sometimes, an additional second-day sleep test is also required for an accurate diagnosis. This process may be uncomfortable for the patient due to the prolonged testing time, and the lab set up to collect various measurements. Moreover, placing various electrodes on the patient's body disturbs the sleep resulting in undesirable measurements. The other discouraging facts include equipment cost and an insufficient number of diagnostic sleep labs [8]. Ambulatory PSG (type -II PSG) is an alternative sleep analysis technique exhibiting a comparable performance with the type-I PSG, where patients need not spend a long time in the sleep-lab [9]. However, this test yields more errors due to an increase in the complexity and the number of sensors. Due to the reasons mentioned above, OSA recognition with a more straightforward measurement with less cost and without any specialized laboratory can be a preferable choice.

Various alternative methods in this direction have been explored: based on study of snoring sounds [10], pulse oximetry [11], and ECG [12]. Sleep-related breath disorders have a significant impact on heart rate, cardiovascular activity, and other ECG characteristics. The ECG data analysis can approximately quantify the disrupted breath during the night, which helps in calculating the apnea scoring [7, 13]. Therefore, in recent studies, an inexpensive and non-invasive single-lead ECG containing relevant information on the cardiovascular activity affected by sleep apnea emerged as a recognizable alternative to the PSG [14].

During an apneic event, a drop in the heart rate is commonly observed, followed by a rise near the end of the event [7, 15]. The presence of these apneic events will result in the change of frequency content in the ECG signal for a certain period. Therefore, the approach of analyzing ECG for detecting OSA is gaining attention from various research communities. In [12], real-time sleep apnea detection using ECG signal and saturation of peripheral oxygen (SpO2) is performed. An online sleep apnea detection method is proposed in [16], using heart rate variability (HRV) derived from ECG. The approach in [17] uses a single-lead ECG signal to extract three sets of features for the analysis using least-squares SVM (LS-SVM) with an RBF classifier. A symmetric weighted local binary pattern (SW-LBP) computed from ECG signals is proposed for OSA detection in [18]. In [19], normal inverse Gaussian (NIG) parameters of ECG subbands obtained from tunable Q-wavelet transform (TQWT) are supplied to AdaBoost classifier. In [20], a combination of statistical and spectral parameters calculated from ECG segments are subjected to the ANOVA statistical test. In [21], segmented

ECG signals are processed using Gabor filters and an SVM classifier. In [22], Fuzzy and log energy entropies of subbands are fed to LS-SVM.

In this work, we propose a simple model to differentiate OSA subjects from healthy subjects using a single-lead ECG. We attempted to capture the underlying information of apnea and normal ECG segments with appropriate features. The choice of features is based on their discriminating capability or adequate representation. Hence, the features that can capture the OSA characteristics of ECG signals provide better classification. It is noticed that many OSA detection methods are developed based on time-frequency characterization approaches such as wavelets [6, 23–25]. Authors in [26] performed a pilot study to investigate the significance of features computed from wavelets for various physiological signals: ECG, EEG, and photoplethysmographic (PPG). The obtained results support the significance of wavelet-based features in capturing appropriate information from the physiological signals. We have analyzed the ECG signals using a Daubechies 6 (db6) wavelet and derive informative features from the subbands in this work. Various studies indicated that the statistical measures are preferred as features for non-stationary ECG signal analysis [20, 27, 28]. Most of these works depend on the statistical measures obtained directly from the time domain signal.

Additionally, we considered statistical moments from the power spectrum density of the subbands. The estimates of the power spectrum moments are utilized in analyzing EEG activity [29–31]. EEG is a non-stationary signal, and its morphology is complex when compared with the ECG. The power spectrum moments are proved to efficiently capture the frequency variations in EEG analysis for better decision making. ECG is a weakly non-stationary and nonlinear signal [32]. During OSA, significant variations in heart rate (bradycardia and tachycardia) are observed [33], which directly influences the frequency components in the ECG signal. Motivated by this, we preferred to use the statistical parameters to quantify the ECG spectrum changes effectively. We have also computed various signal activity measures and then tested using the machine learning methods: linear discriminant analysis (LDA) [34], k-nearest neighbor (k-NN) [35], support vector machine (SVM) [36], and random forest (RF).

The rest of the paper organization is as follows: The proposed method's details are explained in Section 2. In Section 3, the experimental setup, the simulated results, a discussion on the obtained results, state-of-the-presented. The concluding remarks are reported in Section 4.

2. Methodology

In the proposed method, the ECG segments are initially decomposed using wavelet transform, following statistical features computed from the wavelet subbands. To reduce the feature vector length, we employed a correlation-based feature selection algorithm [37]. The final feature vector is given to a classifier for OSA detection. The proposed approach is illustrated in Figure 1, and it is detailed in this section.

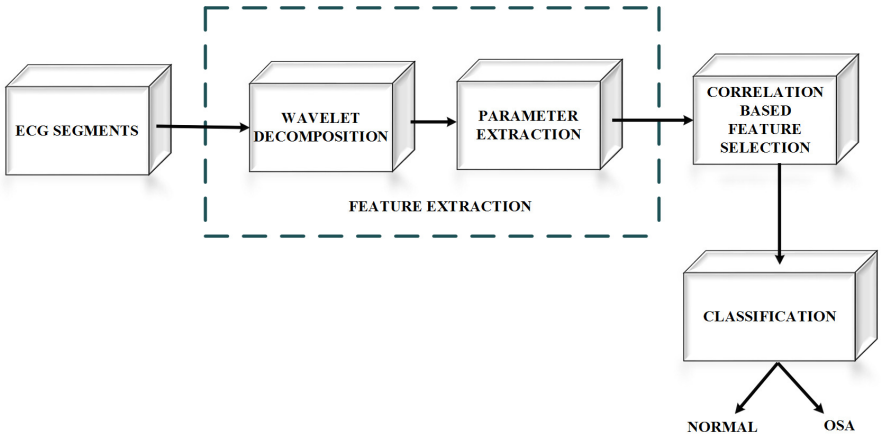

Figure 1: Block diagram for the proposed methodology.

2.1. Dataset

The proposed OSA classification is based on the single-lead ECG, which can capture the prolonged heartbeat cycles associated with sleep apnea [38]. According to Penzel et al. [15], ECG is suitable for the early diagnosis of sleep apnea. To validate the proposed sleep apnea detection mechanism, we used a publicly available ECG-apnea database [7]. This database contains 70 sleep ECG records with a 100 Hz sampling rate collected in two phases. The first phase is recorded between 1993 and 1995. Subjects with moderate and severe sleep apnea have participated in this phase. The apnea-hypopnea index (AHI) is varied between 5 and 75 respiratory events per hour for these subjects. AHI is the ratio of the number of apnea or hypopnea events to the number of sleep hours. The classification of sleep disorders, according to AHI [39], is as follows:

- Normal: AHI$<$ 5

- Mild OSA: $5 \leq \text{AHI} < 15$
- Moderate OSA: $15 \leq \text{AHI} < 30$
- Severe OSA: AHI≥ 30

Twenty-seven recordings from 9 subjects were included in this phase. The number of recordings per subject varied between one to four.

In the second phase, samples from healthy and sleep-apnea subjects are collected from 1998 to 1999, where the AHI varies between 14 and 82. Finally, 43 ECG recordings were collected from 23 subjects, where from each subject at most two recordings are collected.

The single-channel ECG (modified V2) recordings are used for detecting sleep-related breathing disorders. These recordings are manually annotated by a single expert, with a resolution of one minute. Subjects or patients witnessed with sleep apnea during this one-minute are classified as "apnea"; otherwise, it is classified as "normal". Even the segments of hypopnea are labeled as apnea.

According to standard AHI criteria, each recording is grouped into apnea (class A), borderline (class B), and normal (class C) subjects. The details of these subject groups are provided in Table 1.

Table 1: The Apnea-ECG database: Details.

Subject Group	AHI	age	Mean Age	No. of male subjects	No. of female subjects	Total recordings
Class A	> 100	29-63	50	15	1	40
Class B	10-96	39-53	46	4	1	10
Class C	< 5	27-42	33	6	1	20

The 70 records collected from these two phases are further divided into 35 annotated (normal, apnea) training data and 35 withheld test data without annotation records. Each ECG record is approximately 7 to 8 hours duration.

Initially, this database was developed for the computers in cardiology challenge 2000 [40] and is now made freely available in physionet [40]. The first part of the challenge is to discriminate between apnea and normal subjects using training and withheld data. The second part of the challenge is to recognize the apneic event for one- minute ECG segment. The annotation data for one-minute apneic and normal ECG is available for 35 subjects

in the database. In the present work, one-minute ECG segments are classified as apnea, or normal from 35 annotation ECG recordings [41]. The experimental setup followed in this paper is along the direction of the recent works [18, 21, 42–44].

A total of 10454 normal and 6511 apnea ECG segments of one-minute duration are extracted from 35 annotated recordings are used in this work. The sample of normal and apneic ECG signals of one-minute duration are provided in Figure 2.

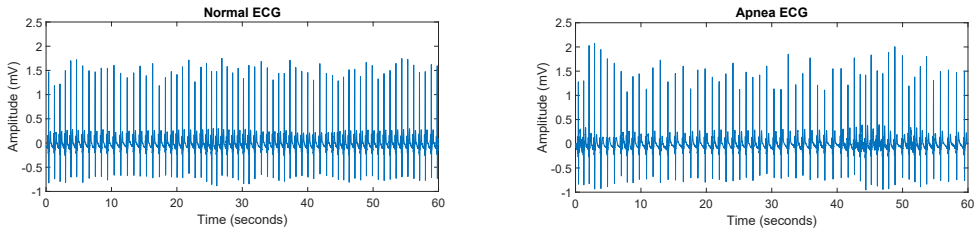

Figure 2: The normal and apnea ECG segments.

2.2. Feature Extraction

Feature extraction has a vital role in computer-aided diagnosis. The selection of proper features enhances diagnosis accuracy significantly. Here, we present the methods and parameters used for feature extraction with its relevancy.

2.2.1. Wavelet Decomposition

ECG is a non-stationary signal originating from a nonlinear system. Wavelet transform can decipher subtle changes in the morphology of the non-stationary signals [45]. Therefore, it is a suitable technique to analyze ECG signals. Fourier transform aims to obtain the frequency information from a signal at the cost of losing the time localized information. To address this short-time Fourier transform with a fixed-length window is preferred. This windowing technique partially succeeded in finding both time and frequency localization [46]. The signal analysis is improved later with wavelet basis function involving translation and scaling; thereby, window length varies based on the requirement of frequency and time resolution [47]. Continuous wavelet transform (CWT) of a signal $x(t)$ is defined as

$$CWT(a,b) = \int_{-\infty}^{+\infty} x(t) \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right) dt \tag{1}$$

Where ψ is a wavelet function and a, b are translation and dilation parameters (scaling factors), respectively.

Implementing CWT is difficult because of its huge memory requirement for storing wavelet coefficients. Therefore, a discrete wavelet transform (DWT) is often used as an implementation technique. In 1989, Mallat [48] proposed a multiresolution signal decomposition for the fast implementation of DWT, using multirate filter bank structures. According to [48], the signal $x(n)$ passed through a series of low pass ($h(n)$) and high pass ($g(n)$) quadrature mirror filters as shown in Figure 3. Here, each stage or level consists of two digital filters $g(n), h(n)$, and two downsamplers by 2. In the first level, a high pass filter followed by a downsampler provide the detail coefficient $D1$, and a low pass filter followed by a downsampler provides the approximation coefficient $A1$. Later, $A1$ is decomposed further to get important information. The details of the frequency ranges of subbands are given below:

- $x(n) : 0 - \frac{f_s}{2} = 0 - 50Hz$
- $A1 : 0 - \frac{f_s}{8} = 0 - 12.5Hz$
- $D1 : \frac{f_s}{8} - \frac{f_s}{4} = 12.5 - 25Hz$
- $A2 : 0 - \frac{f_s}{16} = 0 - 6.25Hz$
- $D2 : \frac{f_s}{16} - \frac{f_s}{32} = 6.25 - 12.5Hz$
- $A3 : 0 - \frac{f_s}{32} = 0 - 3.125Hz$
- $D3 : \frac{f_s}{32} - \frac{f_s}{16} = 3.125 - 6.25Hz$

It is easy to note that the frequency resolution increases with the number of levels. The subbands used in this study are $D1$, $D2$, $D3$, and $A3$. Now, we compute different statistical measures from these individual subbands that will allow us to deduce which frequency level crucial in detecting the OSA ECG segment. The advantage of wavelet analysis is that it can reveal the inherent patterns of a signal by decomposing it into different levels and scales [49]. Various wavelet functions are available to analyze patterns hidden in different signals. Additional details about wavelets can be explored in [26, 47]. In this work, we adopted the db6 wavelet function because it can effectively capture the morphology of the ECG signal [50–54].

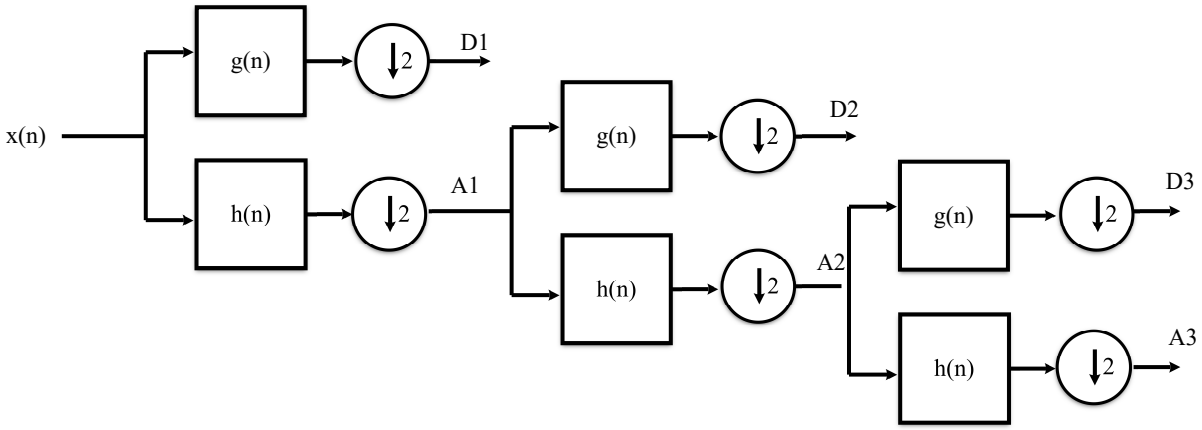

Figure 3: Subband decomposition of ECG signal using DWT.

2.2.2. Parameters

Some vital parameters are computed from the decomposed subbands to serve as features, which help address classification problems. These features are derived from the statistical and power spectral characteristics of the signal. The features can be grouped into three sets: 1. Moments of the power spectrum, 2. Waveform complexity measures, 3. Higher-order moments.

1. **Moments of power spectral density (PSD) function**
   Each wavelet decomposed subband occupies a different frequency scale. Therefore, the first and second-order moments of PSD values are computed as features.

   Mean Frequency (MF)

   It measures the signal power spread over various frequencies. It is considered as the first-order moment of PSD. Generally, MF exhibits high values for muscle contractions and low values for relaxation [55]. Heart rate changes (ventricular muscle contraction and relaxation) can often be observed during sleep apnea events due to switching over sympathetic and parasympathetic actions of the central nervous system. Therefore, it is noticed that MF captures these muscle variations and provides significant information [56, 57].

   For a given signal $x(n)$ of length N, PSD is defined as

$$P_{xx}(k) = \frac{1}{N}|X(k)|^2 \tag{2}$$

where, $X(k)$ is discrete Fourier transform (DFT) of input signal $x(n)$. PSD can be normalized to satisfy the required conditions of a probability density function (pdf) to compute statistical moments. The normalized first-order moment called MF is computed as

$$\mathrm{MF} = \left(\frac{2}{E_x}\right) \sum_{l=0}^{\frac{f_s}{2}} f_l P_{xx}\left(f_l\right) \tag{3}$$

where f_s is sampling frequency, E_x is energy of the given signal:

$$E_x = \sum_{n=0}^{N-1} |x(n)|^2 = \frac{1}{N} \sum_{k=0}^{N-1} |X(k)|^2 \tag{4}$$

Variance (V)

This is considered as second order moment of PSD.

$$\text{Variance} = \mathrm{V} = \left(\frac{2}{E_x}\right) \sum_{l=0}^{\frac{f_s}{2}} \left(f_l - MF\right)^2 P_{xx}\left(f_l\right) \tag{5}$$

These moments are derived from PSD and are useful in measuring the general patterns of the power distribution of a signal over frequency.

2. **Waveform complexity measures**
The waveform complexity or activity measures helpful in understanding the variability of ECG signals. These measures are proved to be efficient in phonocardiogram (PCG) [58], Electromyography (EMG) [59], ECG [60], and EEG [61, 62]. A brief discussion of these measures is presented below.

Root Mean Square (RMS) value

RMS value of a given signal $x(n)$ is defined as

$$\mathrm{RMS}_x = \sqrt{\frac{1}{N} \sum_{n=1}^{N} |x(n)|^2} \tag{6}$$

Form Factor (FF)

It is a useful measure of signal activity proposed by Hjorth [63] for the analysis of non-stationary physiological signals. This parameter is derived based on the concept of variance, as the signal activity. The form factor is computed from two important parameters: activity and mobility. Activity is variance of the signal var_x, and mobility is defined as: $M_x = \sqrt{\frac{\text{var}_{x'}}{\text{var}_x}}$. Here x' is first derivative of the signal. FF is defined as the ratio of mobility of the first derivative of the signal to mobility of the signal.

$$FF = \frac{M_{x'}}{M_x} \tag{7}$$

As ECG related OSA is highly variable and complex, FF would be efficiently measuring the changing complexity.

3. **Higher-order moments**
In addition to the above activity parameters, the statistical measures, including mean (m_x), standard deviation (std), skewness, and kurtosis, are computed as features. They are defined as:

$$m_x = \frac{1}{N}\sum_{n=1}^{N} x(n) \tag{8}$$

$$std = \left(\frac{1}{N}\sum_{n=1}^{N}\left(x(n) - m_x\right)^2\right)^{1/2} \tag{9}$$

$$\text{skewness} = \frac{\frac{1}{N}\sum_{n=1}^{N}\left(x(n) - m_x\right)^3}{\left(\frac{1}{N}\sum_{n=1}^{N}\left(x(n) - m_x\right)^2\right)^{3/2}} \tag{10}$$

$$\text{kurtosis} = \frac{\frac{1}{N}\sum_{n=1}^{N}\left(x(n) - m_x\right)^4}{\left(\frac{1}{N}\sum_{n=1}^{N}\left(x(n) - m_x\right)^2\right)^{2}} \tag{11}$$

Higher-order moments are useful in dealing with non-Gaussian and non-stationary signals, whose variations are neither predictable nor periodic [64, 65].

2.3. Classification

Classification plays a significant role in computer-aided diagnosis. Based on the application demands, various classifiers are developed, among which decision trees are simple yet effective in implementation. Decision trees work on the principle of grouping features [66]. It is a frequently used weak learner since only a few iterations are required for training. The classification efficiency of these tree structures can be further increased by combining these trees. Ensemble learning is a powerful paradigm that combines the predictions of various simple low-accuracy models instead of searching for a complex high-accuracy learning model. Training low-accuracy or weak learners is fast and less complicated, thereby reduces the prediction time. Each decision tree has its own merits. Efficiently combining different decision trees having their merits can enhance the accuracy. For instance, if a given test sample is suggested as OSA by many weak models. The sample is classified as OSA using an ensemble criterion like majority voting. Among the ensemble learning algorithms, decision trees and RF [67, 68] has gained considerable attention.

RF chooses values randomly from the feature vector; otherwise, the training models may be closely related and do not serve the purpose. Random feature selection ensures the development of low correlation decision trees, a critical point in the RF classifier. Therefore, simple low correlation models have to be appropriately constructed from the training data and efficiently combined using different criteria. Bootstrap aggregation (Bagging) and boosting are the two standard approaches used in ensemble learning. RF utilizes the Bagging approach, where multiple copies of training samples, slightly different from one another, are created. Then each of these copies will train all the weak models. Therefore, the basic idea is combining these individual uncorrelated decision tree models enhances the prediction accuracy.

We create K random copies of training samples, C_k from the original training data, with each copy containing S samples ($C_k = \{\text{sample}_1, \text{sample}_2, ...\text{sample}_S\}$, $k = 1, 2, ..., K$). Using the training samples C_k we can build weak models f_k. After training, the class of a new sample X can be predicated from the weak model f_k as $f_k(X)$. An average of all the K model predictions is given by

$$y \leftarrow f(\mathbf{X}) = \frac{1}{K} \sum_{k=1}^{K} f_k(\mathbf{X}) \tag{12}$$

The main advantage of implementing ensemble classifiers is to boost the

prediction performance and diminish over-fitting by selecting random samples from the original data.

2.4. Feature Selection

Feature selection is of paramount interest in machine learning, especially when the models are build using a large set of features. Increasing the number of features may result in redundancy, noise, the curse of dimensionality, and model complexity [12, 16]. In the present work, the tree construction complexity of RF depends on the number of features, as it increases the depth of the tree. In this work, the correlation-based feature selection (CFS) with particle swarm optimization (PSO) search [37, 69, 70] is used for simplifying the model complexity. The CFS+PSO algorithm identifies a relevant feature set with a high degree of correlation to the class value and a low degree correlation with the other features. The PSO algorithm helps, appropriately searching feature space to identify an optimum feature subset for initiating the CFS algorithm.

2.5. Kruskal-Wallis one-way analysis of variance (KW-ANOVA) test

The Kruskal-Wallis (KW) one-way analysis of variance (KW-ANOVA) [71] is a non-parametric test to estimate the differences between two or more dependent data groups. Unlike, ANOVA test, the KW test does not assume any particular distribution of data. Hence, it is useful for both ordinal and continuous data variables [72]. The KW test determines the differences between data using the median values. The hypotheses for the KW test are:

1. **Null hypothesis:** All the population medians are equal.
2. **Alternative hypothesis:** At least one data group is coming from a different distribution.

3. Results and Discussion

The database discussed in Section 2.1 is used to validate the performance of the proposed OSA detection approach. In total, 16,965 ECG segments, each 1-minute duration from 35 subjects of annotated records, are used for experimentation. In this work, RMS, FF, the two moments of the PSD, and the first four order statistical parameters of the wavelet subbands are employed as features. It is because the time-frequency based statistical feature representation can effectively capture the changes that occurred in the ECG

pattern during apneic events. A three-level decomposition is performed on the ECG segments resulting in 4 subbands. The essential features are computed from each subband, producing a final feature vector of length $32(4\times8)$. This data is further subjected to an RF learning model for classifying the ECG segments. The details of the experiment setup, performance measures used, and the simulation results are presented below.

The process of feature extraction and statistical analysis is performed using MATLAB 2016b [73]. WEKA 3.9 version [74] is used to implement feature selection and classification tasks. The system specifications in this experimental setup are Windows 8, 8 GB RAM, and 64-bit OS.

3.1. Performance Measures

The performance of the proposed classification scheme is quantified using the confusion matrix, and various measures [75], including accuracy, sensitivity, specificity, precision, F1-score, and area under receiver operating characteristics (ROC) curve (AUC) are derived from it. Here, accuracy describes the total number of correctly recognized ECG segments from both OSA and normal. Sensitivity report the number of correctly identified OSA from total OSA ECG segments, and specificity report the correctly identified normal from total normal ECG segments. Precision is a measure of positive prediction. F1-score is a measure of the harmonic mean of sensitivity and precision. It is helpful when there is a conflict between sensitivity and precision. AUC measures the level of separability between the classes. The high value of all these measures indicates the effectiveness of the proposed model.

3.2. Experimental Results

The DWT based statistical features extracted from the one-minute ECG segment are fed to RF classifier for classification of normal and apneic episodes. Furthermore, these features' performance is studied using LDA,k-NN, and SVM classifiers for comparison purposes. Each of these classifiers follows a unique approach in prediction. For instance, LDA and SVM are functional type classifiers, k-NN is a lazy classifier, and RF is an ensemble algorithm.

To make a fair comparison with existing methodologies [18–20, 27], two cross-validation methods, namely, hold-out and 10-fold, are explored. Experiments in hold-out validation are carried out by partitioning the entire dataset into independent testing and training sets. Especially in this analysis, 50% of the dataset is randomly selected for training, and the remaining

data is used as testing; further, this process is repeated ten times. The confusion matrices of selected learning models for a single iteration are presented in Table 2. In these matrices, the diagonal entries represent correctly recog-

Table 2: Confusion matrices for various classifiers.

Classifier $-->$	**LDA**		**k-NN**	
Actual\predicted	Apnea	Normal	Apnea	Normal
Apnea	1418	1814	2576	671
Normal	697	4553	714	4521
Classifier$-->$	**SVM-Linear**		**RF**	
Actual\predicted	Apnea	Normal	Apnea	Normal
Apnea	1403	1832	2772	487
Normal	718	4529	389	4834

nized ECG segments, and anti-diagonal represents false identification from both the classes. From Table 2, it is observed that all the classifiers have successfully predicted about 4500 normal class ECG segments out of approximately 5200 ECG segments. RF and k-NN predicted approximately 2700 and 2500 OSA beats correctly out of approximately 3200 ECG segments. The classifiers other than RF and k-NN failed in predicting normal and OSA segments correctly. RF classifier exhibits superiority over k-NN in discriminating samples from both classes. It is to be noted that the individual total of normal and sleep-apnea values are different for all these confusion matrices since hold-out is performed for various random shuffles of samples. The average performance measures (mean $\pm$ standard deviation) of these models for ten different runs is given in Table 3. For each run, all the samples are randomly shuffled.

From Table 3, we can observe that k-NN and RF classifiers are providing superior performance over other classifiers. Expressly, RF has provided better results: sensitivity of 85.07%, a specificity of 92.42% while k-NN sensitivity 79.91%, and specificity is 86.44%. It is noted that good sensitivity values indicate an accurate prediction of OSA. RF is yielding a sensitivity value of 5% more than that of the k-NN. The AUC value of 96% specifies the potential of the class discriminating capability of the proposed model. Furthermore, the RF classifier is providing consistent results with less standard deviation, indicating less variance and more stability.

It is noted that the non-parametric methods: k-NN and RF, are providing noticeable results because They do not presume anything from data but learn

Table 3: Average performance of the proposed approach (values in %) : Hold-out (50-50)cross-validation.

(Performance metric)	**LDA classifier**	**k-NN classifier**
Accuracy	69.68 ± 0.55	83.93 ± 0.32
Sensitivity	43.54 ± 1.26	79.91 ± 1.10
Specificity	85.89 ± 0.56	86.44 ± 0.44
Precision	65.83 ± 0.74	78.44 ± 0.5
F1-Score	52.4 ± 0.99	79.15 ± 0.52
AUC	76.87 ± 0.458	83.16 ± 0.45
(Performance metric)	**SVM-Linear classifier**	**RF classifier**
Accuracy	69.6 ± 0.58	89.6 ± 0.14
Sensitivity	44.02 ± 1.99	85.07 ± 0.39
Specificity	85.61 ± 0.83	92.42 ± 0.22
Precision	65.6 ± 0.98	87.42 ± 0.31
F1-Score	52.66 ± 1.28	86.57 ± 0.31
AUC	64.81 ± 0.68	96.04 ± 0.07

from data.

Further, to understand the role of feature selection on the detection performance, additional experiments have been performed. In Table 4, each of the features obtained from the subbands is provided with an index number. The CFS+PSO algorithm has returned 18 prominent features out of 32: {1,2,4,8,10,11,12,14,15,16,17,18,23,24,25,27,30,32}.

Table 4: Feature number assignment.

Subbands\features	MF	V	RMS	FF	mean	std	skewness	kurtosis
Subband 1	1	2	3	4	5	6	7	8
Subband 2	9	10	11	12	13	14	15	16
Subband 3	17	18	19	20	21	22	23	24
Subband 4	25	26	27	28	29	30	31	32

It is clear from the results mentioned above that the RF classifier is exhibiting superior performance over others. Hence, further experiments are carried out using the RF classifier alone. The confusion matrix of the RF classifier with feature selection is presented in Table 5. This table shows that 7558 samples are correctly recognized out of 8482 samples with an approxi-

mate accuracy of 90%. Table 6 presents the detection performance metrics on the selected features averaged over ten independent simulations. From Tables 6 and 3, it is observed that the RF classifier performance with and without feature selection is almost equal, and interestingly sensitivity value after feature selection is improved by 1%. Hence, the results support the proposed model's ability to effectively detect the OSA segments in a minute-by-minute analysis.

Table 5: Confusion matrix of RF classifier (one iteration) with feature selection: Hold-out (50-50) cross-validation.

	Apnea	Normal
Apnea	2807	437
Normal	487	4751

Table 6: Average performance of the proposed OSA approach (values in %) with RF classifier: Hold-out (50-50) cross-validation on selected 18 features.

Metric	Value
Accuracy	88.9 ± 0.082
Sensitivity	86 ± 0.69
Specificity	91.39 ± 0.35
Precision	85.97 ± 0.57
F1-Score	85.59 ± 0.41
AUC	95.69 ± 0.20

This reduction in the number of features helps in the speedy and effective implementation of the proposed method. Besides, the average time elapsed to classify ECG segments is computed and presented in Table 7.

Table 7: Classification time analysis in testing phase.

Number of features	Average time elapsed for 8482 test samples (seconds)	Average time elapsed for one test sample (seconds)
32	1.05	12.3×10^{-5}
18	0.33	38.9×10^{-6}

From Table 7, it can be observed that the testing time has been reduced by almost three times after feature selection.

As described in Section 3.2, we have tested the proposed method using 10-fold cross-validation [76]. The sample confusion matrices of RF classifier results using 10-fold cross-validation are presented in Table 8. From this table, it is noted that the full feature set correctly classified 15319 samples out of 16965 samples. In comparison, the selected 18 subsets of features can identify 15238 instances out of 16965 samples. It justifies the effectiveness of selected features in classification. Tables 9 and 10 represents the proposed scheme's average performance measures using 10-fold cross-validation with and without feature selection. The 10-fold approach also justifies that the performance is satisfactory, even after the feature reduction.

Table 8: Confusion matrices of RF classifier (one iteration)with and without feature selection: 10-fold cross-validation.

	Using 32 features		**Using 18 features**	
Actual\predicted	Apnea	Normal	Apnea	Normal
Apnea	5642	869	5615	896
Normal	777	9677	831	9623

Table 9: Average performance measure values in % of RF classifier without feature selection: 10-fold cross-validation.

Metric	Value
Accuracy	90.3 ± 0.086
Sensitivity	86.6 ± 0.15
Specificity	92.59 ± 0.07
Precision	87.93 ± 0.11
F1-Score	87.26 ± 0.12
AUC	96.6 ± 0.0

3.3. Discussion

The results demonstrated in Section 3.2 support that the ensemble decision tree classifier called RF classifier shows superior performance with DWT based statistical features. Further, a feature selection process is employed on the feature set to diminish the effect of correlation among the features on the overall performance. The CFS+PSO has reduced the length of the feature vector from 32 to 18. Among 18 features, six are moments of the PSD, four

Table 10: Average performance measures values in % of RF classifier with feature selection: 10-fold cross-validation.

Metric	Value
Accuracy	89.84 ± 0.005
Sensitivity	86.23 ± 0.15
Specificity	92 ± 0.118
Precision	87.3 ± 0.13
F1-Score	86.71 ± 0.09
AUC	96.3 ± 0.03

are activity measures, and eight are higher-order moments. It suggests that all categories of features equally contribute to better classification.

It is noted that, among the selected 18 features, four are from subband 1, six are from subband 2, four are from subband 3, and the remaining four are from subband 4. Each subband provides some unique information required for identifying the OSA ECG pattern. The details are given in Table 11.

Table 11: The selected features from each subband after CFS+PSO.

Subband Number	Features
1	MF, V, FF, and kurtosis
2	V, RMS, FF, std, and kurtosis
3	MF, V, skewness, and kurtosis
4	MF, RMS, std, and kurtosis

From Table 11, it can be observed that the power spectrum moments and kurtosis are the most discriminating features from all the subbands. These features capture the ECG signal patterns from high to low-frequency distribution to differentiate OSA and normal ECG signals. Here, the kurtosis identifies whether the tails of a given distribution contain extreme values [77], which are a result of a change in heart rate. The cardiac muscle variations can change the ECG signal power values [56, 57], which can be represented by the first and second-order moments of PSD (MF and V).

3.3.1. Efficacy of the features

To further ascertain the effectiveness of the features selected, we have performed the KW-ANOVA [71] test. The normalized (min-max normalization) features obtained after performing CFS+PSO are used in this test. If

this test results in a p value of < 0.01, it implies that the chosen attributes (features) are having significant differences in terms of their distribution related to the class label [78]. The KW-ANOVA test is carried out on the features of both normal and OSA data. The statistical test is reported on 6500 samples (approximately equal to OSA ECG segments) of normal and OSA ECG segments. The analysis is performed individually on each feature value from both the classes.

Table 12: p-values of the selected features.

Feature Number	p-value
1	0
2	3.3140×10^{-92}
4	0
8	0
10	1.066×10^{-06}
11	0
12	0
14	0
15	0
16	0
17	0
18	4.9596×10^{-24}
23	0
24	0
25	0
27	0
30	0
32	0

The p-values for all features are presented in Table 12. The table shows that for all the 18 features, $p < 0.01$, which suggests that the DWT-based features are statistically substantial for discriminating the normal and OSA classes [65]. Furthermore, the box-whisker plots are shown in Figure 4, to support the statement mentioned above. In each of these plots, the red dots represent the feature distribution concerning the class, and the black color extreme horizontal lines called whiskers represent the spread of the data. The red dots outside the whisker are outliers. Inside the box, the middle red line

indicated the median of the data, and the other two lines from the median are called quartiles. Additional details about box plots maybe found in [79]. It is observed from these plots; these features exhibit good discrimination ability. Therefore, it is inferred that these statistically significant features play a crucial role in better classification of OSA and normal ECG segments.

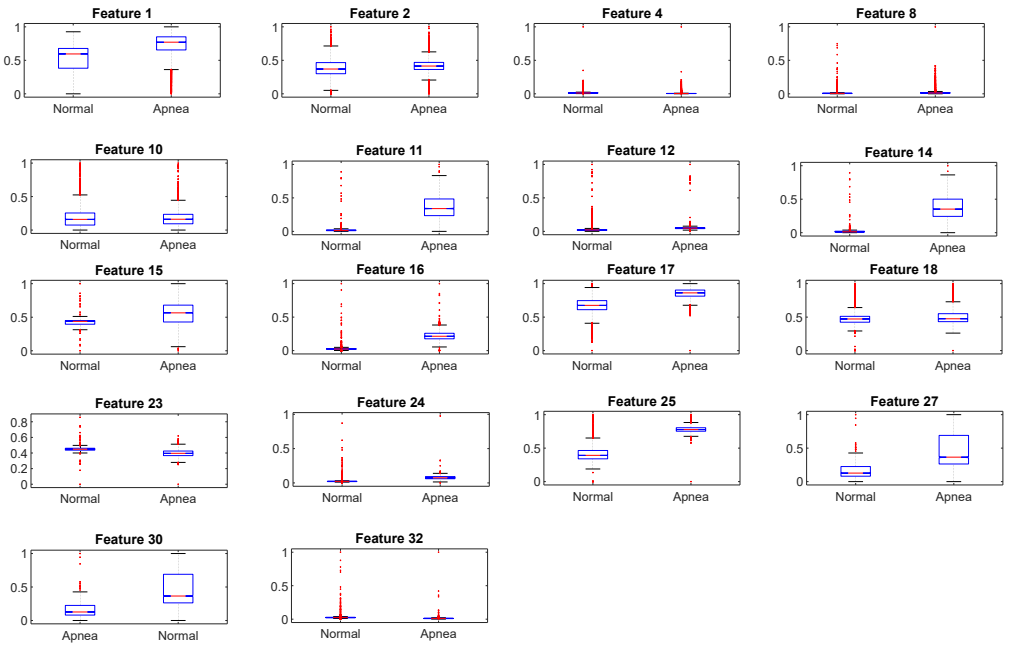

Figure 4: Box plots for the features corresponding to normal and OSA classes.

3.3.2. Performance comparison with existing methodologies

The performance comparison of the proposed approach with the existing works that have used the same dataset as our work is presented in Table 13. Our method has provided better classification accuracies than the approaches in [16, 17, 19, 20, 27, 43, 44] with a few number of features. The advantages and limitations of our approach with other competing approaches are listed below.

Advantages

1. Our approach achieved a good classification accuracy with reduced feature vector length, resulting in less classification time. Specifically, it exhibited an average accuracy of 90.3% with 32 features and 89.84%

with 18 features. The proposed approach has employed significantly fewer features than most of the existing methodologies [16–18, 42, 80].

2. The works in [20], and [43] employed fewer features than our approach, i.e., 8 and 12 features, respectively. However, the performance metrics support our proposed approach.

3. Our classification accuracy is similar to the works [42, 80, 81]. However, we achieved an average classification accuracy of 89.6% with only 50% of training data and 90.3% when 10-fold cross-validation is used. At the same time, the approaches in [42, 80, 81], have employed 35-fold cross-validation, where approximately 97.1% (34/35) data is employed for training. We achieved comparable results with much lesser training data. It is also noteworthy that the approach in [42] has achieved the classification accuracy of 88.88% with 90 features. We achieved a similar performance with only 18 features.

4. Besides, it is observed that the proposed method has outperformed the techniques that have employed 10-fold cross-validation [19, 27, 44].

Limitations

Despite the evident advantages and effectiveness, the proposed approach has some limitations.

1. The overall accuracy needs to be improved to above 90%.

2. The sensitivity of the proposed method is slightly less than some of the state-of-the-art.

3. The proposed approach must be validated on a more extensive and diverse dataset before deploying it for clinical purposes. More specifically, it has to be validated on a dataset that contains subjects with other sleep disorders, cardiac arrhythmias, and breathing-related problems. We plan to consider it as a part of future studies.

4. Conclusion

We have proposed an automated computer-aided approach for OSA detection. More specifically, significant statistical features are computed from

Table 13: Performance comparison.

Methodology (Reference number)	Feature selection	No of Final features	Validation scheme	Performance measures (ACC, SEN, SPE) in %
PCA of QRS complex, orthogonal subspace project, RR intervals+ LS-SVM [17]	F-score and KW test	28	Hold-out	84.74, 84.71, 84.69
RQA statistics of HRV data + SVM and NN [16]	Conditional mutual information	33	3-fold	85.26 , 86.37, 83.47
Normal and Inverse Gaussian of TQWT modes + AdaBoost[19]	No	18	10-fold	87.33, 81.99,90.72
Statistical features and spectral flatness, spectral centroids + Bagging [20]	ANOVA test	8	-	85.97, 84.14,86.83
Statistical features from EMD modes + ELM [27]	ANOVA test	25	10-fold	83.77, 85.20,82.79
Symmetry weighted local binary patterns+ k-NN[18]	No	59	Holdout (50-50)	89.80, 88.46, 90.63
Statistical features from TQWT modes+ RusBoost [42]	No	90	35-fold	88.88, 87.58,91.49
Fuzzy and log energy entropies from optimal orthogonal wavelet filter banks+ ASVM-Gaussian [81]	student's t-test+ forward wrapper feature selection	12	35-fold	90.87, 92.43,88.33
Features based on ECG derived respiration and RR intervals+ ANN [80]	No	85	35-fold	90.9, 89.6,91.8
Entropy features derived from IBF's of HRV and EDR signals+KELM [43]	student's t-test	12	Holdout (70-30)	77.27,79.25,75.3
Features derived from HRV and EDR of ECG [44]	Set of feature section methods	20	10-fold	88.12, 88.41, 72,29
In this work DWT based statistical features+RF	-	32	Holdout (50-50)	89.6 ± 0.14, 85.07 ± 0.3, 92.48 ± 0.24
	CFS+PSO	18	Holdout (50-50)	88.9 ± 0.08, 86 ± 0.69, 91.39 ± 0.35
	-	32	10-fold	90.3 ± 0.08, 86.6 ± 0.15, 92.59 ± 0.07
	CFS+PSO	18	10-fold	89.84 ± 0.005, 86.23 ± 0.15, 92 ± 0.118

Note
ACC: Accuracy, SEN: Sensitivity, SPE: Specificity item RQA:Recurrence Quantification Analysis, HRV: Heart Rate Variability, TQWT: Tunable Q-wavelet Transform, EMD: Empirical Mode Decomposition, NN: Neural Network, ELM: Extreme Learning Machine, KELM: Kernel ELM, EDR: Electrocardiogram-derived, respiration, IBF: intrinsic band functions

ECG subbands. RF classifier has utilized these features for discriminating normal and apneic ECG segments. The proposed method attained a classification accuracy of 90%, demonstrating that wavelet-based features can discriminate apnea and normal ECG signals and provide better classification metrics than most of the existing methodologies.

A simple yet effective approach for OSA detection is presented in this paper. However, the proposed method needs to be validated on a larger dataset before using it for clinical purposes. We plan to develop a deep learning-based approach for OSA detection in future work.

References

[1] R. Boostani, F. Karimzadeh, M. Nami, A comparative review on sleep stage classification methods in patients and healthy individuals, Computer methods and programs in biomedicine 140 (2017) 77–91.

[2] A. C. West, D. A. Bechtold, The cost of circadian desynchrony: Evidence, insights and open questions, Bioessays 37 (2015) 777–788.

[3] D. A. Calhoun, S. M. Harding, Sleep and hypertension, Chest 138 (2010) 434–443.

[4] P. Fassbender, F. Herbstreit, M. Eikermann, H. Teschler, J. Peters, Obstructive sleep apnea—a perioperative risk factor, Deutsches Ärzteblatt International 113 (2016) 463.

[5] R. J. Thomas, M. D. Weiss, J. E. Mietus, C.-K. Peng, A. L. Goldberger, D. J. Gottlieb, Prevalent hypertension and stroke in the sleep heart health study: association with an ecg-derived spectrographic marker of cardiopulmonary coupling, Sleep 32 (2009) 897–S2.

[6] A. Zarei, B. M. Asl, Automatic detection of obstructive sleep apnea using wavelet transform and entropy-based features from single-lead ecg signal, IEEE journal of biomedical and health informatics 23 (2018) 1011–1021.

[7] T. Penzel, G. B. Moody, R. G. Mark, A. L. Goldberger, J. H. Peter, The apnea-ecg database, in: Computers in Cardiology 2000. Vol. 27 (Cat. 00CH37163), IEEE, 2000, pp. 255–258.

[8] P. De Chazal, C. Heneghan, E. Sheridan, R. Reilly, P. Nolan, M. O'Malley, Automated processing of the single-lead electrocardiogram for the detection of obstructive sleep apnoea, IEEE Transactions on Biomedical Engineering 50 (2003) 686–696.

[9] L. Andrade, T. Paiva, Ambulatory versus laboratory polysomnography in obstructive sleep apnea: comparative assessment of quality, clinical efficacy, treatment compliance, and quality of life, Journal of Clinical Sleep Medicine 14 (2018) 1323–1331.

[10] A. K. Ng, T. Koh, E. Baey, K. Puvanendran, Speech-like analysis of snore signals for the detection of obstructive sleep apnea, in: 2006 International Conference on Biomedical and Pharmaceutical Engineering, IEEE, 2006, pp. 99–103.

[11] U. J. Magalang, J. Dmochowski, S. Veeramachaneni, A. Draw, M. J. Mador, A. El-Solh, B. J. Grant, Prediction of the apnea-hypopnea index from overnight pulse oximetry, Chest 124 (2003) 1694–1701.

[12] B. Xie, H. Minn, Real-time sleep apnea detection by classifier combination, IEEE Transactions on information technology in biomedicine 16 (2012) 469–477.

[13] A. Zarei, B. M. Asl, Automatic classification of apnea and normal subjects using new features extracted from hrv and ecg-derived respiration signals, Biomedical Signal Processing and Control 59 (2020) 101927.

[14] R. Atri, M. Mohebbi, Obstructive sleep apnea detection using spectrum and bispectrum analysis of single-lead ecg signal, Physiological measurement 36 (2015) 1963.

[15] T. Penzel, J. McNames, P. De Chazal, B. Raymond, A. Murray, G. Moody, Systematic comparison of different algorithms for apnoea detection based on electrocardiogram recordings, Medical and Biological Engineering and Computing 40 (2002) 402–407.

[16] H. D. Nguyen, B. A. Wilkins, Q. Cheng, B. A. Benjamin, An online sleep apnea detection method based on recurrence quantification analysis, IEEE journal of biomedical and health informatics 18 (2013) 1285–1293.

[17] C. Varon, A. Caicedo, D. Testelmans, B. Buyse, S. Van Huffel, A novel algorithm for the automatic detection of sleep apnea from single-lead ecg, IEEE Transactions on Biomedical Engineering 62 (2015) 2269–2278.

[18] T. S. Kumar, V. Kanhangad, Automated obstructive sleep apnoea detection using symmetrically weighted local binary patterns, Electronics Letters 53 (2017) 212–214.

[19] A. R. Hassan, Computer-aided obstructive sleep apnea detection using normal inverse gaussian parameters and adaptive boosting, Biomedical Signal Processing and Control 29 (2016) 22–30.

[20] A. R. Hassan, M. A. Haque, Computer-aided obstructive sleep apnea screening from single-lead electrocardiogram using statistical and spectral features and bootstrap aggregating, Biocybernetics and Biomedical Engineering 36 (2016) 256–266.

[21] T. S. Kumar, V. Kanhangad, Gabor filter-based one-dimensional local phase descriptors for obstructive sleep apnea detection using single-lead ecg, IEEE sensors letters 2 (2018) 1–4.

[22] M. Sharma, S. Agarwal, U. R. Acharya, Application of an optimal class of antisymmetric wavelet filter banks for obstructive sleep apnea diagnosis using ecg signals, Computers in biology and medicine 100 (2018) 100–113.

[23] F. Ng, I. Garcia, P. Gomis, A. La Cruz, G. Passariello, F. Mora, Bayesian hierarchical model with wavelet transform coefficients of the ecg in obstructive sleep apnea screening, in: Computers in Cardiology 2000. Vol. 27 (Cat. 00CH37163), IEEE, 2000, pp. 275–278.

[24] M. E. Tagluk, M. Akin, N. Sezgin, Classıfication of sleep apnea by using wavelet transform and artificial neural networks, Expert Systems with Applications 37 (2010) 1600–1607.

[25] O. Fontenla-Romero, B. Guijarro-Berdiñas, A. Alonso-Betanzos, V. Moret-Bonillo, A new method for sleep apnea classification using wavelets and feedforward neural networks, Artificial Intelligence in Medicine 34 (2005) 65–76.

[26] D. Cvetkovic, E. D. Übeyli, I. Cosic, Wavelet transform feature extraction from human ppg, ecg, and eeg signal responses to elf pemf exposures: A pilot study, Digital signal processing 18 (2008) 861–874.

[27] A. R. Hassan, M. A. Haque, Computer-aided obstructive sleep apnea identification using statistical features in the emd domain and extreme learning machine, Biomedical Physics & Engineering Express 2 (2016) 035003.

[28] A. Jezzini, M. Ayache, L. Elkhansa, Z. al abidin Ibrahim, Ecg classification for sleep apnea detection, in: 2015 international conference on advances in biomedical engineering (ICABME), IEEE, 2015, pp. 301–304.

[29] J. S. Barlow, Computerized clinical electroencephalography in perspective, IEEE Transactions on Biomedical Engineering (1979) 377–391.

[30] M. van de Velde, I. R. Ghosh, P. J. Cluitmans, Context related artefact detection in prolonged eeg recordings, Computer Methods and Programs in Biomedicine 60 (1999) 183–196.

[31] B. Saltzberg, W. Burton Jr, J. Barlow, N. Burch, Moments of the power spectral density estimated from samples of the autocorrelation function (a robust procedure for monitoring changes in the statistical properties of lengthy non-stationary time series such as the eeg), Electroencephalography and clinical neurophysiology 61 (1985) 89–93.

[32] C. Maji, P. Sengupta, A. Batabyal, H. Chaudhuri, Nonlinear and statistical analysis of ecg signals from arrhythmia affected cardiac system through the emd process, arXiv preprint arXiv:2002.03840 (2020).

[33] M. Mendez, A. M. Bianchi, S. Cerutti, Non stationary analysis of heart rate variability during the obstructive sleep apnea, in: The 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, volume 1, IEEE, 2004, pp. 286–289.

[34] S. Mika, G. Ratsch, J. Weston, B. Scholkopf, K.-R. Mullers, Fisher discriminant analysis with kernels, in: Neural networks for signal processing IX: Proceedings of the 1999 IEEE signal processing society workshop (cat. no. 98th8468), Ieee, 1999, pp. 41–48.

[35] D. W. Aha, D. Kibler, M. K. Albert, Instance-based learning algorithms, Machine learning 6 (1991) 37–66.

[36] S. S. Keerthi, S. K. Shevade, C. Bhattacharyya, K. R. K. Murthy, Improvements to platt's smo algorithm for svm classifier design, Neural computation 13 (2001) 637–649.

[37] M. A. Hall, Correlation-based feature selection for machine learning (1999).

[38] T. Penzel, J. W. Kantelhardt, R. P. Bartsch, M. Riedl, J. F. Kraemer, N. Wessel, C. Garcia, M. Glos, I. Fietze, C. Schöbel, Modulations of heart rate, ecg, and cardio-respiratory coupling observed in polysomnography, Frontiers in physiology 7 (2016) 460.

[39] A. Zarei, B. M. Asl, Performance evaluation of the spectral autocorrelation function and autoregressive models for automated sleep apnea detection using single-lead ecg signal, Computer Methods and Programs in Biomedicine 195 (2020) 105626.

[40] G. Moody, R. Mark, A. Goldberger, T. Penzel, Stimulating rapid research advances via focused competition: The computers in cardiology challenge 2000, in: Computers in Cardiology 2000. Vol. 27 (Cat. 00CH37163), IEEE, 2000, pp. 207–210.

[41] A. Nishad, R. B. Pachori, U. R. Acharya, Application of tqwt based filter-bank for sleep apnea screening using ecg signals, Journal of Ambient Intelligence and Humanized Computing (2018) 1–12.

[42] A. R. Hassan, M. A. Haque, An expert system for automated identification of obstructive sleep apnea from single-lead ecg using random under sampling boosting, Neurocomputing 235 (2017) 122–130.

[43] R. Tripathy, Application of intrinsic band function technique for automated detection of sleep apnea using hrv and edr signals, Biocybernetics and Biomedical Engineering 38 (2018) 136–144.

[44] A. Pinho, N. Pombo, B. M. Silva, K. Bousson, N. Garcia, Towards an accurate sleep apnea detection based on ecg signal: The quintessential of a wise feature selection, Applied Soft Computing 83 (2019) 105568.

[45] P. S. Addison, Wavelet transforms and the ecg: a review, Physiological measurement 26 (2005) R155.

[46] N. Kehtarnavaz, Chapter 7 - frequency domain processing, in: N. Kehtarnavaz (Ed.), Digital Signal Processing System Design (Second Edition), second edition ed., Academic Press, Burlington, 2008, pp. 175 – 196. URL: http://www.sciencedirect.com/science/article/pii/B9780123744906000076. doi:https://doi.org/10.1016/B978-0-12-374490-6.00007-6.

[47] K. Soman, Insight into wavelets: From theory to practice, PHI Learning Pvt. Ltd., 2010.

[48] S. G. Mallat, A theory for multiresolution signal decomposition: the wavelet representation, IEEE transactions on pattern analysis and machine intelligence 11 (1989) 674–693.

[49] M. Sifuzzaman, M. Islam, M. Ali, Application of wavelet transform and its advantages compared to fourier transform (2009).

[50] W. Li, Wavelets for electrocardiogram: Overview and taxonomy, IEEE Access 7 (2018) 25627–25649.

[51] I. Kaur, R. Rajni, A. Marwaha, Ecg signal analysis and arrhythmia detection using wavelet transform, Journal of The Institution of Engineers (India): Series B 97 (2016) 499–507.

[52] A. Balachandran, M. Ganesan, E. Sumesh, Daubechies algorithm for highly accurate ecg feature extraction, in: 2014 International Conference on Green Computing Communication and Electrical Engineering (ICGCCEE), IEEE, 2014, pp. 1–5.

[53] X. L. Wang, J. M. Eklund, Using daubechies wavelet functions to generate masks for accurate qrs detection, in: 2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE), IEEE, 2017, pp. 1–4.

[54] P. Sabherwal, L. Singh, M. Agrawal, Aiding the detection of qrs complex in ecg signals by detecting s peaks independently, Cardiovascular engineering and technology 9 (2018) 469–481.

[55] R. M. Rangayyan, Biomedical signal analysis, volume 33, John Wiley & Sons, 2015.

[56] M. R. Bonsignore, S. Romano, O. Marrone, M. Chiodi, G. Bonsignore, Different heart rate patterns in obstructive apneas during nrem sleep, Sleep 20 (1997) 1167–1174.

[57] T. Penzel, Is heart rate variability the simple solution to diagnose sleep apnoea?, 2003.

[58] D. S. Gerbarg, A. Taranta, M. Spagnuolo, J. J. Hofler, Computer analysis of phonocardiograms, Progress in Cardiovascular Diseases 5 (1963) 393–405.

[59] Y.-T. Zhang, C. B. Frank, R. M. Rangayyan, G. D. Bell, A comparative study of simultaneous vibromyography and electromyography with active human quadriceps, IEEE transactions on biomedical engineering 39 (1992) 1045–1052.

[60] R. F. Rushmer, Cardiovascular dynamics, Academic Medicine 36 (1961) 742.

[61] C. Binnie, B. Batchelor, P. Bowring, C. Darby, L. Herbert, D. Lloyd, D. Smith, G. Smith, M. Smith, Computer-assisted interpretation of clinical eegs, Electroencephalography and clinical neurophysiology 44 (1978) 575–585.

[62] C. Binnie, B. Batchelor, A. Gainsborough, D. Lloyd, D. Smith, G. Smith, Visual and computer-assisted assessment of the eeg in epilepsy of late onset, Electroencephalography and clinical neurophysiology 47 (1979) 102–107.

[63] B. Hjorth, Time domain descriptors and their relation to a particular model for generation of eeg activity, CEAN-Computerized EEG analysis (1975) 3–8.

[64] C. L. Nikias, J. M. Mendel, Signal processing with higher-order spectra, IEEE Signal processing magazine 10 (1993) 10–37.

[65] T. S. Kumar, V. Kanhangad, Detection of electrocardiographic changes in partial epileptic patients using local binary pattern based composite feature, Australasian physical & engineering sciences in medicine 41 (2018) 209–216.

[66] T. M. Mitchell, Machine learning, 1997.

[67] L. Breiman, Random forests, Machine learning 45 (2001) 5–32.

[68] A. Burkov, The hundred-page machine learning book, Andriy Burkov Quebec City, Can., 2019.

[69] R. Poli, J. Kennedy, T. Blackwell, Particle swarm optimization: An overview: Swarm intelligence, 1, 33–57, 2007.

[70] A. Moraglio, C. Di Chio, R. Poli, Geometric particle swarm optimisation, in: European conference on genetic programming, Springer, 2007, pp. 125–136.

[71] W. H. Kruskal, W. A. Wallis, Use of ranks in one-criterion variance analysis, Journal of the American statistical Association 47 (1952) 583–621.

[72] P. E. McKight, J. Najab, Kruskal-wallis test, The corsini encyclopedia of psychology (2010) 1–1.

[73] MATLAB, 9.1.0.441655 (R2016b), The MathWorks Inc., Natick, Massachusetts, 2016.

[74] I. H. Witten, E. Frank, M. A. Hall, C. J. Pal, Data Mining: Practical machine learning tools and techniques, Morgan Kaufmann, 2016.

[75] D. M. Powers, Evaluation: from precision, recall and f-measure to roc, informedness, markedness and correlation (2011).

[76] R. Kohavi, et al., A study of cross-validation and bootstrap for accuracy estimation and model selection, in: Ijcai, volume 14, Montreal, Canada, 1995, pp. 1137–1145.

[77] A. Papoulis, S. U. Pillai, Probability, random variables, and stochastic processes, Tata McGraw-Hill Education, 2002.

[78] R. Freund, W. Wilson, D. Mohr, Statistical methods. 3rd editon, 2010.

[79] R. McGill, J. W. Tukey, W. A. Larsen, Variations of box plots, The American Statistician 32 (1978) 12–16.

[80] P. Janbakhshi, M. Shamsollahi, Sleep apnea detection from single-lead ecg using features based on ecg-derived respiration (edr) signals, IRBM 39 (2018) 206–218.

[81] M. Sharma, M. Raval, U. R. Acharya, A new approach to identify obstructive sleep apnea using an optimal orthogonal wavelet filter bank with ecg signals, Informatics in Medicine Unlocked (2019) 100170.