Obstructive Sleep Apnea Detection based on ECG Signal using Statistical Features of Wavelet Subband

Original Scientific Paper

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Abstract *– One of the respiratory disorders is obstructive sleep apnea (OSA). OSA occurs when a person sleeps. OSA causes breathing to stop momentarily due to obstruction in the airways. In this condition, people with OSA will be deprived of oxygen, sleep awake and short of breath. Diagnosis of OSA by a doctor can be done by confirming the patient's complaints during sleep, sleep patterns, and other symptoms that point to OSA. Another way of diagnosing OSA is a polysomnography (PSG) examination in the laboratory to analyze apnea and hypopnea. However, this examination tends to be high cost and time consuming. An alternative diagnostic tool is an electrocardiogram (ECG) examination referring to changes in the mechanism of ECG-derived respiration (EDR). So digital ECG signal analysis is a potential tool for OSA detection. Therefore, in this study, it is proposed to classify OSA based on ECG signals using wavelets and statistical parameters. Statistical parameters include mean, variance, skewness kurtosis entropy calculated on the signal decomposition results. The validation performance of the proposed method is carried out using a support vector machine, k-nearest neighbor (k-NN), and ensemble classifier. The proposed method produces the highest accuracy of 89.2% using a bagged tree where all features are used as predictors. From this study, it is hoped that ECG signal analysis can be used to complete clinical diagnosis in detecting OSA.*

Keywords*: Obstructive sleep apnea, electrocardiogram, Wavelet transform, statistical parameter*

1. INTRODUCTION

An electrocardiogram (ECG) signal is a biomedical signal generated by bioelectric phenomena in the heart. The ECG signal describes the process of contraction of the heart muscle to pump blood out of the heart [1]. In addition to providing information about heart health, ECG signals can also provide other health information. One information the ECG signal can provide is the occurrence of obstructive sleep apnea (OSA) [2]. OSA is a disorder that occurs during sleep, where a block in the upper respiratory tract occurs during sleep [3]. The occurrence of OSA can be seen from the mechanism of ECG-derived respiration (EDR), where a disturbance in breathing will cause a change in the pattern of the ECG signal [4]. Changes to this ECG signal can be a change in signal orientation, a change in signal shape, or a change in signal rhythm.

OSA can be detected or monitored using several methods. The standard method used is Polysomnography (PSG) [5]. PSG is less practical because it requires monitoring throughout the night and uses a lot of devices. PSG is also only used for patients with OSA with a certain severity [2]. The following method is OSA monitoring using a camera that detects the patient's movement during sleep [6]. The advantage of this method is that the system is contactless but requires heavy processing to be carried out on video recordings over a long period. OSA detection using a camera can only be done if the subject makes specific movements in OSA conditions. Another method is to use the sound of snoring as input. This method uses voice processing techniques to detect sleep apnea [7]. Because the voice frequency is relatively high, the sampling frequency will also be quite high, affecting the computational complexity. Sound signal processing for OSA detection is strongly influenced by environmental noise, for example, in patients with sleep talking. Other investigators have used a combination of ECG, electromyogram (EMG), and electroencephalogram (EEG) signals [8], or ECG and photoplethysmogram (PPG) signals by exploiting changes in oxygen saturation caused by OSA [9]. Simultaneous use of multiple signals for OSA detection creates complexity in installation and has the potential to cause subject discomfort. However, the use of a single ECG as an input signal to detect OSA has become the choice of many researchers because it is more practical with more straightforward computations [2], [10]–[12].

Various methods have been developed to detect OSA using ECG signals. OSA detection using ECG rhythm changes is usually initiated by seeing the R wave in the ECG signal. The cessation of breathing results in a difference in the distance between the R waves so that by calculating several parameters such as the standard deviation of the RR-interval, NN50 measure (type1 and type 2), pNN50, RMSSD, etc. [13][14][15]. The determination of the HRV of the ECG signal is highly dependent on the detection of the QRS of the ECG signal. If any QRS fails to detect, then the HRV parameter will change, which will cause misclassification. The short length of the ECG signal segmentation also affects the accuracy because if the ECG signal segment is too long, the HRV changes due to OSA cannot be detected [13]. Changes in the rhythm of this signal will result in a difference in the shape or orientation of the ECG signal. For this reason, several researchers use the morphology of the ECG signal as a feature for classifying normal and OSA ECG signals. The morphology of the ECG signal was measured using the entropy [16], the intrinsic mode function (IMF) of the ECG signal [17][18], or signal fluctuations in the wavelet subband [19]. The use of EMD in the decomposition of the ECG signal for OSA detection has the potential to eliminate the information contained in the ECG signal. As we know, in EMD, the local oscillation of the signal is removed to obtain the intrinsic mode function (IMF) of the signal [17].

The wavelet method has its advantages in processing ECG signals for OSA detection. The advantage is due to the flexibility of wavelets in decomposing the signal to obtain a subband with the desired information content. In this study, it is proposed to classify OSA on ECG signals using DWT and statistical parameters. The decomposition level equals 3, so it only produces four subbands. Meanwhile, for characteristics, statistical characteristics of order 1. are used. These statistical characteristics will display signal characteristics such as mean, variance, skewness, kurtosis, and entropy. The level of decomposition used in this study is less than that proposed in [19]. In [19], decomposition level 8 is used to obtain nine subbands. Meanwhile, the features used include several types of entropy (ApEn, FE, Shannon entropy, Correct Conditional Entropy), Poincare Plot Features, recurrent plot, mean absolute deviation, and variance. Although the proposed method is more straightforward than previous studies, It is hoped that this feature will be able to produce high accuracy in the classification of normal ECG and OSA.

2. MATERIAL AND METHODS

The method proposed in this study is shown in Figure 1. The recording of ECG signal is segmented into 1 minute of recording and then normalized. In the next stage, decomposition is carried out using the discrete wavelet transform (DWT) method to obtain the signal subband. The statistical parameters are calculated in each subband, which will be used as features. The last process is classification to determine whether OSA occurs or not. The details of each process will be explained in the following subsection.

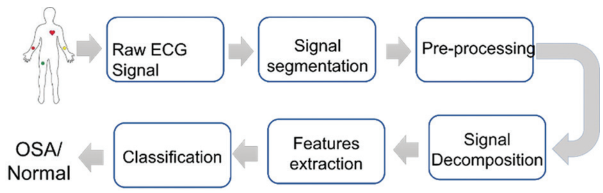

Fig. 1. The proposed method

2.1. DATA, SIGNAL SEGMENTATION, DAN PREPROCESSING

ECG signal data on OSA was obtained from Physionet, which consisted of 70 records, with 35 records being training data and 35 recordings of testing data [20][21]. Each record lasts 7-10 hours with a sampling frequency of 100 Hz. Each 1-minute segment or 6000 samples has been annotated by experts in the form of OSA or normal. In this study, the ECG signal data with and without OSA were combined for different subjects, so the method used was subject-independent.

In the segmentation signal, the normalization process is carried out using Eq. (1).

$$y = \frac{x - \bar{x}}{\sigma_x} \tag{1}$$

where y = ouput signal, x = input signal, $\bar{x}$ = mean of input signal, and σ_x = standard deviation of x.

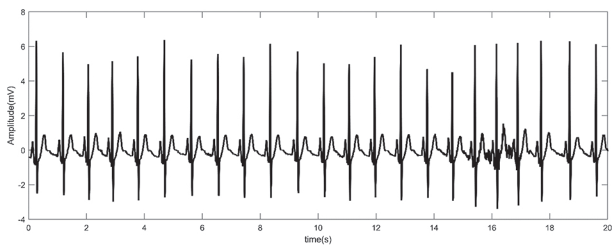

Fig. 2. The ECG signal in normal condition

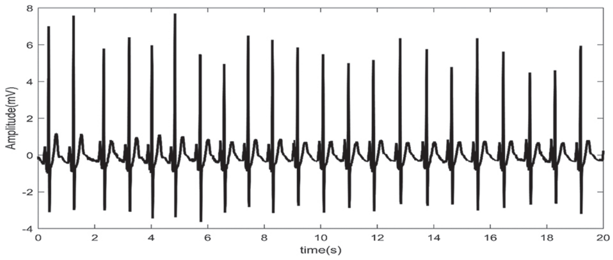

Fig. 3. The ECG signal with OSA condition

The number of data tested is 17010, with 10496 normal data and 6514 ECG data on OSA. Figure 2 and Figure 3 show examples of normal and OSA ECG signals.

2.2. WAVELET DECOMPOSITION

Wavelet transform aims to decompose the signal into several subbands, which are assumed to be stationary. The wavelet decomposition process involves a filtering process using a low-pass filter and an orthogonal high-pass filter and downsampling, which will reduce the number of signal samples by half [22]. This process will divide the signal into two subbands with energy that is maintained. In this study, Db2 is used as the mother wavelet with the decomposition level shown in Figure 4.

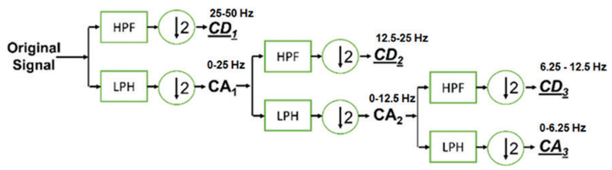

Fig. 4. Wavelet decomposition scheme which is implemented in this study

The bandwidth for each subband will be obtained in the ECG signal with a sampling frequency of 100 Hz, as shown in Table 1. In this study, the original signal is decomposed at three levels to obtain high-frequency information which is represented as detail coefficients (CD) and low-frequency information which is represented as approximation coefficients (CA). Most of the signal components will occupy the CA3 subband according to the characteristics of the ECG signal.

Table 1. Bandwidth of each subband

Subband	Band of frequency
CD1	25-50
CD2	12.5 – 25
CD3	6.25 – 12.5
CA3	0 – 6.25

2.3. FEATURE EXTRACTION

The result of wavelet decomposition is calculated statistical parameters as a signal feature in each subband. The statistical characteristics include mean, variance, skewness, kurtosis, and entropy. The five statistical features can be calculated using a mathematical formula as in Eq. 2 – 6.

$$Mean\ (\bar{Y}) = \frac{\sum_{i=1}^{N} Y_i}{N} \tag{2}$$

$$VAR = \frac{1}{N-1} \sum_{i=1}^{N} {Y_i}^2 \tag{3}$$

$$Skewness = \frac{\sum_{i=1}^{N}(Y_i - \bar{Y})^3/N}{s^3} \tag{4}$$

$$Kurtosis = \frac{\sum_{i=1}^{N}(Y_i - \bar{Y})^4/N}{s^4} \tag{5}$$

$$H = -\sum_{i=1}^{N} P_i \log P_i \tag{6}$$

The five statistical parameters are expected to differentiate between normal ECG signals and ECG signals under OSA conditions.

2.4. CLASSIFICATION

A. Support Vector Machine (SVM)

SVM is a learning system used to test linear function hypotheses in high-dimensional feature space; the computer will be trained using an algorithm based on optimization theory and statistical learning theory [23]. SVM can work on non-linear data by applying a kernel approach to the data set's initial features. Lower dimensions are mapped to higher dimensions by kernel functions [24].

B. K-nearest neighbor (KNN)

K-nearest neighbor (KNN) is a distance-based classification method that determines classification results based on the largest training data class with the closest distance to test data [25]. The following are the steps of the K-Nearest Neighbor algorithm:

1. Determine the value of the parameter K; K is the number of nearest neighbors.
2. Determine the distance between the test data and all existing data in the training data.
3. Sort the distances and find the nearest neighbor based on the shortest distance to the K data.
4. Determine the closest neighbor's category.

The Euclidean distance was used in this study as in Eq. (7). In this study, various variations of KNN were used to obtain the highest accuracy.

$$D_e(xi, yi) = \sqrt{(x1 - y1)^2 + (x2 - y2)^2 + \cdots + (xp - yp)^2} \tag{7}$$

C. Ensemble Classifier

The ensemble classifier is a data-driven approach to improving class balance. The goal of the ensemble algorithm approach is the same: to improve the algorithm without changing the data. There are two approaches that can be taken: the data level approach and the algorithm level approach [26]. Boosting and bagging are two popular ensemble algorithms. AdaBoost is a classification algorithm that improves classification performance. At the same time, bagging is a simple but effective ensemble method that has been used in many real-world applications to improve the accuracy of classification algorithms. The results outperform random sampling [27].

D. N-Fold Cross-Validation

In this study, the N-fold cross-validation (NFCV) was used to avoid overfitting in the classification accuracy testing process. In NFCV, the data is divided into N datasets, with 1 data set used as the test while the N-1 dataset is used as the training data. The testing process is carried out N times so that each data set has been used as test data. Accuracy is taken from the average of each test. Because the classifiers used in this study are all supervised learning, NFCV is appropriate in this case. This study used N = 10.

3. RESULTS AND DISCUSSION

Figure 5 and Figure 6 show the decomposition results of normal ECG and ECG signals with OSA. From the number of signal samples, it can be seen that on CD1, the number of signal samples is half of the original signal, meanwhile, on CD2, the number of signal samples is half that of CD1, and the number of signal samples on CD3 and CA3 each has half the number of signal samples of CD2. This result occurs because there is a downsampling of 2 processes at each decomposition level, as shown in Figure 4. There is no difference between the decomposition results of normal ECG signals and ECG signals with OSA. For this reason, the feature extraction process is carried out by calculating statistical features in each subband, such as mean, variance, kurtosis, skewness, and entropy.

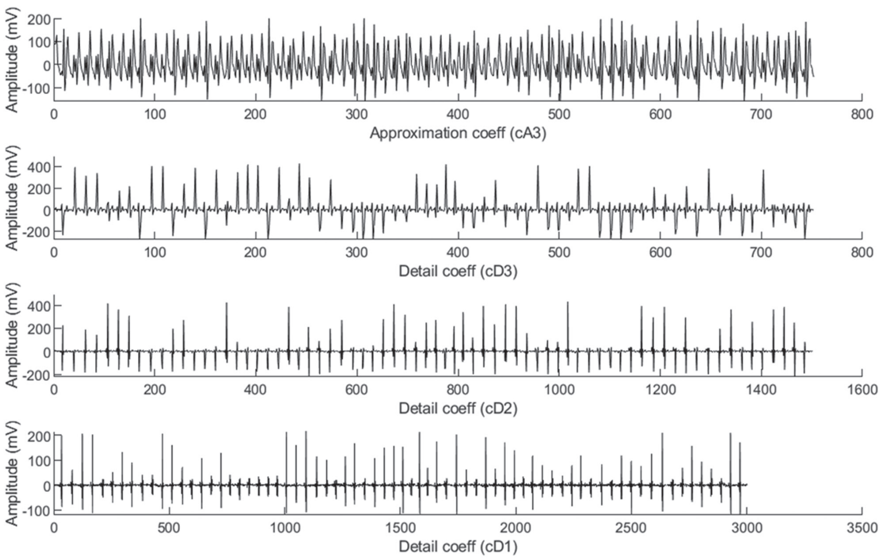

Fig. 5. Decomposition result of 60 s normal ECG from Fig. 2

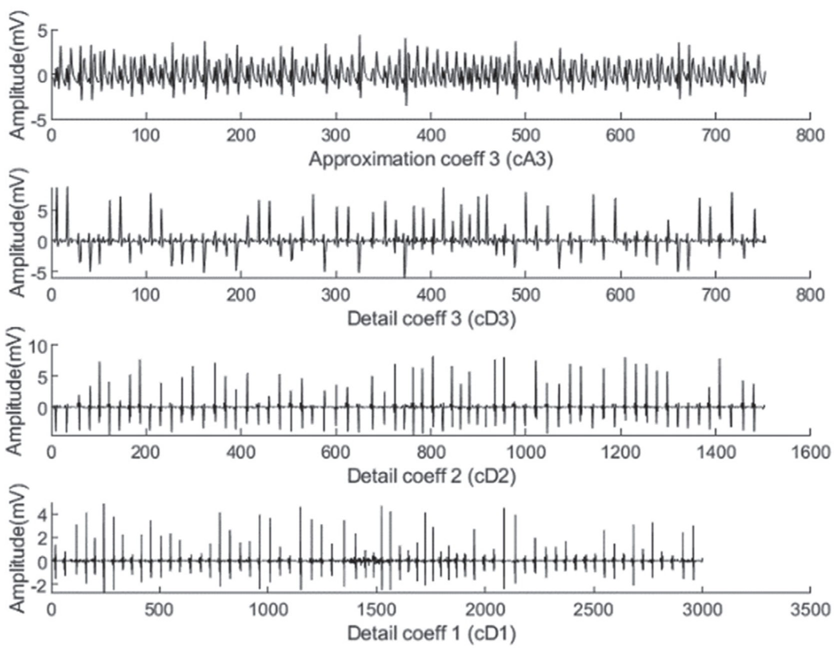

Fig. 6. Decomposition result of 60 s ECG with OSA from Fig 3

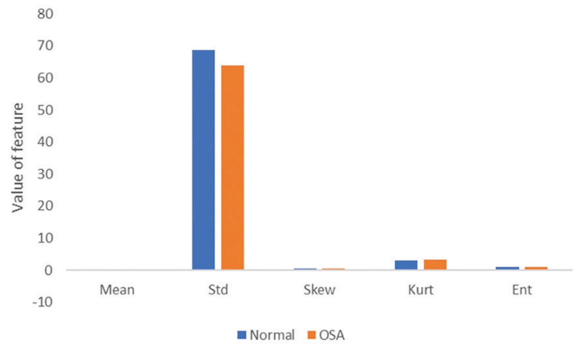

Fig. 7. Generated features from CA3

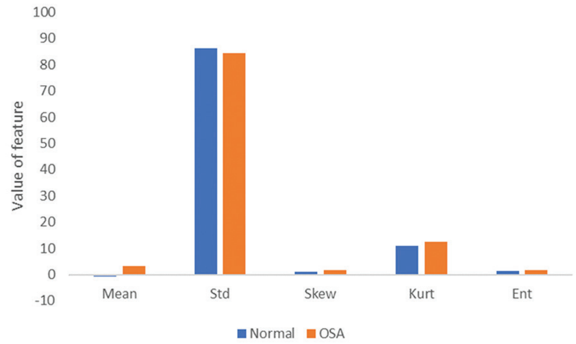

Fig. 8. Generated features from CD3

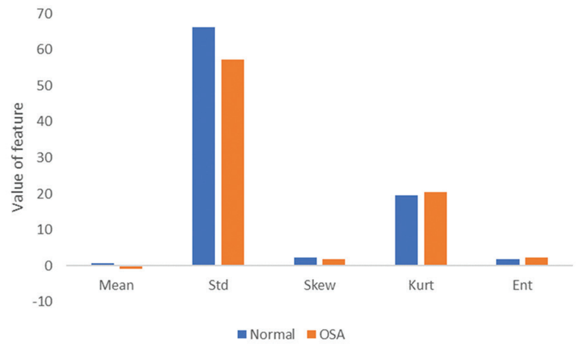

Fig. 9. Generated features from CD2

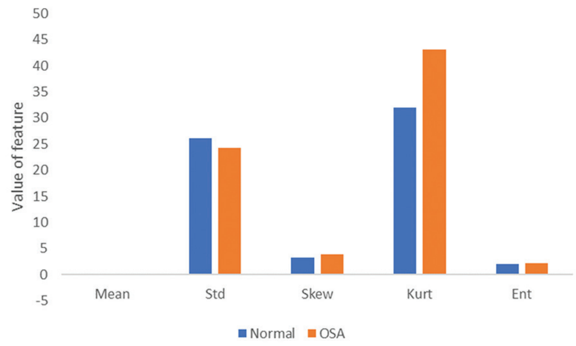

Fig. 10. Generated features from CD1

Figure 7 - Figure 10 show the statistical characteristics generated for each subband. Some of the resulting characteristic values are small enough that they are insignificant compared to other features. The mean feature looks very small because the mean value of the signal is close to zero due to the normalization process. Meanwhile, the standard deviation value tends to produce a reasonably significant value, and there is a tendency for the standard deviation of the normal ECG signal to be greater than the standard deviation of the OSA ECG. Kurtosis on a normal ECG tends to be lower than on an OSA ECG. Based on the distribution of the resulting characteristics, the accuracy will tend to be high even though it will not reach 100% because some values tend to be the same as entropy.

Table 2. Accuracy using SVM

	all feature	CA3	CD3	CD2	CD1
Linear SVM	75.1	61.7	62.7	67.4	61.7
Quadratic SVM	85.3	55.7	59.2	69.5	50.2
Cubic SVM	82.1	46.6	39.9	53.2	39
Fine Gaussian SVM	86.5	79.1	84.5	84.4	81.5
Medium Gaussian SVM	84.6	74.6	80.9	77.4	74.6
Coarse Gaussian SVM	78.4	61.8	76.2	72	64.4

Table 3. Accuracy using K-NN

	all feature	CA3	CD3	CD2	CD1
Fine KNN	82.9	77.7	79.4	79.7	79.7
Medium KNN	84.8	79.8	83.4	83	82.3
Coarse KNN	82.9	76.9	80.9	79.8	78.5
Cosine KNN	83.9	77.4	80.5	80.2	78.8
Cubic KNN	83.6	79.3	83.3	82.6	82
Weighted KNN	85.4	80.3	83.4	83	82.6

Table 4. Accuracy (%) using Ensemble Classifiers

	all feature	CA3	CD3	CD2	CD1
Boosted trees	83.1	78.8	80.5	78.4	76.6
Bagged trees	89.2	81.5	83.6	84.6	84.4
Subspace discriminant	64.3	61.5	60.6	62.3	62.2
Subspace KNN	87.1	76.9	78.3	77.6	78
RUSBoosted Trees	82.5	70.7	78.7	76.9	72.4

Table 2 - Table 4 show the classification accuracy using SVM, KNN, and ensemble classifier. Table 2 presents that the highest accuracy is 86.5% using all features with fine gaussian SVM as a classifier. This accuracy value is better than only using features in one subband, 84.5%, with the same SVM features on the CD3 subband.

Table 3 shows the highest accuracy of 85.4% generated by the overall characteristics with weighted KNN as a classifier. One subband yields the highest accuracy of 83.4% using CD3. Meanwhile, the ensemble classifier in Table 4 produces the highest accuracy of 89.2% using bagged trees and overall characteristics. Meanwhile, one subband only has the highest accuracy of 84.6% on CD2.

Individual CD3 subbands tend to produce the highest accuracy compared to other subbands because significant changes due to OSA occur in the CD3 subband, which occupies a frequency of 6.25 – 12.5 Hz. This is because the change in heart rate due to OSA is not very significant.

A significant change is precisely in the regularity of the heart rate and the sudden change in orientation that occurs in recording the ECG signal.

The difference between a normal ECG and an OSA ECG is in the sudden change in heart rate or orientation due to apnea. This study's 1-minute recording time will display 60-80 QRS for each data plot. The pattern produced by the OSA condition mainly affects only 1-2 QRS patterns. This condition generally does not provide a significant change in the pattern in the frequency domain. Several studies cut the ECG recording to 30 seconds with the consequence of adding a label to the data cut-off [28].

Table 5. Comparison with previous research

Author	Method	Accuracy (%)
Rizal, Iman, & Fauzi [16]	Multiscale entropy, SVM	85.6
Rizal, Siregar, & Fauzi [13]	Heartrate variability, SVM	89.5
Zhu et al. [29]	Plot of pointcare & recurrent, entropy, SVM	94.63
Razi, Einalou, & Manthouri [15]	LDA, random forest	95.1
Proposed method	Wavelet transform, first order statistical, bagged trees	89.2

Table 5 presents a comparison between the proposed method and previous studies. Multiscale entropy produces the highest accuracy of 85.6% [16]. HRV used in other studies yielded the highest accuracy of 89.5%. Meanwhile, LDA and random forest as a classifier produce the highest accuracy of 95.1% [15]. Even though it does not produce higher accuracy than previous research, the proposed method has several advantages, including a simple process, and still leaves some development possibilities. If, in this study, the statistical parameters were calculated in the subband, then in the following research, the use of entropy, fractal dimensions, or other parameters can be explored [30]. In addition, in this study, only level 3 decomposition was used; the exploration of selecting the right subband as a feature of the OSA ECG becomes an exciting topic in future research. The proposed method is expected to be an alternative feature extraction method in the ECG OSA classification.

4. CONCLUSION

This study proposes a method for OSA detection based on ECG signal. In the feature extraction stage, the ECG signal is decomposed into three subbands using a wavelet to calculate the statistical parameters for each subband. Statistical parameters calculated include mean, variance, skewness, kurtosis, and entropy. The proposed method was then tested on the OSA ECG dataset taken from Physionet. In the classification stage, the number of data tested is 17010 consisting of 10496 normal and 6514 OSA. Several feature usage scenarios and classifiers are applied to find the best classification performance. The classifiers used in this study are SVM, KNN and ensembles with various variations of the trick kernel. From all test scenarios, the highest accuracy is obtained if all features are used as predictors. The highest accuracy achieved was 89.2% using bagged trees. This study is expected to be a reference method in the detection of OSA ECG so that it can complete the clinical diagnosis. This study shows that ECG signal analysis can be an alternative tool in OSA detection considering the low cost, simple to manage, and is closely related with OSA compared to the PSG examination. Future studies still offer opportunities to explore feature extraction methods especially time domain based methods and other classifiers to improve detection accuracy. In addition, the detection method using a deep learning approach is also interesting to study.

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