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Improving the Recognition Performance of Apnea from Electrocardiogram Signal Based on Convolutional Neural Network (CNN)



Abstract: - Due to the consequences of apnea heart disease, include high blood pressure, heart failure, and heart attacks, early diagnosis is important and has now become a subject of interest for researchers in the world. So far, many researches have been done in this field. Among these, we can mention the use of various pre-processing in the field of time and frequency, along with classifications based on machine learning. These classifications work well in most cases. But in cases where the number of features extracted from the input data increases or the hidden patterns in the data are complex, they do not perform well. In addition to classification, the poor performance of these studies can be caused by pre-processing or feature extraction itself. In this article, in order to solve the problems of previous studies, pre-processing of the ECG signal has been done using a Butterworth pass filter, Golay Savizki filter and wavelet transform. Pre-processing makes the R peaks in the input to be well distinguished. Finally, by extracting the exact position of the R-R interval in the ECG with minimal error, efficient features that enable the proper description of different classes can be extracted. These features include the wavelet, can provide good results due to their time-frequency nature. The simulation results also show these features well. In terms of choosing the classification, a convolutional neural network (CNN) has been used to diagnose the disease. The accuracy percentage of 97.91% obtained from the simulation of the proposed method on the sleep apnea database of University College Dublin is a proof of good performance of this method.

Keywords: Electrocardiogram signal, Apnea diagnosis, Convolutional neural networks, Wavelet transform, Gula's Savitzky filter

I. INTRODUCTION

In recent years, the industrialization of different societies as well as environmental pollution, have brought irreparable effects to the health of the society. One of these cases is the tsunami of heart diseases, which accounts for a high number of deaths in societies every year. One of these diseases that occurs due to the abnormal function of the heart is obstructive sleep apnea, which causes disturbances in people's sleep. Today, according to the World Health Organization, more than 939 million people in the world suffer from obstructive sleep apnea, the importance of investigating this issue has doubled [1]. Statistical studies have shown that 30% of people between the ages of 30 and 70, that is, approximately 5% of the world's population, suffer from sleep apnea [2]. In the age range of 30 to 60 years, approximately 2% of women and 4% of men suffer from obstructive sleep apnea. Some consequences and effects of apnea disease include increased blood pressure, heart attack, lack of sexual activity, accidents with vehicles, depression and memory loss due to sleepiness [4,3]. Diagnosing apnea in its early stages and treating it can have a direct effect on improving the quality of life of patients, which shows the importance and necessity of addressing the issue of diagnosing this disease.

In most countries, polysomnography (PSG) is used to diagnose sleep apnea. This process is the most common technology used to collect physiological signals during sleep. The data collected usually includes electroencephalography, electrocardiography, electrooculography, and electromyography data. This process is done in the sleep laboratory of advanced hospitals. Diagnosing obstructive sleep apnea from the patient while sleeping on the basis of polysomnogram signals requires testing and recording at night. This night stay and sleep in the hospital is an annoying and unpleasant experience for the patient. In addition, a polysomnogram device is connected to people with 24 electrodes to record signals from the patient. This causes disturbance to the patient during normal sleep. Also, to record night signals, sleep technicians and special systems are needed, which increases the cost. Due to the small number of sleep apnea diagnosis clinics and the high cost, a limited number of patients can use these facilities.

The stated problems indicate the limited application field of PSG data. Therefore, in this research, the basis of work is focused on the use of electrocardiography (ECG) data. In the field of research done with ECG analysis, we can refer to the study [5] that in this research linear analysis method (time domain and frequency domain) and non-linear analysis were used to extract features. In this paper, researchers obtained three sets of features from ECG and SpO2 signals, including features of RR interval, R wave amplitude and SpO2. And finally, they used the recursive feature elimination with cross-validation (RFECV) to search for the subset of optimal feature selection using the KW-ANOVA test.

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Fatimah et al.[6] in a research on the diagnosis of sleep apnea was conducted on two data sets, namely the data of the University of Massachusetts and the sleep apnea database of University College Dublin. In this research, the ECG segments were analyzed using the Fourier-Moore analysis method. In the proposed method, the best accuracy is 92.59, sensitivity is 89.70 and specificity is 94.67%. In [7] Almutairi et al., the diagnosis of obstructive sleep apnea by ECG signals using CNN architecture with LSTM has the best performance with accuracy of 89.11%, sensitivity of 89.91% and specificity of 87.78% for the diagnosis of OSA.

The proposed method presented in this article is based on the use of several basic parts to improve the results. The first is the preprocessing of the ECG signal using a Butterworth pass filter, a wavelet transform, and a Savitzky Golay filter. This action finally causes the R peaks in the input to be well differentiated and by extracting the exact position of the R-R interval, efficient features can be extracted that enable a proper description of different classes. The next part is the use of Discrete Violet, which combines feature extraction with it and the use of deep neural networks, resulting in a classifier with very good accuracy.

In this article, in the second part, the basics of the research will be examined, and then in the third part, the proposed method will be presented along with its basics. In the fourth part of this article, the simulation will be presented along with the results of displaying the outputs of each part, and finally, the last part will be devoted to the final conclusion of this research.

II. RESEARCH BASICS

Comfortable sleep is a necessary mechanism for maintaining the mental health of people, which, like physical health, is very important in maintaining the quality of people life. One of the most common diseases related to sleep is apnea. Although several years have passed since the recognition of apnea disease, researchers have not yet fully understood its causes and physiological mechanism. But empirically, it can be said that many conditions and diseases and disorders such as allergies and breathing problems, nocturnal urination, chronic pain, stress and anxiety can cause sleep disorders. There are different types of sleep disorders, some of which may be caused by underlying health problems.

On average, humans spend more than a third of their lives in sleep. The quality of sleep can have a very important effect on people's health, so that its direct effect on the lives of people in a society is quite evident. Sleep apnea is a breathing interruption during sleep and may have serious cardiovascular consequences [8]. Sleep apnea is a breathing pause in the respiratory passages for at least 10 seconds [9, 10], which patients are forced to wake up to continue breathing due to a short breathing pause during sleep. Sleep apnea disease is divided into three general types: obstructive sleep apnea, central and mixed sleep apnea.

A. Obstructive sleep apnea

The process of breathing during sleep in two normal states and in the state of obstructive sleep apnea is shown in Figure 1. As you can see in part (a), in the blue path, oxygen and in the yellow path, carbon dioxide are normally exchanged. In part (b), the pharyngeal collapse created leads to the blockage of the upper airway and prevents the exchange of oxygen and carbon dioxide, which causes obstructive sleep apnea [11].

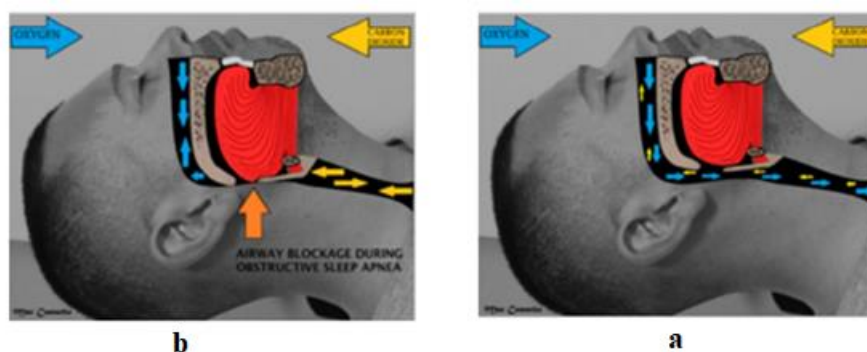


Figure 1 breathing process in a) a person with normal sleep b) a person with obstructive sleep apnea

B. Central sleep apnea

In central sleep apnea, the respiratory control center of the brain becomes unbalanced during sleep. Due to the impaired activity of the nerves that control the level of carbon dioxide and the level of oxygen in the blood, the neural feedback mechanism does not create an appropriate response to have a constant breathing rate during central sleep apnea attacks.

During an attack of central sleep apnea, as in Figure 2, there is no air flow and respiratory effort [9,11]. In recent years, breathing effort signals in the abdomen and chest areas have been used as a powerful method to diagnose apnea events. The two signals of abdominal and thoracic respiratory effort are almost in the same phase during normal breathing, but during the occurrence of apnea, the phase difference is almost equal to 90 degrees, which is shown in Figure 2.

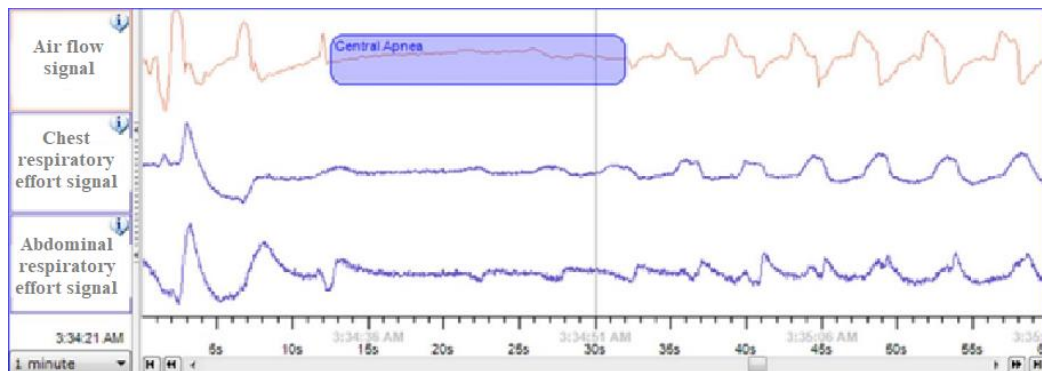


Figure 2. Signals recorded during a central sleep apnea attack in one minute [9,11].

C. Mixed sleep apnea

Mixed sleep apnea is a combination of two types of obstructive and central apnea. First, central sleep apnea and then obstructive sleep apnea occurs. Figure 3 shows the signals of different types of apnea disease [12,13].

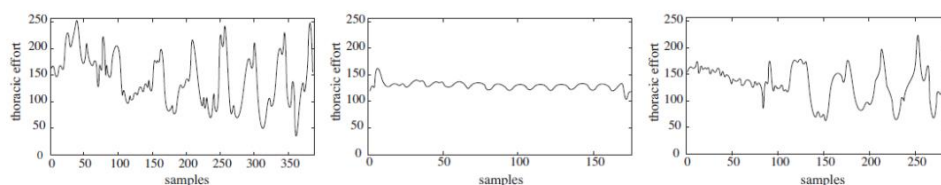


Figure 3 obvious changes in respiratory effort signal a) obstructive sleep apnea (left figure), b) central (middle figure), c) mixed apnea (right figure) [12,13]

Almost all patients with obstructive sleep apnea do not know about their disease and during the research conducted in Australia, about 80% of patients with obstructive sleep apnea remain untreated [14]. Insomnia, sleepiness, short-term forgetfulness, dry mouth and throat, headache and fatigue are other symptoms of apnea [15]. Obesity is directly related to obstructive sleep apnea, which narrows the upper airway. Nasal obstruction is an important feature of central apnea. In the world, people with sleep apnea syndrome are about 2 to 5 percent [16]. About 84% of these people have obstructive sleep apnea, 0.4% have central sleep apnea, and 15.6% have mixed sleep apnea. Based on the statistical results of a study, about 35% of Iranian children have sleep disorders. Among these children, about 1 to 3% have obstructive sleep apnea and about 21% have serious sleep disorders [17].

D. Input data

The recorded paper graph of electrical potential changes caused by heart muscle stimulation is called an electrocardiogram (ECG) signal. Figure 4 shows the components of the electrocardiogram signal of a normal person from the electrical activity of the heart cells. These components are conventionally named by the same names all over the world.

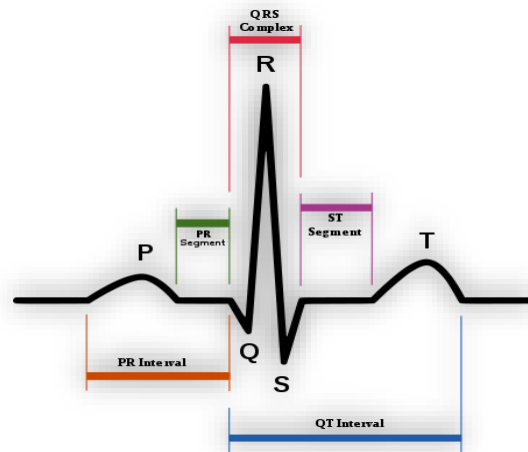


Figure 4: ECG signal [10]

The P wave is round, flat and parallel in normal state and is caused by the passage of electric current through the atria and indicates the depolarization of the atria.

PR interval: starts from the beginning of the P wave and continues to the QRS complex. This interval indicates the time it takes for the depolarization wave to reach the ventricles from the atria. Due to the interruption of the impulse, most parts of this interval are formed in the Atrio-Ventricular (AV) node.

The QRS complex: consists of three waves, Q, R, S, which indicate the depolarization of the ventricles. The Q wave is the first negative wave after P, and the R wave is the first positive wave after P, and the S wave is the first negative wave after R. The total of these three waves is called QRS complex.

ST segment: from the end of the QRS complex to the beginning of the T wave is called the ST segment, which indicates the initial stages of repolarization of the ventricles.

T wave: This wave appears after the QRS and is a round and positive wave that indicates the end stages of repolarization of the ventricles.

QT interval: It is called from the beginning of the QRS complex to the end of the P wave and it represents the time required for one cardiac cycle in the activity of the ventricles.

U wave: It is a round and small wave that appears after T. This wave is not always visible.

III. PREVIOUS METHODS

A. Pre-processing

The preprocessing methods of ECG signals are very diverse and are generally divided into two categories: using filters and methods based on machine learning. The use of filters is very common and they are one of the oldest methods that have been introduced for pre-processing so far. Among these filters, it is possible to mention the use of frequency domain filters and time domain filters. Methods based on machine learning have a high diversity and are divided into two categories: adaptive and non-adaptive methods. In adaptive methods, a recursive structure is used to improve the results, which is associated with a very good result. But in the non-adaptive structure of this path, there is no return. It should be mentioned that in adaptive methods, using the recursive structure provides very good capabilities to remove disturbing and interfering components in the original signal. But non-adaptive structures do not have this advantage. Articles by Sharma and Sharma [18], Song et al. [19], and Varun et al. [20] focused on feature engineering-based methods. In the paper by Wang et al. [21] and Hong Yu Chang et al. [22], and the papers by Singh and Majumder [23], and Li et al. [24] proposed methods based on feature learning which can automatically learn the features of ECG signals or RR intervals using neural networks.

However, the apnea detection system proposed by Singh and Majumder [23] is based on a two-dimensional CNN model. Therefore, a continuous wavelet transform is needed to transfer one-dimensional ECG signals to two-dimensional scalogram images in the signal preprocessing stage. Compared to the one-dimensional CNN model, the two-dimensional CNC model requires more parameters and has higher computational costs. The other articles all required the detection of R peaks and the calculation of the RR interval. Median filter [18,21,24] and correction of R peaks [20] have often been used to remove physiologically uninterpretable points. QRS complex extraction and EDR extraction are also included in the papers by Sharma and Sharma [18], Song et al. [19], and Varun et al. [20], respectively. Table 1 shows the comparison of apnea system signal preprocessing methods.

Table 1. Comparison of apnea system signal preprocessing methods

Row	References	Pre-processing method
1	Sharma and Sharma [18]	Cross-pass filter + detection of R peaks + RR interval calculation + QRS complex extraction + zero layering
2	Song et al.[19]	Detection of R peaks based on filter bank + calculation of RR distance + median filter + EDR extraction
3	Varun et al. [20]	Slot filter + DC component removal + Upsampling + R peaks detection + R peaks correction + RR distance calculation + EDR extraction
4	Wang et al. [21]	FIR filter + detection of R peaks + calculation of RR distance + median filter + spline interpolation
5	Hong Yu Chang et al. [22]	Low-pass filter + Z-score normalization
6	Singh and Majumdar [23]	Intermediate filter + continuous wavelet transform + zero center normalization
7	Li et al. [24]	Intermediate filter + detection of R peaks + calculation of RR distance + median filter + interpolation

It is noteworthy that in the proposed method of this article, the Savitzky-Golay filter [25] is used, which is used for the first time in this field. The main advantage of using this method is the improvement of peaks compared to other components of the ECG signal, which was mentioned in the previous section. Finally, it leads to improving the accuracy of R-R interval extraction, which has important information for the classifier used in this research.

The Savitzky-Golay filter was proposed by Savitzky and Golay in 1964. It is one of the most common and widely used filters in the fields of science and technology and is especially used for signal processing. This filter can be used to reduce high frequency noise in the signal due to its smoothing property and reduce the low frequency signal using differentiation. The origin of this method can be traced to polynomial interpolation [25].

B. Extraction of features

The feature extraction process in most articles is based on the use of four general categories, which are discussed below. The two characteristics of the median frequency and the mean frequency are used as two efficient tools in most researches. They can be calculated according to what can be seen in relation 1[25].

$$MNF = \frac{\sum_{j=1}^M f_j P_j}{\sum_{j=1}^M P_j} \quad (1)$$

It should be noted that f_j in the above relation represents the frequency size of the desired signal power spectrum, j , P_j is the signal power spectrum at the j th frequency value and M is the length of the entire frequency range.

Median frequency is the frequency at which the power spectrum of the desired signal is divided into two regions with the same amplitude. In fact, the median frequency is calculated as half of the total power. The median frequency is calculated in the form of equation 2.

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^M P_j = \frac{1}{2} \sum_{j=1}^M P_j \quad (2)$$

In the above relation j , P_j is the signal power spectrum in the j th frequency value, also M is the length of the entire frequency range and MDF represents the frequency median. Considering that the use of wavelet-based features in most biological signals has been associated with good results, it is expected that it will also be associated with good results in our research. Some indicative examples of the features used include features based on discrete wavelet transform (DWT) and features based on stationary wavelet transform (SWT), features derived from wavelet packet decomposition (WPD) and finally features will be based on fast wavelet transform (FWT). Standing wavelet transform is one of the wavelet transforms. Its most important property is its time immutability. This method is similar to discrete wavelet transform. In the case of WPD, it can be said that in this case the signal is passed through more filters than the discrete and standing and fast wavelet transform. In discrete wavelet transform, at each step, the approximation coefficient is passed through low-pass and high-pass filters, but in wavelet packet transform, both approximation coefficients pass through the filter. Fast wavelet transform is also a mathematical algorithm to find higher speed wavelet transform.

To calculate the non-linear feature, it should first be noted that the R-R intervals in different patients have significant differences. To reduce these differences, we normalize the R-R intervals for each heartbeat. In this research, the Haar wavelet function was chosen because of its simplicity and it is shown as an ideal wavelet for short time signal analysis.

C. Classifications

In [26], four different types of random forest (RF), k-nearest neighbor (KNN), logistic regression (LR) and support vector machine (SVM) classifiers were selected for testing to select the most suitable classifier for this research. Feng et al. [27] have used a sleep apnea diagnosis method based on unsupervised feature learning and single-lead ECG signal. The results of its per-segment classification were 85.1, 86.2 and 84.4% respectively for accuracy, sensitivity and specificity in diagnosing sleep apnea. Pombo et al. [28] have achieved 82.12% accuracy, 88.41% sensitivity, and 72.29% specificity with artificial neural network (ANN) classification for sleep apnea diagnosis. Bai et al [29] have used classification (CNN) with accuracy and sensitivity of 94% and 88%, respectively, to diagnose sleep apnea syndrome. In the article [30], Karunakaran et al. used Grid Search based on SVM with 89% accuracy to diagnose obstructive sleep apnea from the ECG signal.

Mostafa et al. [31] have used multi-objective hyper-parameter optimization of convolutional neural network to diagnose obstructive sleep apnea. They obtained the best average accuracy of 94%, sensitivity of 92% and specificity of 96%. The main feature of convolutional neural network classification is the use of high-order features during the training process. Convolutional neural network has shown very high accuracy for various applications. It is expected that the very good performance of the convolutional neural network in detecting hidden patterns in the data will also be effective in the process of this article and among the classifications used for comparison, the use of this classification should be associated with the best result.

IV. THE PROPOSED METHOD

The block diagram of the proposed method can be seen in the figure 5.

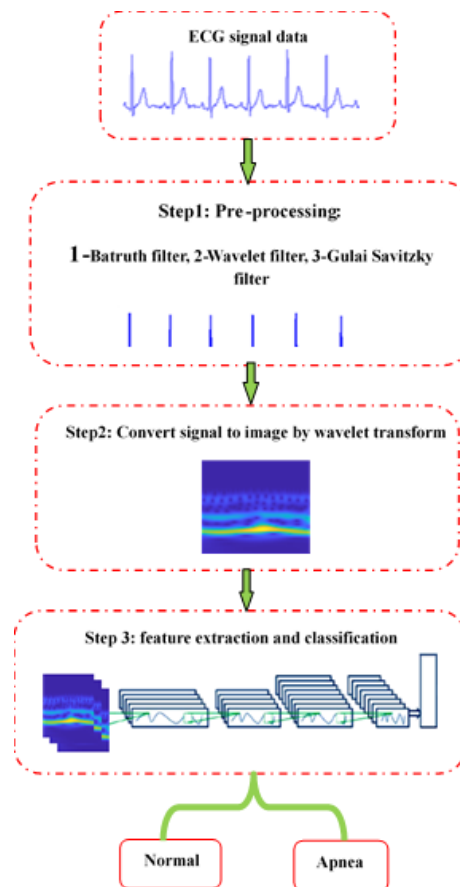


Figure 5- Block diagram of the proposed method based on CNN

The proposed method in this paper is based on a hybrid algorithm. In which, first, the pre-processing is done by using the Butterworth filter, Savitzky Golay and Violet transform. Butterworth filter is used to remove the noise added to the signal during the recording process. A Savitzky Golay filter is applied to distinguish the R peak and a one-dimensional wavelet to remove other residual noise in the signal. The noteworthy point in pre-processing is that the Savitzky Golay filter provides accurate extraction of the R-R interval with minimum error, and other filters are used to remove noise. In the feature extraction phase, using an efficient tool like Violet will lead to providing a suitable platform for classification. At this stage, the images resulting from the wavelet transformation are applied directly to the deep convolutional neural network. The process that is not needed to use conventional classifiers and only by using the conventional features obtained from the output of Violet will be taught. Finally, the last step of the proposed method will be the use of classifications based on deep learning such as CNN and other conventional classifications such as KNN, decision tree and support vector machine (SVM). Our main purpose for using these classifications will be to compare the performance of other classifications with our proposed method.

In this article, an attempt is made to significantly improve the accuracy and the speed of diagnosis compared to previous researches. The most significant part of this block diagram, which has been given special attention in this research, is pre-processing. The arrangement of the filters used with two main goals of removing noise and artifacts, recording time and increasing the R peak compared to other signal components in order to better recognize the R_R interval that has significant clinical information. Butterworth filter was used to remove noise and artifacts. And removing the remaining noises with the help of wavelet and finally applying the Savitzky-Golay filter with the aim of improving the signal conditions in order to extract the R-R peaks.

Finally, it should be noted that in this research, the main classifier is CNN. However, the results of each of the classifications are checked once separately and once in the form of combination with the conventional methods of combining classifications. In these methods, a powerful structure made of several weaker structures are trained independently. Then, the predictions of weaker learners are combined in special ways for the final prediction. For example, one of the methods is averaging the results of all classifications, which is known as average votes or maximum vote. To create a combination of classifications, most of the effort should be on creating diverse base classifications and also building a better mechanism for combining weak classifications to improve the final accuracy.

D. Database

University College Dublin (UCD) Sleep Apnea Database [32]: includes nocturnal PSG records from 25 people with sleep-disordered breathing, with 14 different types of signals from each patient in the middle-aged category which 21 patients are men and 4 patients are women. It has labels of sleep stages and different types of sleep apnea. 10 of these patients have all three types of apnea. Each ECG record contains a continuous single-lead ECG signal and annotation of the onset time and duration of apnea/hypopnea events. The patients of this database did not have any previous history of heart diseases or other diseases. The records of these patients have three channels of heart rate along with other signals, including electro-oculography, electromyography, electroencephalography with two different channels, oxygen saturation, patients' snoring, air flow, abdominal and chest breathing signals. The length of each ECG signal is between 6 to 10 hours. It can be said that this database has all the necessary signals to diagnose apnea and the information needed by each patient. The input data used in this research is related to this sleep apnea database of University College Dublin, which includes 25 data with specific dimensions and labeled as normal or apnea for 60 second intervals of each of the signals.

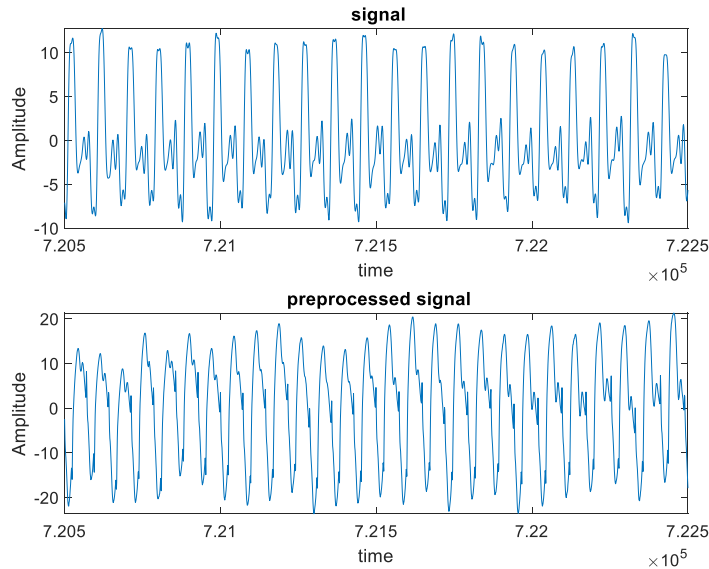
E. Evaluation criteria

The evaluation criterion in this article includes the conventional criteria of this field such as accuracy, recall, sensitivity and precision, which will be calculated with the four basic components of the correct and false diagnosis rate for the healthy class and the correct and false diagnosis rate for the apnea class. These criterion are calculated as follows:

$$\text{Accuracy} = \frac{TP+TN}{TP + TN + FP + FN} \quad (3)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (5)$$



$$\text{Proprietary} = \frac{TN}{TN + FP} \quad (6)$$

Where TP (True positive) is applied when the sample is a member of the apnea category and is recognized as a member of the same category (correctly identified). FN (False negative) is employed when the sample is a member of the apnea category and is recognized as a member of the normal category (misidentified). TN (True negative) is applied when the sample is a member of the normal category and is recognized as a member of the same category (correctly rejected). FP (False positive) is employed when the sample is a member of the normal category and is recognized as a member of the apnea category (Wrongly rejected).

F. Results

As can be seen in Figure 6, the pre-processing process has led to the sharpening of the peaks, which are actually the R's in the cardiac QRS complex. The distance of these R's from each other provides meaningful information about the patient's condition, which ultimately leads to high accuracy of the classification process.

Figure 6. Input signal and preprocessing

It is worth mentioning that the input of the CNN network contains 1620 images, 162 images for testing and 1458 images for training. The dimensions of the input image are 120*10000*3, which includes three red, green and blue channels. In this simulation, the cross-validation method is used for K equal to 10, and the classification result for 10 sections is presented below. It should be noted that other conventional classifications such as KNN, decision tree and support vector machine (SVM) have also been used to compare the performance of CNN. Finally, to compare the proposed method with other studies conducted on this database, it can be seen that the average accuracy percentage of our proposed method based on CNN in ten times of 10fold repetition is equal to 97.91.

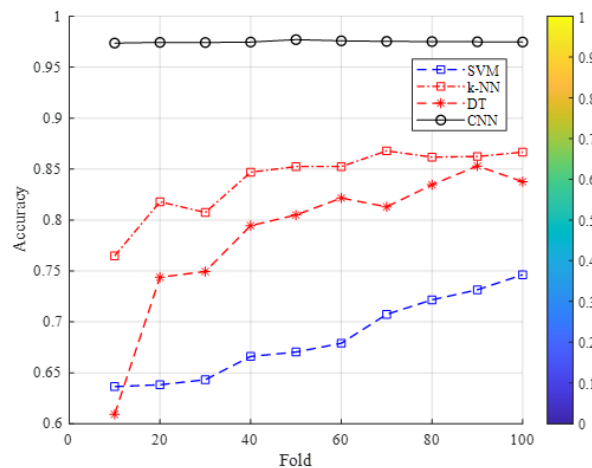


Figure 7 Comparison of the proposed method with other classifications

It is expected that considering that the proposed method has a better performance than the best percentage of accuracy presented in previous researches, more reliability can be imagined from it in the automatic diagnosis of apnea. Table 2 expresses the outstanding performance of the proposed method in comparison with the other studies.

Table 2- Comparison of the proposed method with previous studies for apnea diagnosis

References	Feature extraction/selection method	Classification	accuracy%
Hilmaison et al., 2018 [33]	Frequency features	Statistical analysis	93
Janbakhshi et al., 2018[34]	EDR	SVM-KNN-NN-LD-QD	90.9
Ma et al., 2019[35]	Statistical features	Statistical analysis	87
Zaree and Asl 2018[36]	DWT + SFFS	SVM (RBF kernel)	92.98
Hassan et al., 2017[37]	DT-CWT	AdaBoost	84.4
Nishad et al., 2018[38]	Tunable-Q wavelet transform features	Random Forest	92.78
Ossi and Akbas 2015 [39]	DWT + PCA	Random forest	92.98
Rakhim et al., 2014 [40]	DWT + PCA	SVM	94.3
Hasan and Haq 2017[41]	Normal invers Gaussian modeling	AdaBoost	87.33
Hassan and Haq 2016[42]	TQWT	RUSBoost	88.88
Hassan 2016[43]	Statistical and spectral	Bootstrap aggregating	85.97
Wang et al., 2019[21]	RR-intervals	CNN (LeNet-5)	92.3
Singh et al., 2019[23]	Time-frequency Scalogram features	CNN (AlexNet)	86.22
Ortenasan et al., 2018[44]	RR-intervals	CNN	96
Wang et al., 2018[23]	RR-intervals	CNN	97.8
Wang et al., 2019[45]	RR-intervals and frequency features	DNN	97.1
Javad Estadieh and colleagues 2023[46]	DT-CWT + MCFS	Hybrid “k-means, RLS”RBF	95.62
Our proposed method	CNN+RR-intervals	CNN	97.91

V. CONCLUSION

In this study, a classification method based on CNN is proposed to diagnose sleep apnea from ECG signal. In the proposed method of this research, an innovative method has been considered for pre-processing, which leads to the differentiation of R peaks. Then, the feature extraction process from the peak intervals and finally the features derived from the wavelet transform mapping leads to the achievement of a substrate. With its help and the CNN classifier, it is possible to distinguish between healthy and diseased class with very good accuracy and close to 98%. The proposed method of this research based on CNN can be used as a reliable method to diagnose sleep apnea. By implementing the proposed method in this article, 97.91 percent accuracy has been achieved, which has high reliability in detecting apnea from the ECG signal. Data recorded with the help of portable ECG signal recorder for apnea diagnosis can solve the problem of complicated, expensive and inappropriate diagnosis of apnea disease.

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