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Optimal Classification of Atrial Fibrillation and Congestive Heart Failure using Machine Learning

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ABSTRACT

Cardiovascular disorders, including atrial fibrillation (AF) and congestive heart failure (CHF), are the major causes of mortality worldwide. The diagnosis of cardiovascular disorders is heavily reliant on electrocardiogram (ECG) signals. Therefore, extracting significant features from ECG signals is the most challenging aspect to represent each condition of the ECG signals. Earlier studies have claimed that the Hjorth descriptor is assigned as a simple feature extraction algorithm that has the capability of class separation among AF, CHF, and normal sinus rhythm (NSR) conditions. However, owing to noise interference, certain features do not represent the characteristics of the ECG signals. This study addressed this important gap by applying a discrete wavelet transform (DWT) prior to applying the Hjorth descriptor as a feature extraction method. Furthermore, the feature selection process and optimization of various classifier algorithms, including k-nearest neighbor (k-NN), support vector machine (SVM), and artificial neural network (ANN), were investigated to provide the best system performance. This study obtained accuracies of 95 %, 92 %, and 95 % for the k-NN, SVM, and ANN classifiers, respectively. The results demonstrated that the optimization of the classifier algorithm could improve the classification accuracy of AF, CHF, and NSR conditions, compared to earlier studies.

INTRODUCTION

Atrial fibrillation (AF) is one of the most common sustained arrhythmias affecting 59.7 million people in 2019, which is more than twice the number of cases reported in 1990 [1]. Meanwhile, congestive heart failure (CHF) is an increasingly frequent cardiovascular disease that affects 64.34 million cases according to the current worldwide prevalence in 2017 [2]. As cardiovascular disorders affect millions of people and potentially lead to death, AF and CHF have become a major public health concern worldwide [3]. Early diagnosis of AF and CHF could potentially prevent long-term complications and sudden cardiac death [4].

To develop an early diagnostic system of cardiovascular conditions, researchers have used a non-invasive method by measuring and analyzing electrocardiographic characteristics, which have a strong correlation with cardiovascular conditions [5]. Electrocardiogram (ECG) signals are extremely important in diagnosing abnormalities, such as cardiac arrhythmia [6] and heart failure. Therefore, in recent decades, there has been a significant increase in interest in the field of automatic classification of cardiovascular disorders, including AF and CHF, based on ECG signals and machine learning approaches [7–13].

Rizal et al. used the Hjorth descriptor approach to evaluate ECG signals based on activity, mobility, and complexity features [7,8]. Several classifier algorithms used in the classification process included k-mean clustering, k-nearest neighbor, and multilayer perceptron and obtained 88.67 %, 99.3 %, and 99.3 % accuracy, respectively, in 2015 and obtained 94 % accuracy using the k-NN classifier in 2017 [8].

Furthermore, Thaweesak et al. used 90 recordings from the primary datasets of these three conditions and provided 84.89 %, 88.22 %, and 76 % accuracy using least-squares (LS), maximum likelihood (ML), and support vector machine (SVM), respectively [9]. Their results demonstrated that the Hjorth descriptor efficiently separated patient groups with cardiac arrhythmia.

The most challenging aspect of the classification of ECG signals is the feature extraction process. The aforementioned studies [7–9] applied the Hjorth descriptor method to extract features from ECG signals. However, certain limitations of earlier studies that used Hjorth descriptors include susceptible noise that impacts the value of variance or activity in Hjorth descriptor features. Therefore, noise reduction is required without changing the ECG signal information. Another limitation of the earlier studies is that it does not implement signal decomposition before calculating the Hjorth descriptor features [7].

To overcome certain limitations of the aforementioned studies, we proposed a new approach by applying a discrete wavelet transform to decompose the ECG signal into sub-bands prior to applying Hjorth descriptor features as a feature extraction method. Furthermore, the feature selection process and optimization of various classifier methods, including k-NN, SVM, and ANN, were investigated to improve the performance accuracy in classifying AF, CHF, and NSR conditions.

RESULTS

A total of 38 test data that included 12 AF, 14 CHF, and 12 NSR data were used to evaluate the system performance. The feature selection method of Hjorth descriptor features was applied to observe the influence of the classification performance using k-NN, SVM, and ANN classifiers. Table 3 summarizes the classification accuracy of each feature set for each algorithm.

For the k-NN algorithm, optimization was conducted by selecting the best k values. The optimal value of k = 1 obtained using the Euclidean distance was selected as the best parameter of the k-NN algorithm that provided the highest accuracy for each feature set (Table 1). The performance accuracy of the k-NN method already reached 95 % using the feature sets of activity and mobility. For the SVM method, the best values of C = 1 and $\gamma = 0.001$ were selected as the optimal parameters to provide the highest accuracy of 92 % using the feature sets of activity and mobility and the feature sets of activity, mobility, and complexity (Table 2). The ANN method provided the highest accuracy of 95 % using the feature sets of activity; activity and mobility; mobility and complexity; and all the three features (Table 3).

As presented in Table 3, compared to mobility and complexity features, the feature set of activity better distinguished AF, CHF, and NSR conditions by providing accuracies of 92 %, 89 %, and 95 % for k-NN, SVM, and ANN methods, respectively. This was followed by the feature set of mobility, which provided an accuracy of 89 % for each algorithm. Meanwhile, the feature set of complexity provided the lowest accuracy of 71 %, 58 %, and 66% for k-NN, SVM, and ANN methods, respectively. Therefore, the combination of features by including complexity with the other features did not improve the accuracy, or even decreased the accuracy (Table 3). Classification performance systems based on machine learning algorithms rely on the feature extraction process. The selection of appropriate features is an important step in improving accuracy.

Table 4 presents the confusion matrix and the detailed performance of the overall classification algorithm by evaluating the accuracy value. The k-NN algorithm successfully classified AF and NSR conditions according to their class and misclassified two CHF data as AF conditions. The SVM algorithm also perfectly classified AF and NSR conditions and misclassified three CHF data as AF conditions. The ANN algorithm correctly classified the NSR conditions, misclassified one data of AF as CHF, and misclassified one data of CHF as AF conditions. According to the results, the classification error almost occurred for AF and CHF conditions owing to the same characteristics that indicate heart abnormalities.

The performance accuracy of the reconstruction of the aforementioned method, after applying a discrete wavelet transform (DWT) and Hjorth descriptor features using the k-NN, SVM, and ANN classifiers, achieved the accuracies of 95 %, 92 %, and 95 %, respectively. This result outperformed the system performance achieved in earlier studies, which also used the Hjorth descriptor as a feature extraction method.

DISCUSSION

The broader objective of this study is to develop machine learning algorithms that would improve the accuracy performance achieved by the earlier studies in classifying AF, CHF, and NSR conditions [7,8]. To achieve this objective, we applied the DWT and Hjorth descriptors as feature extraction methods to generate the feature sets and trained them using several classifier algorithms, including SVM, k-NN, and ANN, to recognize a set of features that are associated with a particular ECG signal condition.

The feature extraction process is the most challenging part of extracting the important features of ECG signals. The aforementioned studies directly calculate the ECG signal using the Hjorth descriptor features—activity, mobility, and complexity. In this study, we decomposed the ECG signal into six sub-bands using five-level decomposition of the DWT method. Subsequently, we calculated the Hjorth descriptor features for each sub-band. Thus, 18 features were generated. Furthermore, the best features

that reflect the characteristics of each condition were also investigated as a part of the feature selection process.

During the classification process, we trained the features using several classification algorithms, including SVM, k-NN, and ANN. Each classifier algorithm included a specific parameter that influenced the accuracy performance. Therefore, the optimization of each classifier algorithm was investigated to obtain the highest classification accuracy.

Because such an approach has been reported in earlier studies [7–9], we applied our SVM, k-NN, and ANN models to classify the feature sets. Before using the model, the feature sets were applied to the feature selection process to obtain the appropriate features (activity, mobility, and complexity) that were used as inputs for our model. The appropriate parameters of the SVM model obtained 92 % accuracy, which was a significant increase from 76% to 92 % from the earlier studies that used a similar approach using the SVM model to classify AF, CHF, and NSR conditions [9]. The classification performance of the k-NN algorithm slightly increased from 94 % to 95 % to classify the three conditions [8]. Similarly, the classification performance of the ANN model provided an accuracy of 95 % to identify the three conditions.

According to the results, we can consider that this improvement could be attributed to the application of the DWT method prior to the Hjorth descriptor method, feature selection process, and extensive optimization for each classifier algorithm, including SVM, k-NN, and ANN. We believe that it will improve even further when we use a larger dataset with more features, which is currently being developed. However, before proceeding to such comprehensive experimental efforts, it was necessary to demonstrate that our approach could overcome the limitations of the earlier studies and improve the classification accuracy, which was the primary goal of this study.

METHODS

In this study, we reconstructed the method used in earlier studies [7,8] to classify ECG signals into three conditions—AF, CHF, and NSR. In contrast to earlier studies, we applied DWT to the decomposition signal prior to the Hjorth descriptor as a feature extraction method, followed by several classifier algorithms, namely, k-NN, SVM, and ANN (Fig. 2a).

Dataset

This study used the same dataset that was used in the earlier studies [7,8]. The ECG signal data that comprised three conditions, including NSR, AF, and CHF, were collected from the MIT-BIH public dataset that can be accessed in PhysioNet [14]. Each class included 50 data points with a sampling rate of 250 Hz and 2–3 s period of time. Therefore, one dataset comprised 2–3 cycles of QRS of the ECG signal. A total of 150 ECG signals included 112 train data and 38 test data.

Preprocessing

In the preprocessing step, the ECG signal amplitude was normalized. If the ECG signal is x (n), where n=1, 2,..., N, the value of N indicates the length of the signal; then, the signal is normalized using equations (1) and (2) [7,8].

$$y(n) = x(n) - \frac{1}{N}\sum_{i=1}^{N} x(n) \tag{1}$$

$$z(n) = \frac{y(n)}{|y(n)|} \tag{2}$$

The amplitude of the z (n) signal is -1 to +1, such that the difference in the amplitude range of the signal owing to differences in signal recording can be eliminated.

Discrete Wavelet Transform (DWT)

The ECG signal was passed into the low-pass filter (LPF) and high-pass filter (HPF) according to the mother wavelet used and then down-sampled [15]. The output of the LPF produced an approximation component (cA), and the output of the HPF produced a detailed component (cD) [16]. At the next level for the one-dimensional discrete wavelet transform (1-D DWT), the same process was performed only on the approximation components. In this study, we applied five-level decomposition that generated six sub-bands, which comprised one approximation component and five detailed component sub-bands (Fig. 1).

During the feature extraction process, we calculated the Hjorth descriptor parameters, that is, activity, mobility, and complexity for each sub-band. Therefore, 18 features were generated as input for the classifier algorithms.

Hjorth Descriptor

Consider $x(n)$ as a signal, for $n = 0,1,2,3 \ldots . N-1$. Then, $x(n)'$ can be defined as the first difference of the signal [17–19].

$$x(n)' = x(n) - x(n-1) \text{ for } n = 0,1,2,3 \ldots . N-1 \tag{3}$$

Furthermore, $x(n)''$ is defined as the second difference of the signal.

$$x(n)'' = x(n)' - x(n-1)' \text{ for } n = 0,1,2,3 \ldots . N-1 \tag{4}$$

Consider σ_x as the deviation standard of $x(n)$. Then, σ_{x1} and σ_{x2} can be defined as the deviation standard of $x(n)'$ and $x(n)''$, respectively. The deviation standard of x(n) can be calculated using equation (5).

$$\sigma_x = \sqrt{\frac{\sum_{n=0}^{N-1}(x(n)-\bar{x})^2}{N}}, \tag{5}$$

$$\text{where } \bar{x} = \frac{1}{N}\sum_{n=0}^{N-1} x(n). \tag{6}$$

Activity refers to the signal variation or the squared standard deviation of the amplitude, as shown in equation (7) [17–19].

$$activity = variance = {\sigma_x}^2 \tag{7}$$

Mobility calculates the standard deviation of the slope in relation to the standard deviation of the amplitude, as shown in equation (8). As shown in equation (9), complexity measures the number of standard slopes generated in the average time to generate one standard amplitude, as determined by the mobility.

$$mobility = M_x = \frac{\sigma_{x1}}{\sigma_x} \tag{8}$$

$$complexity = FF = \frac{M_x{}'}{M_x} = \frac{\frac{\sigma_{x2}}{\sigma_{x1}}}{\frac{\sigma_{x1}}{\sigma_x}} \tag{9}$$

Classifier Algorithms

The general process of the k-NN algorithm is illustrated in Fig. 2b. The training data were projected into a multidimensional space, with each dimension representing the features extracted from the training data. The algorithm of the training process included storing feature vectors and labels from the training data. Meanwhile, the unlabeled testing data were simply assigned to the label of its k closest neighbors during the classification process. The Euclidean distance was used to measure the distance between two feature vector positions of the training and the testing data in multidimensional space. The features of the ECG signal were classified as NSR, AF, and CHF conditions using majority votes based on the labels of its k nearest neighbors.

The classification performance of the k-NN algorithm depends on the features used as the input of the k-NN algorithm and the k-value of the k-NN algorithm. To ensure the best possible optimization, the optimal parameters were selected, including the feature selection of features—activity, mobility, complexity—and the best k value selection for varying values of k (1,3,5,7, 9,11).

Fig. 2c illustrates the general process of the SVM algorithm. The input feature vector was transformed into higher-dimensional feature spaces using a kernel mapping function. Two types of kernel functions, linear and radial basis functions (RBF), were applied in this study. The optimization procedure of the SVM algorithm was evaluated using feature selection as input to the SVM algorithm, the best γ parameter selection of the linear and RBF kernel functions (from 1e – 01 to 1e – 06), and the best regularization parameter C selection for SVM (from 1 to 1e + 05).

An ANN is a fully connected structure that includes three main layers—input, hidden, and output layers (Fig. 2d). Input layers receive input from external resources. The feature extraction results (activity, mobility, and complexity) for each sub-band of the one-dimensional DWT were assigned as inputs for the ANN architecture. The hidden layers process the input of the previous layers and transfer the result to the output nodes. In this study, four hidden layers were used in the ANN, with the number of nodes in hidden layers 1 to 4 being 256, 128, 64, and 32, respectively. The ReLU activation function was applied for each hidden layer, and the softmax activation function was applied to the output layers, which comprised three nodes that represent the AF, CHF, and NSR conditions.

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AUTHOR CONTRIBUTIONS

This manuscript is an intellectual product of the entire team. YNF wrote the machine learning source code and manuscript, performed data analysis, and interpreted the results. KML designed the study, reviewed, and revised the manuscript based on the results. All authors have read and approved the final manuscript.

ADDITIONAL INFORMATION

Data availability

Publicly available datasets were analyzed in this study. Datasets can be accessed here: https://www.physionet.org/.

Competing interests

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

FIGURE LEGENDS

Figure 1. One-dimensional wavelet decomposition. The ECG signal is passed into the low-pass filter (LPF) to produce an approximation component (cA) and is passed into high-pass filter (HPF) to produce a detailed component (cD). In one-dimensional wavelet decomposition five-level decomposition generated six sub-bands, which comprised one approximation component and five detailed component sub-bands.

Figure 2. Overall diagram of the proposed system. The general block diagram of the classification system based on discrete wavelet transform and Hjorth descriptor feature extraction (a), the flowchart of the k-nearest neighbor classifier algorithm (b), the flowchart of the support vector machine classifier algorithm (c), and the architecture of the artificial neural network algorithm (d).

FIGURES

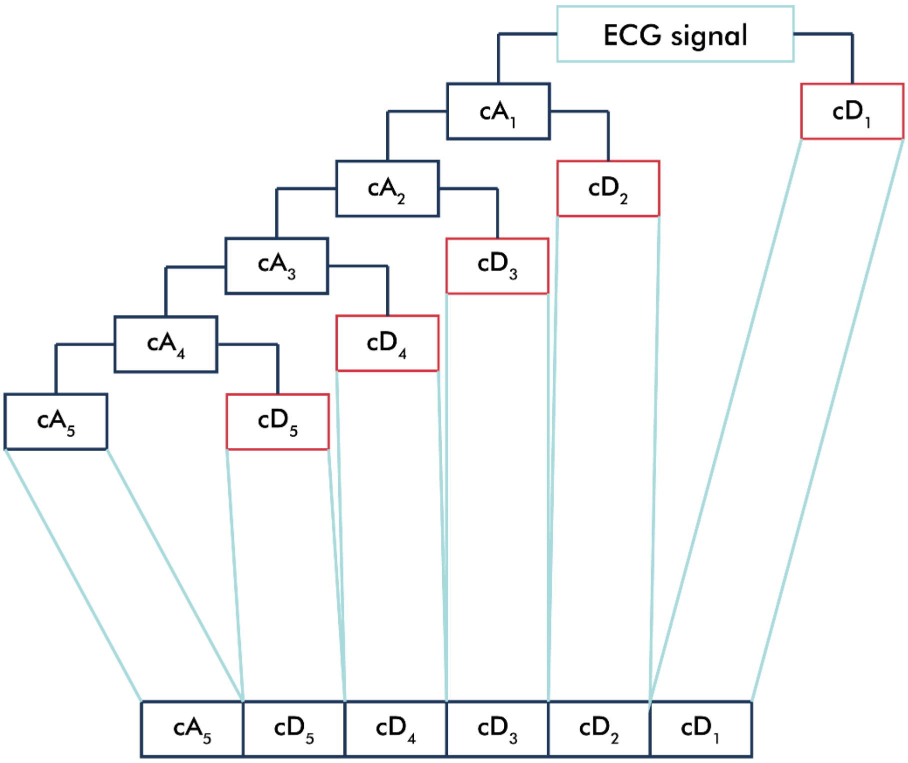

Figure 1

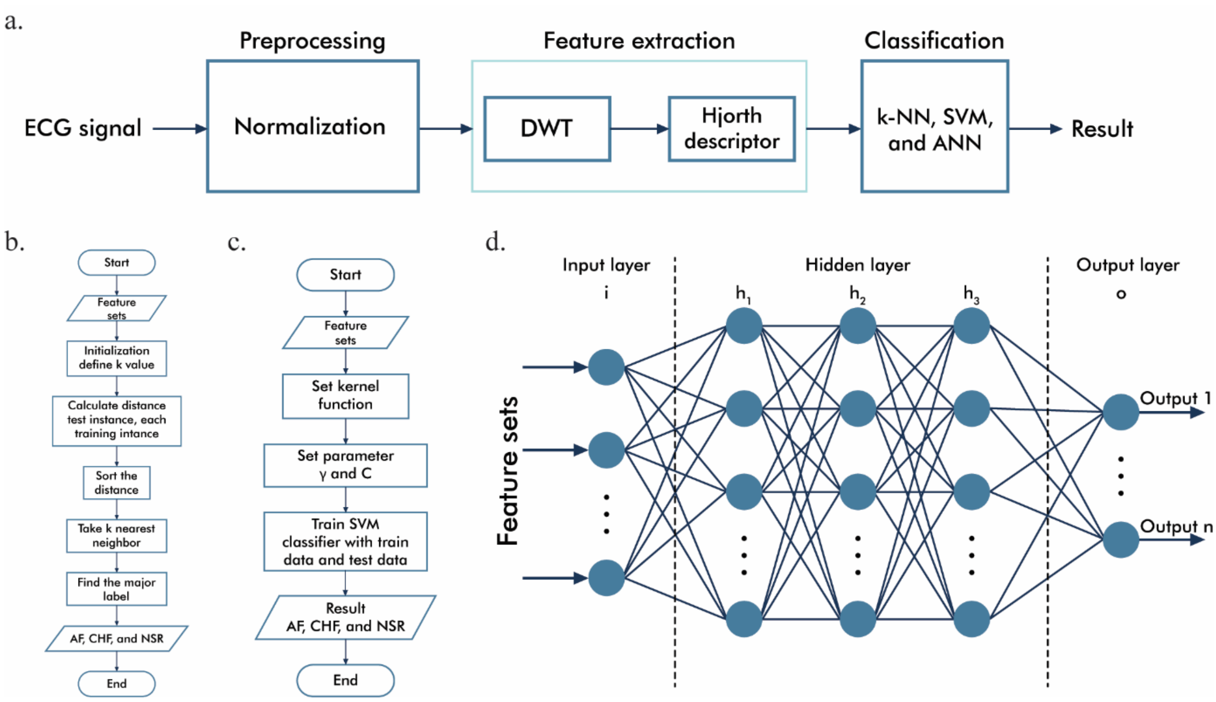

Figure 2

TABLES

Table 1. Significance of feature and k values selection on the performance of the k-NN classifier algorithm.

Feature sets	Accuracy (%)					
	k = 1	k = 3	k = 5	k = 7	k = 9	k = 11
Activity	92	92	89	92	89	89
Mobility	89	89	87	82	79	82
Complexity	71	66	66	63	61	58
Activity, mobility	95	92	92	92	92	92
Activity, complexity	92	92	92	89	92	89
Mobility, complexity	84	79	82	82	79	71
Activity, mobility, complexity	95	92	92	92	89	84

Table 2. Significance of feature, kernel function, C, and γ values selection on the performance of the SVM classifier algorithm.

Feature sets	Kernel	C	γ	Accuracy (%)
Activity	RBF	1	0.001	89
Mobility	RBF	10000	0.001	89
Complexity	Linear	10	0.001	58
Activity, Mobility	Linear	1	0.001	92
Activity, Complexity	RBF	1000	0.001	92
Mobility, Complexity	RBF	100	0.001	87
Activity, Mobility, Complexity	Linear	1	0.001	92

Table 3. Classification performance of each feature set.

Feature sets	Accuracy of k-NN (%)	Accuracy of SVM (%)	Accuracy of ANN (%)
Activity	92	89	95
Mobility	89	89	89
Complexity	71	58	66
Activity, mobility	95	92	95
Activity, complexity	92	92	92
Mobility, complexity	84	87	95
Activity, mobility, complexity	95	92	95

Table 4. Confusion matrix of each algorithm.

<table>
<tr><th>Method</th><th>Class</th><th>AF</th><th>CHF</th><th>NSR</th><th>Accuracy (%)</th></tr>
<tr><td rowspan="3">k-nearest neighbor</td><td>AF</td><td>12</td><td>2</td><td>0</td><td rowspan="3">95</td></tr>
<tr><td>CHF</td><td>0</td><td>12</td><td>0</td></tr>
<tr><td>NSR</td><td>0</td><td>0</td><td>12</td></tr>
<tr><td rowspan="3">Support vector machine</td><td>AF</td><td>12</td><td>3</td><td>0</td><td rowspan="3">92</td></tr>
<tr><td>CHF</td><td>0</td><td>11</td><td>0</td></tr>
<tr><td>NSR</td><td>0</td><td>0</td><td>12</td></tr>
<tr><td rowspan="3">Artificial neural network</td><td>AF</td><td>11</td><td>1</td><td>0</td><td rowspan="3">95</td></tr>
<tr><td>CHF</td><td>1</td><td>13</td><td>0</td></tr>
<tr><td>NSR</td><td>0</td><td>0</td><td>12</td></tr>
</table>

Figures

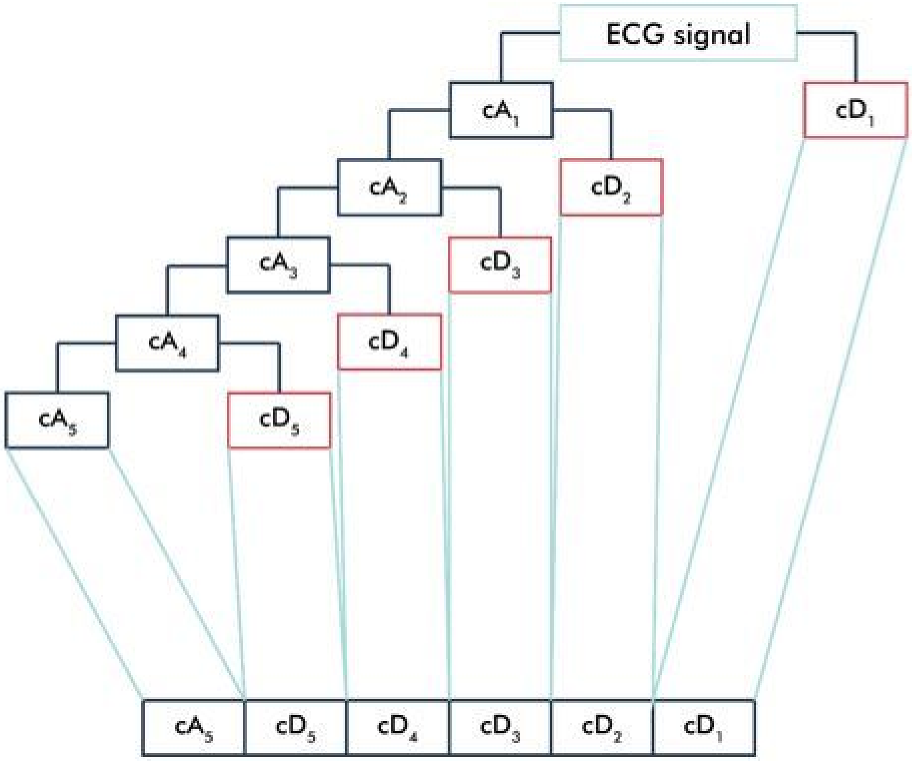

Figure 1

One-dimensional wavelet decomposition. The ECG signal is passed into the low-pass filter (LPF) to produce an approximation component (cA) and is passed into high-pass filter (HPF) to produce a detailed component (cD). In one-dimensional wavelet decomposition five-level decomposition generated six sub-bands, which comprised one approximation component and five detailed component sub-bands.

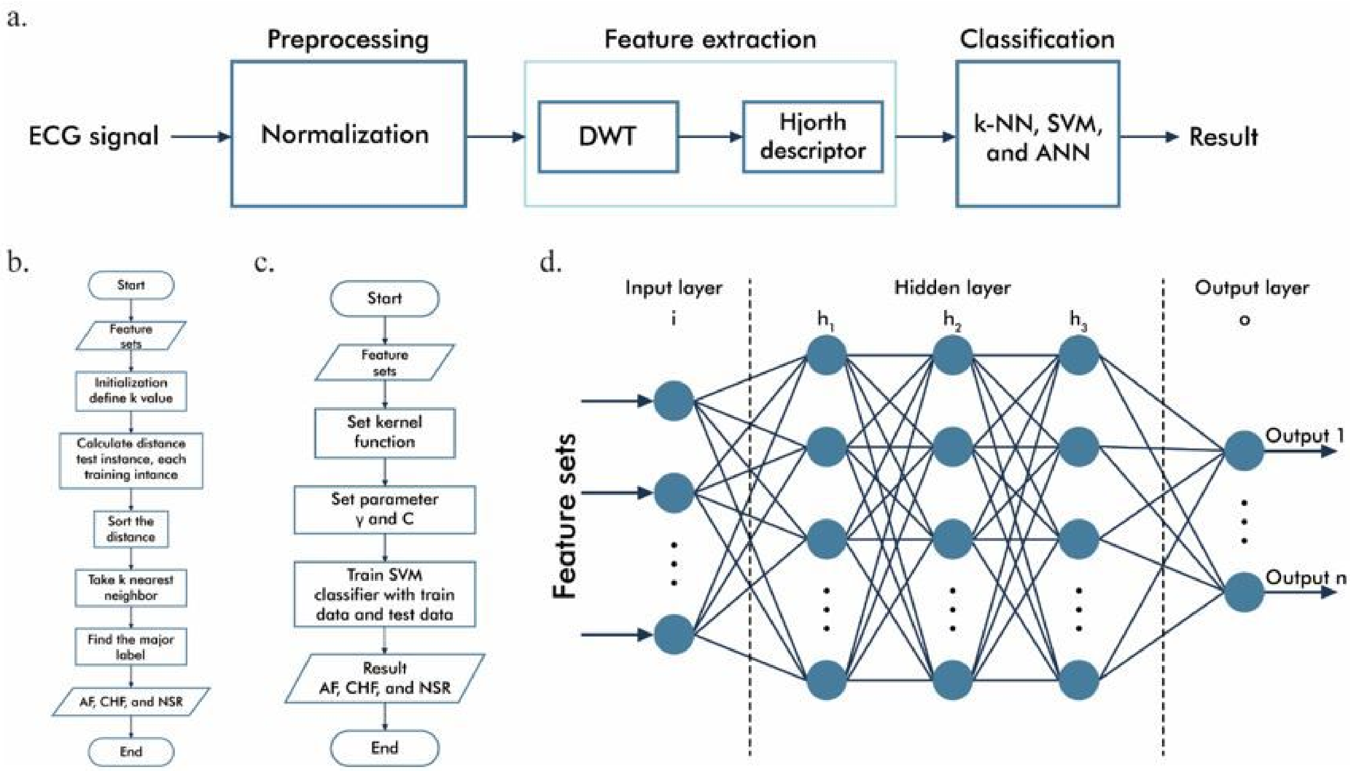

Figure 2

Overall diagram of the proposed system. The general block diagram of the classification system based on discrete wavelet transform and Hjorth descriptor feature extraction (a), the flowchart of the k-nearest neighbor classifier algorithm (b), the flowchart of the support vector machine classifier algorithm (c), and the architecture of the artificial neural network algorithm (d).