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Congestive Heart Failure from ECG Prediction Using Empirical wavelets transform Algorithm

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Abstract

Heart diseases are the leading cause of death worldwide as such the use of an advanced information processing method to diagnose heart disease is one of the most critical fields of medical research. Among various heart diseases, congestive heart failure refers to a difficulty in the heart's pumping, and its symptoms vary depending on the body organ being the most involved in reducing pumping performance. Accordingly, several studies have been conducted to diagnose heart problems using Heart rate variability (HRV) analysis of cardiac signals even though the signals are not accurate enough. The HRV signal extracted from the ECG signal was analyzed to classify the Congestive heart failure's signals and normal signals in the proposed method. Signal decomposition into a series of subbands was performed using Empirical Wavelets Transform (EWT), and the values were calculated based on different subbands. In this case, the extracted features were classified by the SVM classification method. The method was used to classify normal individuals and those with CHF into two normal or abnormal groups. Finally, by implementing the proposed model and simulating the data of the PhysioNet site, the CHF problem could be automatically detected. The evaluation of the proposed method in comparison to other methods revealed that the proposed method has a significant advantage over other methods, as indicated by the accuracy value of 98.30.

Keywords: Heart congestion, Heart failure, Empirical wavelets transform.

1. INTRODUCTION

Worldwide, nearly 26 million people suffer from congestive heart failure (CHF) as a pathophysiological disease in which the heart fails to supply enough blood to meet the

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body's needs because of its structural or functional disorders. These disorders reduce the ability of the ventricles to pump blood. Shortness of breath and fatigue are common symptoms of CHF, which is the last stage of several heart diseases, including heart valve disease, myocardial infarction (MI), and cardiomyopathy [1]. In other words, CHF is a common chronic cardiovascular syndrome with an abnormal autonomic nervous system (ANS). Patients present no obvious symptoms during the early stages and die after one year due to the poor prognosis of CHF in about 30-40% of diagnosed patients. Accordingly, the early detection and diagnosis of heart problems are highlighted in medical research [2]. In this regard, developing a system to detect healthy individuals and patients with CHF automatically by using heart rate change analysis (HRV) is of paramount importance. The HRV signal is extracted from the electrocardiogram (ECG) signal and carries useful information about heart disease. The visual detection of changes in the HRV signals is tedious, and the inappropriate classification of the signals of patients and healthy individuals are likely as well [2]. In this regard, several studies have been carried out to diagnose heart problems using the HRV analysis of the cardiac signal by techniques such as experimental state analysis (EMD) [3], discrete wavelet transform [4] (DWT), and continuous wavelet transform (CWT) [5], and two-three mixed wavelet transform (DTCWT) [6]. HRV signals have been used to collect data and are widely used to diagnose heart diseases such as coronary artery disease (CAD), arrhythmia, and hypertension, predict the risk of cardiovascular disease, and assess patients' status after using myocardial infarction [2]. Due to the non-static nature of the heart signal, cardiac signal processing methods can be divided into three general categories: frequency, time, and frequency-time. Among these categories, frequency-time domain processing provides better results than the other methods. Experimental mode analysis (EMD) is one of the new signal analysis tools used in potential field methods to isolate regional anomalies from local anomalies. The EMD method is based on the spatial or temporal refinement of the signals according to the characteristics of the extreme points. The decomposition components consist of high to low-frequency bands, respectively. In this method, intrinsic mode (IMF) functions are extracted from the data, and the last mode obtained under the remaining title indicates an area anomaly. Previous studies have presented a nonlinear model based on the experimental state analysis method and cardiac electrocardiogram signals for the automatic detection of CHF.

The EMD method was first used in 2001 to analyze changes in heart signals (HRV) [4]. Further models focusing on heart problems have been proposed to diagnose heart disease such as coronary artery disease (CAD) automatically [5]. EMD analysis method was first used in 2016 to diagnose CHF [6]. One of the advantages of the EMD technique is that it allows determining the instantaneous frequency of the signal and combining this method with Hilbert conversion; however, the main problem of the EMD method is mixing the modes and not having a strong cut-off criterion in the sieving process. Mixing occurs during the EMD execution process due to the direct implementation of the screening method. The mixing model of feature extraction (and thus noise reduction) makes model training and pattern recognition difficult [7]; hence, it is necessary to use a model to solve these problems with high accuracy and appropriate speed.

Empirical Wavelet Transform (EWT) is a method first introduced by Gilles (2013) [8] to overcome some limitations of the EMD method. The model is designed based on processed signals, and due to the proper design of its wavelet format, it focuses on time and frequency, thus facilitating time and frequency resolution. On the other hand, by defining different parameters, this model has a high signal removal capability and causes less damage to the signal, so the EWT model seems to be more accurate in detection, in comparison to EMD. Moreover, the EWT wavelet transform is based on the actual quantified scale factor and is implemented using complete reconstruction and the sampled filter bank with real quantified sampling coefficients. Ideally, the decomposed coefficients should be adjusted according to the oscillation behavior of the used signal (e.g., when using wavelets to analyze and process oscillating signals (speech, EEG, etc.)). One of the strengths of this method is that it is underpinned by a strong theory and has adjusting redundancy. This method is similar to other conversion techniques used in many scientific fields, including medicine, to diagnose problems such as sleep spindle and EEG signal analysis [9]. However, due to the diagnosis sensitivity in the field of medicine and due to the high efficiency and accuracy of this new conversion, this method has been adopted in the automatic diagnosis of many heart disorders such as PCG signal segmentation [10], automatic CAD detection, septal defects and heart murmur [11], the diagnosis of heart valve disorders and coronary artery disease, the compression of cardiac signals, and other heart disorders [9]. In this study, EWT was used for the first time to diagnose CHF.

In 2016, a model was first proposed to diagnose CHF based on EMD [6]. The main part of the EMD method is filtering to decompose each time series into a set of AM-FM (frequency and amplitude modulation) or IMF components expressing the oscillation states of the signal. To this end, the signals were divided into 2000 components for preprocessing, and they were then subdivided into six independent components by an experimental model analysis. Afterward, from the decomposed components of EMD, different properties (13 properties) such as entropy, fuzzy entropy, Shannon entropy, Renyi's entropy, and wavelet entropy, and so on were extracted. Finally, they were classified into two normal and abnormal groups using the SVM classifier. In this regard, the best performance of the above method was evaluated with an accuracy rate of 97.64%. Due to the algorithmic nature of the EMD method, different sub-bands will likely be extracted each time the decomposition is less similar to the original signal during reconstruction.

In [13], deep learning techniques - recurrent neural networks (RNNs) with long short-term memory (LSTM) were proposed to create a diagnostic algorithm to achieve high accuracy with limited information and automatic feature extraction. The ECG signals used in this study were extracted from public PhysioNet databases. In this method, the parameters of 24 LSTM models were over-adjusted to obtain the best model. Moreover, ECG signal segmentation between the first five and fifteen minutes was compared as a feature. Out of 24 LSTM models, the model with the first 15 minutes of ECG signals (model 1) obtained the highest accuracy of 99.85%.

In [14] the multiscale residual network(ResNet) was proposed for the automatic classification of CHF into four categories according to the New York heart association (NYHA) functional classification system. In addition, ECG signals were divided into two different intervals. Experimental results showed that the several proposed ResNet-34 scales were averaged for positive prediction, sensitivity, and accuracy of 93.49%, 93.44%, and 93.60% for two seconds of the ECG segment, respectively.

In [15], a deep learning architecture was proposed to classify normal sinus rhythm ECG (NSR), abnormal arrhythmia (ARR), and CHF signals. The proposed architecture was based on the Hybrid Alex net-SVM (Support Vector Machine). To demonstrate the classification performance of the deep learning architecture, the ARR, CHR, and NSR signals were first classified by the SVM algorithm and KNN with accuracy rates of 68.75% and 65.63%, respectively. Then, the signals were then classified in raw form by LSTM (Short-Term Memory) with 90.67% accuracy.

In [16], a one-dimensional convolutional neural network with 12 strong and efficient deep layers was proposed to classify five micro-classes of heart rates in the MIT-BIH arrhythmia database. Five types of heart rate characteristics were detected, and the experiments used the slow self-adaptive wavelet method. The results show that the proposed model performed better in terms of accuracy, sensitivity, strength, and anti-noise capability.

The structure of the article is as follows: In the second part, the proposed method will be described. In the third section, the results are evaluated. In the fourth and fifth sections, the discussion and conclusion will be presented, respectively.

2. METHODOLOGY

This section illustrates different phases of the proposed method, including preprocessing, EWT parsing, feature extraction, feature reduction by t-test, and signal classification, as shown in Figure 1.

2.1. Pre-Processing

In the preprocessing section, the collected datasets, including normal and CHF datasets,

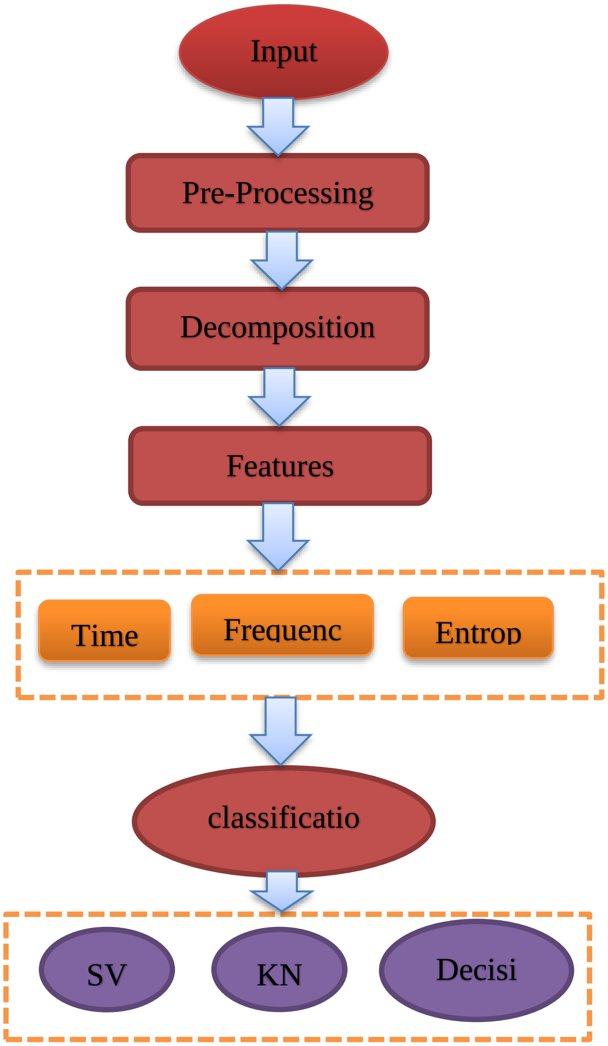


Fig. 1. Methodology.

were used to classify affected or normal individuals. The recorded HRV signals were obtained from the Fusion site, including the normal and fantasy sets as a part of the normal dataset for heart palpitations. Fifty-eight signals were used for normal individuals, of which 40 signals are for normal people and 18 components are for fantasy. Moreover, 15 patients were included in the infected group. Then, 70% and 30 %of these signals were considered as training and test data, respectively. It should be noted that each first extracts the RR-Interval, and the signals are then segmented into 2000 samples.

2.2. Signal Decomposition Using EWT

Given the problems in EMD, namely the lack of mathematical theory and its algorithm city, the EWT method was developed to overcome the weaknesses of previous algorithms (having mathematical theory and processing according to the signal) [17]. Experimental wavelet transform (EWT) is a method producing a multi-modal signal analysis by an adaptive wavelet division scheme. EWT begins with the signal spectrum segmentation and provides a complete reconstruction of the input signal. The EWT coefficients divide the input signal energy into separate bandwidths. Accordingly, EWT provides the Fourier transform of the signal using the er'sMeyer's and Littlewood-Paley wavelets, which are the Fourier transform sets of the scale function and the experimental wavelet transform function $B=\{\mathfrak{F}_t\phi_1(t),\{\mathfrak{F}_t\varphi_m(t)\}_{m=1}^{M-1}\}$ [18]. Once the exacted frame of the wavelets is determined, the approximation layer is obtained using Equation (1), and the partial layer from each signal is provided by using Equation (2):

$$W(f_i)(0,t)=\mathfrak{F}_\omega^{-1}\left(\mathfrak{F}_t(f_i)(\omega)\overline{\mathfrak{F}_t(\phi_1)(\omega)}\right) \quad (1)$$

$$W(f_i)(m,t)=\mathfrak{F}_\omega^{-1}\left(\mathfrak{F}_t(f_i)(\omega)\overline{\mathfrak{F}_t(\varphi_m)(\omega)}\right) \quad (2)$$

Finally, the inverse of the simultaneous experimental wavelet transform is shown as Equation (3):

$$f_i(t)=W(f_i)(0,t)\diamond(\phi_t) + \sum_{m=1}^{M-1} W(f_i)(m,t)\diamond\varphi_m(t) \quad (3)$$

Equation (3), $\diamond$ is the convolution operator. In other words, the internal multiplication of the Fourier transform of the

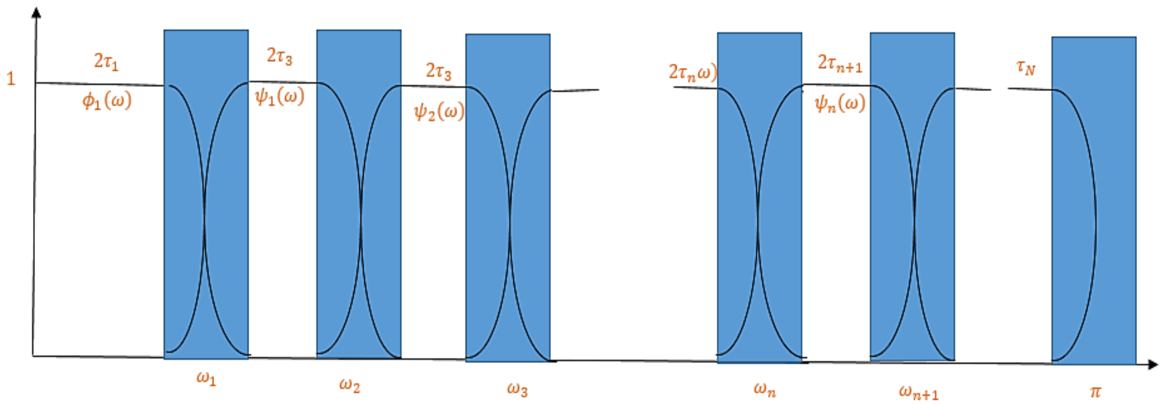


Fig. 2. Structure of EWT.

input images in the layer is approximately equal to the sum of the Fourier transform of the input images by the internal multiplication of the sublayers. Figure 2 shows the basic structure of the EWT based on the low-pass filter bank (i.e., scale function) and the overpass (i.e., Violet function).

In the proposed method, the signals related to normal people and people with the disease are analyzed in 4 levels.

2.3. Extracted Features

In this section, the features were extracted from the four parsed levels performed by the EWT in the previous section. The procedure is described below.

2.3.1. Approximate Entropy

This parameter measures variations and instability in HRV signal using Equation (4):

$$E_{ap}^{x} = ln\frac{S_l(k)}{C_{l+1}(k)} \quad (4)$$

where, $S_l(k)$shows a pattern that has an average length l. Also, $C_{l+1}(k)$ represents a pattern with the mean length of l + 1. *K* indicates the similarity of the coefficient. The high and low values of E_{ap}^{x} indicate signal irregularity [6].

2.3.2. Sample Entropy

Regardless of the signal length, this feature determines the regular values in the HRV signal, which is obtained from Equation

$$E_s^x = -log\left(\frac{M}{N}\right) \quad (5)$$

where, *M* represents the total number of pairs of vectors of *length α + 1*, and *N* represents the total number of pairs of vectors of length α. The high value of this feature indicates the unpredictability of HRV.

2.3.3. Fuzzy Entropy

This feature evaluates the occurrence of unpredictable values in the HRV signals according to Equation (6).

$$E_f^x(a,x,b,S)=ln\varphi^x(x,b)-ln\varphi^{x+1}(x,b) \quad (6)$$

In this equation, (a,x,b, S) show the parameters of the fuzzy variable, *a* represents the length of the sequence, *x* and *b* are the slope and width, and *S* is the length of the signal. In the proposed method, we have a = 3, x = 2, b = 0.2, and signal length S = 2000.

2.3.4. Kolmogorov Sinai

This parameter measures the time series uncertainty of the signal calculated in Equation (7).

$$E_{ks}^{x} = \lim_{x \to 0} \lim_{a \to \infty} \frac{1}{\tau} \frac{K_a(x, C_a)}{K_{a+1(x, C_{a+1})}} \quad (7)$$

In this equation, $K_a(x,C_a)$ represents the correlation function. The high and low values of E_{ks}^{x} show the signal irregularity. In the proposed method, we have a = 3, x = 2, and the signal length=2000.

2.3.5. Modified Multiscale Entropy

This feature describes a method for correlating unstable HRV signals. This parameter measures the correlation strength in signals. The entropy value decreases with an increase in the time scale in the unstructured system and can distinguish different degrees of complexity in time serials denoted by $E_{mms_y}^{x}$.

2.3.6. Shannon Entropy

This property measures entropy using the amplitude of HRV signals and is one of the spectral entropies. This entropy property evaluates the signal propagation and the dynamic order of the system as follows:

$$E_{sh}^{x} = log_2 \frac{1}{m(x)} \quad (8)$$

2.3.7. Renyi's Entropy

This parameter calculates the complexity of HRV spectral signals using the following equation:

$$E_{r}^{x} = -\frac{a}{1-a} \sum log\ m_i^a \quad (9)$$

2.3.8. Tsallis Entropy

This parameter measures sudden changes in HRV signals and long-term memory effects.

$$E_{ts}^{x} = \frac{1-\sum_{x=1}^{M} \alpha_x^p}{p-1} \quad (10)$$

In the above equation, α_x is a set of probabilities configured with M. P indicates lack of development. In the proposed method, 2 probabilities were considered [6].

2.3.9. Wavelet Entropy

This feature measures the degree of distortion in HRV signals. This entropy is effective in detecting the intermittent behavior of the HRV signal.

$$E_{w}^{x} = -\sum_{x<0} \alpha_x ln\ \alpha_x \quad (11)$$

where, α represents the possible distribution of HRV, and x represents the resolution level.

2.3.10. Statistical Features

In this section, Hjorth's parameters are used (i.e., the three statistical properties of S_a^x, including signal activity, Hjorth mobility H_m^x, and Hjorth complexity H_c^x). These three parameters measure signal strength, average frequency, and signal changes and are used to measure statistical behaviors from the HRV signal [6].

2.3.11. Fractal Dimensions

The fractal theory was written in 1975 by Benoit Mandelbrot. The word fractal is derived from fractus, which means broken stone (brittle and regular). Fractals are geometric shapes that, unlike Euclidean shapes, are not regular. In this regard, these shapes are completely irregular, and irregularity remains the same at any scale. A fractal object is similar when viewed from near and far. The fractal object itself is the same. The self-similarity requires each subsystem of a fractal system to be equivalent to the whole system. Fractals also directly connect us to nature. Trees and mountains are two examples of fractals. In fractal forms, we do not have characteristic length, indicating that we cannot estimate the whole object with a given object such as a cylinder, sphere, or cube because of the complexity of the issue. For the class of introduction, we have a quantity called dimension, which calculates the complexity of the fractal shape after a fractal dimension. Statistical analysis of vital signals was usually based on moderate self-regulatory systems, standard deviation, and so on, and many fluctuations in the signals were considered as noise, thereby providing no information. However, today, with the methods presented in modern statistical physics and nonlinear dynamics, the oscillations have unexpected scaling properties to be used in understanding the basis of the work, the production mechanism of the signals, and the use of their practice. Many non-equilibrium systems are also nonlinear and can exhibit interesting fractal structures. The fractal properties of a signal can be detected at the singular points of the signal. A sharp characteristic determines each singular point at that point, which is called the singular point. The expansion of a function at the singular point is as follows: wavelet transforms α [19].

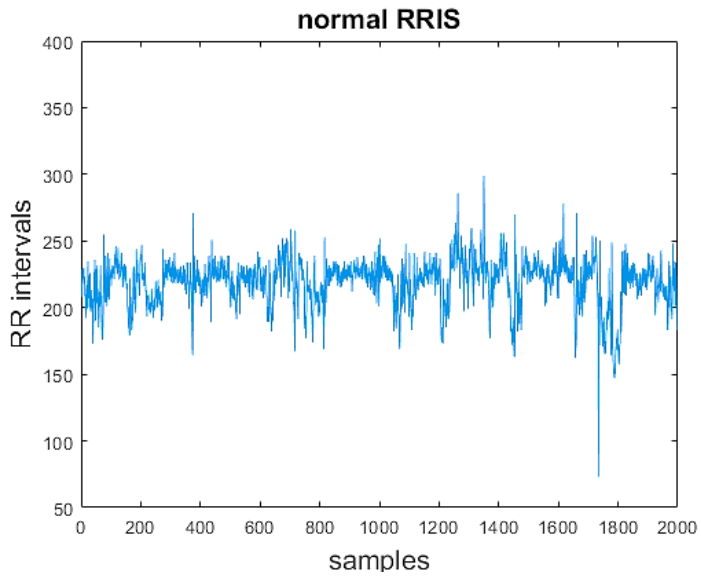
$$f(t) = (t - t_0)^a \quad (12)$$

2.3.12. Similarity index

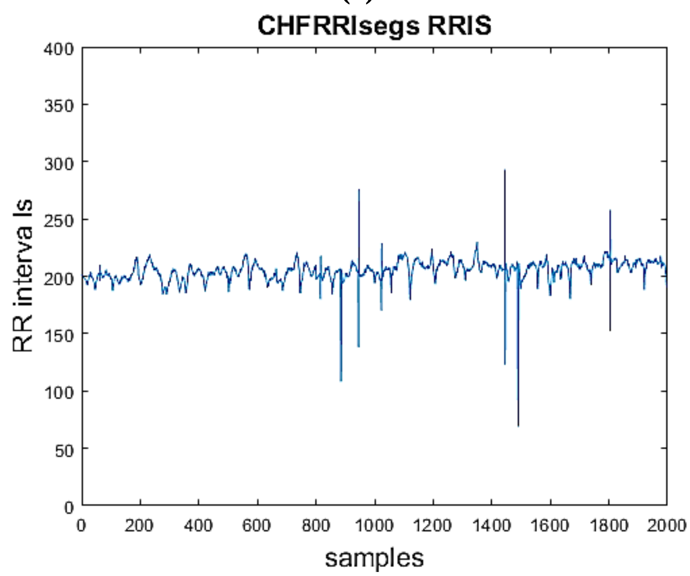
Given the high sensitivity of nonlinear systems to the starting points, common similarity criteria for time-domain signals such as correlation and symbol sum approximation (SAX) are not appropriate for nonlinear signal analysis. Accordingly, a similarity measurement for nonlinear signal analysis must be constant at the initial points and determine the quantity of similarity by considering the main dynamics of the signals. The statistical behavior of the local extreme method (SBLE) was previously proposed to solve this problem. The SBLE similarity index uses the localized extreme quantization amplitude to quantify the dynamic analogy of

Table 1. ***Details of HRV databases obtained from various databases.***

Database	Diagnosis	Heart rate records	Subject(s)
BIMC CHF	CHF database	15	11 males(age22-71)
			4 females(age54-63)
			With severe CHF(NYHA class3-4)
MIT-BIH Normal Sinus Rhthm(NSR)	Normal	18	5 males(age26-45)
Fanrasia	Normal	40	13 females(age20-50)
			20 young(age21-34)
			20 elderly(age68-85)



(a)



(b)

Fig. 3. Display of reference data signals a) RR interval segmentation of ECG normal signal b) RR interval segmentation of ECG cardiac congestion signal.

signals by considering successive localized extreme patterns. This provides a new similarity indicator for long-term nonlinear signal analysis by adding time information from local extremes and specifying quantized values, which extends the SBLE method. These new features provide further information about signals and reduce noise [20].

2.4. Feature Reduction by T-Test

index uses the localized extreme quantization amplitude to quantify the dynamic analogy of signals by considering successive localized extreme patterns. This provides a new similarity indicator for long-term nonlinear signal analysis by adding time information from local extremes and specifying quantized values, which extends the SBLE method. These new features provide further information about signals and reduce noise [20].The T-test is a test in inferential statistics determining significant differences between the means of the two groups. In other words, this test is a parametric test of spatial parameters in cases where the standard deviation of a population is unknown. It is estimated using the following equation:

$$t = \frac{\bar{x}-\mu}{s/\sqrt{n}} \tag{13}$$

In the above equations, $\bar{x}$ is the mean of the sample, μ is the mean of the population of the hypothesis, s is the standard deviation sample, and n is the total number of samples.

2.5. Classification by SVM

The support vector machine classification method, one of the linear classification methods, finds the best super frame separating the data of the two classes with maximum margin. To better understand the content, the backup vector machine method selects the best super surface to separate these classes. It is used for classification in the proposed method.

3. RESULTS

The samples of this set, including HRV signals lasting several hours, were divided into 2000 sections. The dataset includes 58 normal signals divided into 981 sections of 2000 (including 125 sections of 2000 fantasy signals and 856 sections of 2000 normal signals) and 15 signals of CHF disease divided into 805 sections of 2000. Table 1 shows an example of the signals.

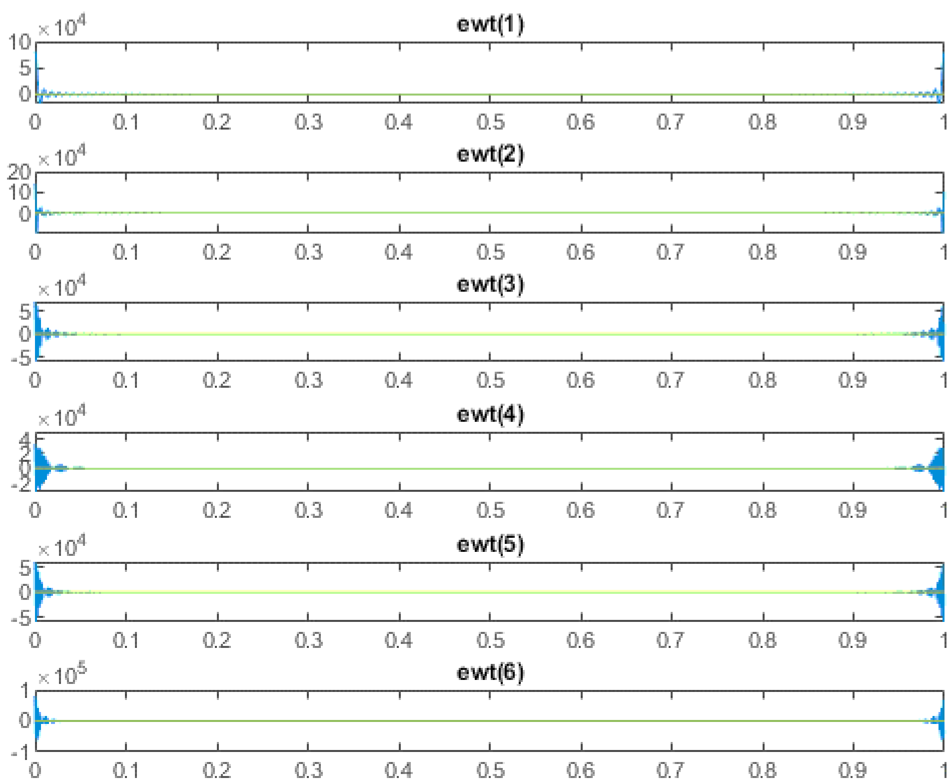


Fig. 4. Decomposition using EWT six levels.

The criteria of Sensitivity, Specificity, and Accuracy have been used to evaluate the proposed method with other methods. Furthermore, the dataset was tested by MATLAB 2019 software using 12 GB of memory and a five-core CPU.

In this RR-Interval section, the initial signals of individuals with CHF are extracted and then segmented into 2000 sections, as shown in Figure 3.

As shown in Figure (3), the signals in the preprocessing and segmentation sections are divided into 2000 samples, and the fluctuations in the normal signal are greater than the CHF. Now, the normal and abnormal signals preprocessed and segmented in the previous section are broken down by the EWT into six levels., four of which are shown in Figures (4).

As shown in Figure (5), the decomposition was performed by EWT in 1 second, which in the proposed method used these levels to extract different frequency characteristics. Finally, feature ranking by t-test, as presented in Figure (6)

As shown in figure (6), the features rated by the t-test gradually increase the accuracy of the classification as they increase, thereby differentiating the signals.

The best features in terms of ranking include approximate entropy (EAP), sample entropy (Es), fuzzy entropy (Ef), Kolmogorov Sinai entropy (Eks), multidimensional entropy (EMM), Shannon entropy (Esh), Renyi entropy (Er), Tsallis (Et) entropy, RAQ, whose similarity is obtained from four different subbands.

As shown in Figure 7, when the RBF (*radial basis function network*) radial core was used in the SVM classification, the accuracy criterion reached its maximum; hence, it was used in the next section, compared to other methods. Also, according to the standard for CNN, this accuracy reached 93.45. DT, KNN, and Bayse Naive were in the following categories.

In the following, the right and wrong diagnoses rates were obtained according to the SVM classification, as shown in Figure (7).

As presented in Figure 7 the distinctive features cause the correct diagnosis rate to reach its highest accuracy, leading to the better segregation of CHF patients. This can

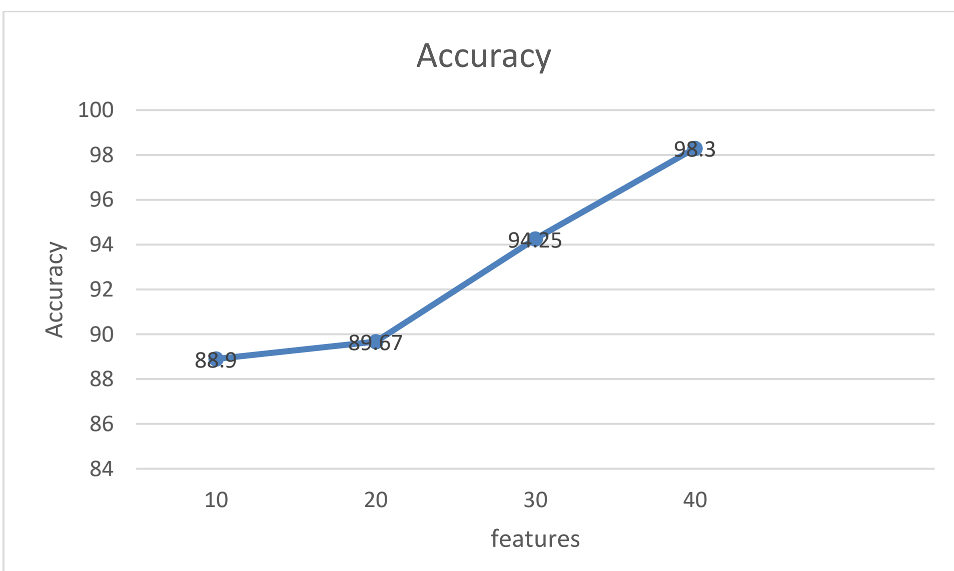


Fig. 5. The accuracy obtained using T-test.

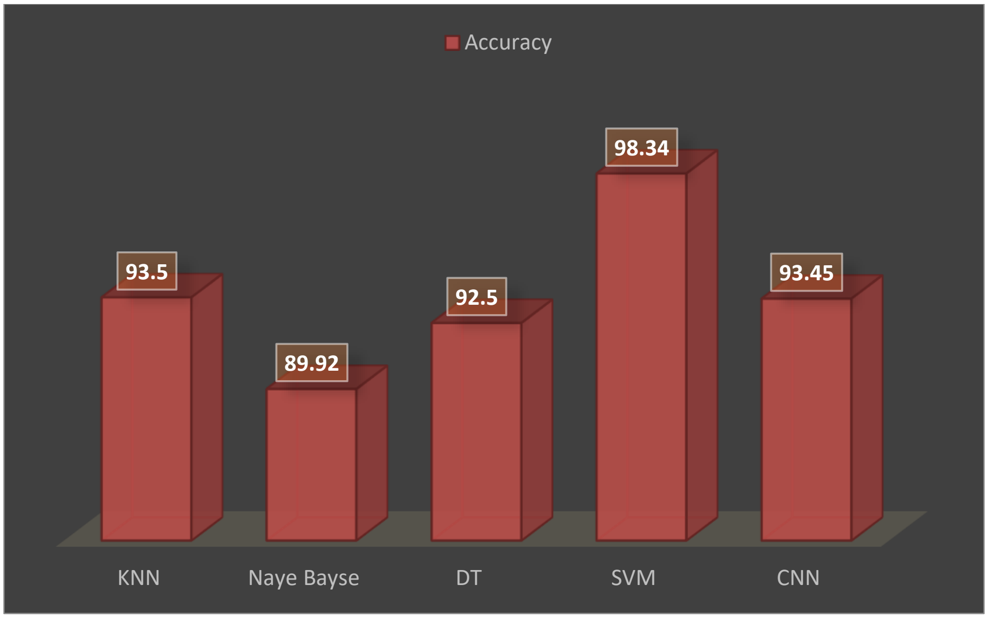


Fig. 6. The Accuracy of different classifications.

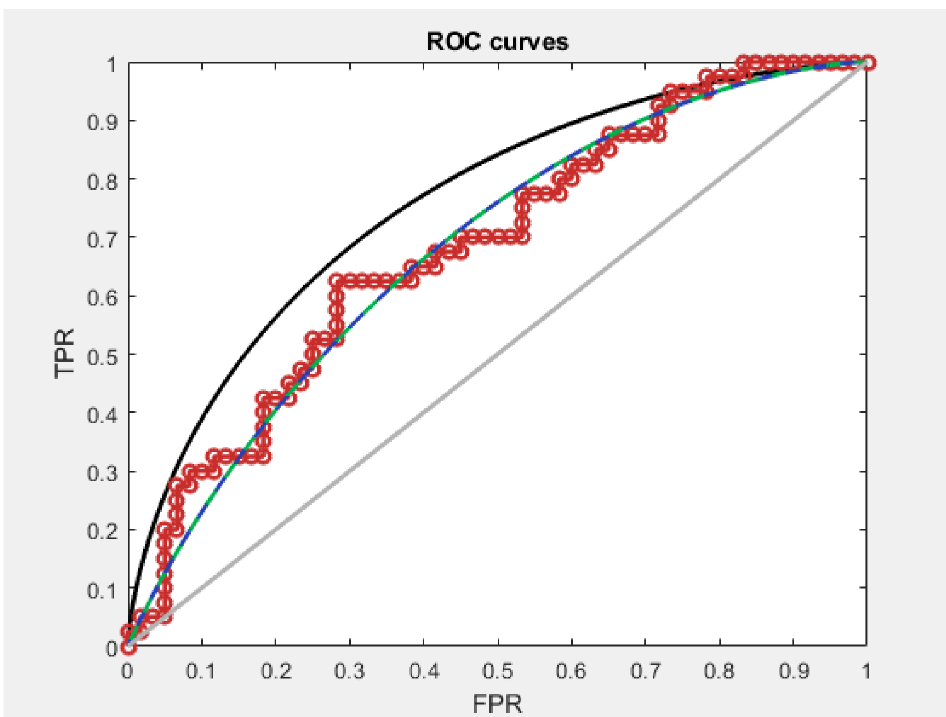


Fig. 7. ROC Curve.

also be due to the excellent design of the Violet EWT having a poor resolution at high frequencies and strong resolution at low frequencies. This is highly effective in extracting ECG features.

In the following, the proposed method is compared with the methods [6], [7], [8], and [9] according to the accuracy estimated in the previous section using the SVM classifier. Figure 8 compares the aforementioned methods.

Figure (8) shows the superiority of the proposed method (given the uniformity of the data set in all the four methods and the use of 70% of the data as training data and 30% of the data as the test data). However, the combined method is in the second category, followed by the methods in [6], [22], [21], and [23]. Table (2) shows the details of the evaluation criteria.

4. DISCUSSION

In the proposed method, the EWT algorithm, if the parameters are not adjusted well, can cause signal entanglement, and the signals are sampled too much, which leads to overlap, and in this regard, we can point to a weakness of EWT. Therefore, in the EWT method, the correct selection of parameters

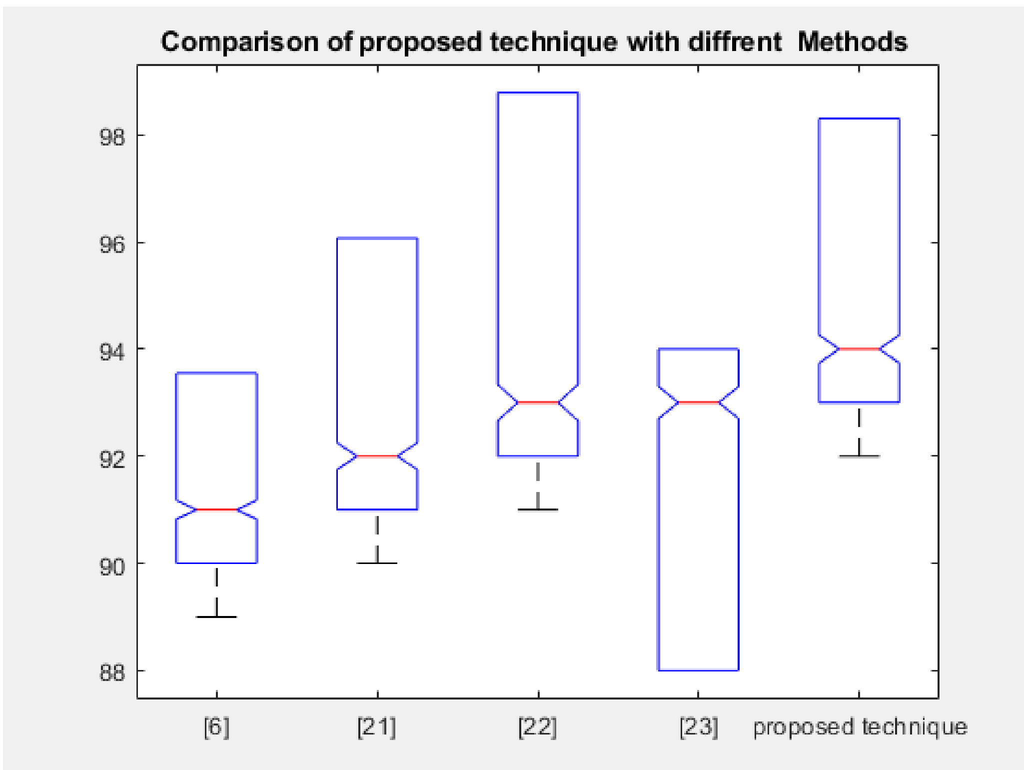


Fig. 8. Compare different methods.

Table 2. ***Compare different methods.***

Methods	Accuracy	Sensitivity	Specificity
[6]	96.07%	98.04%	95.02%
[21]	93.33%	94.41%	94.90%
[22]	98.78%	98.48%	99.09%
[23]	88.00%	87.04%	88.00%
Proposed	**98.30%**	**99.01%**	**99.25%**

and analysis levels can be very effective in the quality of accuracy and detection. Also, feature selection, when it includes 8 properties, which we call the first group here, includes: approximate entropy (EAP), sample entropy (Es), fuzzy entropy (Ef), Kolmogorov Sinai entropy (Eks), modified multiscale entropy (EMM), Shannon entropy (Esh), Renyi entropy (Er), Tsallis entropy (Et) is better than the six properties we call the second group (excluding Renyi and Tsallis entropy properties). The opinion has criteria for the accuracy of diagnosis and sensitivity, which depends on the level of analysis. Therefore, in the proposed method, other features such as fractal dimensions and similarity index were used.

5. CONCLUSION

The HRV signal extracted from the ECG signal was analyzed to classify the CHF signals and normal signals in the proposed method. EWT estimated signal analysis into a series of subbands and values were calculated from different sub-bands. Then, the entropy criterion was proposed based on the entropy of the ECG signal in different frequency bands. The extracted features were classified by the SVM classification method. To evaluate the desired method, EWT was compared with other methods. Then, the collected data set, including normal and CHF data, was used to classify normal/normal individuals to identify normal and CHF individuals. Finally, by implementing the proposed model by simulating the data of the PhysioNet site, the existence of the CHF problem can be automatically detected. To evaluate the proposed method, three criteria (namely accuracy, sensitivity, and diagnosis) were used to analyze the proposed method in this paper. The study showed that the proposed method performs better than other methods in terms of quality criteria. It was also quantitatively 98.30 compared to other methods, indicating the strong performance of this method.

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