

Research Article

An Approach for Cardiac Coronary Detection of Heart Signal Based on Harris Hawks Optimization and Multichannel Deep Convolutional Learning

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Automatic diagnosis of arrhythmia by electrocardiogram has a significant role to play in preventing and detecting cardiovascular disease at an early stage. In this study, a deep neural network model based on Harris hawks optimization is presented to arrive at a temporal and spatial fusion of information from ECG signals. Compared with the initial model of the multichannel deep neural network mechanism, the proposed model of this research has a flexible input length; the number of parameters is halved and it has a more than 50% reduction in computations in real-time processing. The results of the simulation demonstrate that the approach proposed in this research had a rate of 96.04%, 93.94%, and 95.00% for sensitivity, specificity, and accuracy. Furthermore, the proposed approach has a practical advantage over other similar previous methods.

1. Introduction

As the World Health Organization notes [1], heart disease is one of the most common causes of death. One of these types of diseases is irregular heartbeat or arrhythmia. Heart rhythm problems occur when the heart's electrical pulses, which are responsible for coordinating the heartbeat, do not work well, resulting in a very rapid, too slow, or irregular heartbeat. Some types of arrhythmias can be dangerous and even life-threatening. The heart of a person with an arrhythmia cannot pump sufficient blood around the body. Low blood flow causes damage to the heart, the brain, and various other organs. Prompt, timely diagnosis and intensive medical care of patients with these diseases can greatly prevent their sudden death. Cardiac arrhythmia can be treated easily if diagnosed early. The early stages of the disease have no symptoms so that it can be easily diagnosed. Due to the annoyance of this disease and the similarity of cardiac arrhythmia symptoms to other heart diseases, designing an intelligent system to diagnose this disease seems necessary [2–11].

In this study, a combination of neural networks and evolutionary algorithms based on Harris hawks optimization (HHO) [12] is used to diagnose arrhythmic heart disease according to the underlying factors. There are several reasons for using a neural network in this study. Artificial neural networks have a simple structure for physical (natural) applications and can easily classify complex classes. The main characteristic of artificial neural networks is assigning the results to the entry vectors that are not found in the network training. The reason for the use of evolutionary algorithms is the large number of features and background factors influencing the large and complex state of arrhythmia detection, which start with a random population that is a set of available solutions to the problem. During the optimization process and at each stage of the algorithm implementation, the optimal solutions are selected to be transferred to the next stage or in other words to be transferred to the next generation, which ultimately leads to the optimal answer to the problem [13–19].

During this study, after identifying the factors influencing the diagnosis of cardiac arrhythmia, including the

occurrence of a heart attack simultaneously, damage to heart tissue due to a heart attack that has already occurred, changes in heart structure such as changes due to cardiomyopathy, obstruction of the main arteries of the heart, diabetes, high blood pressure, hyperthyroidism, excessive alcohol or caffeine intake, smoking, drug use, stress, the consumption of certain medications, herbal medicines or dietary supplements, and air pollution, a suitable classifier is used to diagnose this case according to the background factors. For this purpose, the structure of neural networks combined with evolutionary algorithms is used. First, the structure of the neural network, that is, the number of neurons, is determined. Neural network weights are then determined using evolutionary algorithms. The use of neural networks based on evolutionary algorithms is effective in achieving optimal responses and, in particular, diagnosing arrhythmic heart disease. The purpose of this study was to use intelligent systems for the early diagnosis of arrhythmic heart disease according to underlying factors so that it can be treated in a timely manner [20–24].

2. Literature Review

Arrhythmia is an irregular heartbeat. Cardiac arrhythmias are often diagnosed in advanced stages because the disease has no signs or symptoms in the early stages. This disease needs to be diagnosed at an early stage in order to be treated in a timely manner. This requires an intelligent system that can be used to detect cardiac arrhythmias at an early stage. Heart disease is the most important health problem and the most frequent cause of death. However, early diagnosis and treatment of heart disease can be effective in reducing deaths from this disease. Electrocardiogram signals are among the tools that can be used to diagnose heart disease. These signals are a graphical representation of the electrical potential generated by the heart and are a valuable diagnostic tool for the physician. In Ref. [25], an artificial neural network is used as a method to prevent cardiac arrhythmias, to be classified into five classes. The classified classes include time interval, prediction of normal sinus rhythm, premature block contraction, atrial fibrillation, left branch block, and quadratic. The proposed system is trained and tested using 70% and 30% of the data, respectively. The system has achieved 97% overall accuracy. The arrhythmia database used in this study to educate and test the model proposed includes electronic recording of the heart rate of 47 people for 48 and a half hours. In total, the data used include 554 samples. The proposed method is done in six steps. The first step is to obtain electrocardiogram signal data. The second step involves the preprocessing method for filtering noise in signals [26]. The third step is to detect the time interval between heartbeats. In the fourth step, the data are distributed to train and test the system. In the fifth step, the frequency range and nonlinear methods are used to extract different characteristics. In the final stage, the features extracted are used to train the neural network with regard to classification. Both linear and nonlinear methods have been used to extract these characteristics. Linear methods include time-frequency domain analysis, while nonlinear methods

include spectral entropy. According to the obtained results, it can be seen that a combination of linear methods and nonlinear features provides very good predictions [25]. The heart is a particularly specialized muscle; its cells (myocytes) are controlled by force feedback in two main functions, namely, mechanical stress and neural activity. Electrocardiogram signals are used to analyze the heart rate.

In Ref. [27], the effect of using decision tree classification to extract time-consuming features on electrocardiogram signals with heart rate values is investigated. The proposed decision tree examines the time interval of the heartbeat, the irregular heart rhythm, and the waveform of the electrocardiogram signals. The arrhythmia database includes recordings of about 30 minutes' length of the heart rates of 47 patients and uses six types of heart rate, including normal rhythm, left bundle block classification, right bundle block classification, premature heart rate, premature ventricular contraction, and heart rate while moving. Different heart rates are used in this study, and arrhythmic classification of heart rate is examined using decision tree classification. Manually extracting the proposed features for electrocardiogram signals is very time-consuming, and human errors are inevitable. For this reason, in Ref. [27], an intelligent decision tree classification method for electrocardiogram signals is presented and the results show that the decision tree classification model has a high degree of accuracy; 37% of the data used as malicious data were deleted, and the remaining data were used to educate and test the system using a 10-segment validation method. The decision classification accuracy of the decision tree is 99.51% [27].

Reference [28] presented a wireless sensor network to detect the heart rate and its changes, and also designed a fuzzy model to detect the normal and arrhythmic heart rate. The method of checking irregular heartbeat is done using electrocardiographic signal. The marking of arrhythmic forms depends to a large extent on medical professionals. In addition to the time taken in this process to examine the arrhythmias, there also exists the possibility of errors in the diagnosis. To deal with these issues, it is necessary to use intelligent systems. In Ref. [28], an arrhythmia database was used and the characteristics of arrhythmias and related heart rate types were investigated. Data rate sampling involves 360 Hz in 30 minutes. Arrhythmic data consist of the parameters of the left bundle branch block, right bundle branch block, premature ventricular contractions, atrial fibrillation failure, and premature heart rate. This study is to select the features that are necessary for the diagnosis of arrhythmia [28]. The features selected are used as the input variables in fuzzy. Each file in the database is given a unique index number that indicates the type of heartbeat. The proposed system for detecting cardiac arrhythmias has reached 95.42% accuracy [28].

Cardiac arrhythmia shows an irregular heartbeat. This irregularity may just be a momentary pause, and it may be so brief that it does not have an effect on overall heart rate; alternatively, it may make the heart beat too slowly or too fast. In Ref. [29], a new tool for automatic differentiation of invasive and noninvasive arrhythmias is proposed and an artificial neural network is used. The electrocardiogram

signals employed in this study were collected through three databases. Electrocardiogram signals were obtained from the database at 360 Hz, while they were sampled at two other databases at 250 Hz. The data used contain 500 samples. The proposed artificial neural network [29] is a class of neural network models that are able to process multidimensional data, including entire images or time series, and that has a hidden layer. The layers in the proposed model are as follows. Input layer: initially, the input signal enters the network and holds the weights of the raw signal. Hidden layer: this layer is the main layer in which feature extraction and feature selection are performed. The goal of the sampling layer is to cut down the number of parameters in a gradual way. The fully connected layer has full connections; it performs the activation in the previous layer. For system validation, the 10-segment validation method has been used and the maximum accuracy, sensitivity, and features rate obtained are 93.18%, 95.32%, and 9.04%, respectively. High performance of the proposed system can be effective in diagnosing cardiac arrhythmias and increase the probability of survival [29].

In Ref. [30], an arrhythmia diagnosis system based on an artificial neural network is presented with recorded electrocardiogram signal data. In this study, the disease is mainly classified into abnormal and normal categories. Electrocardiogram signal data were used to educate and test three different models of artificial neural network. In analyzing arrhythmic data, certain amounts of data may be missing. Missing attributes for the data are replaced with the closest value to each class. Artificial neural network models are taught using the reverse algorithm with the law of movement learning to diagnose cardiac arrhythmias. The neural network models used include multilayer neural network, forward neural network, and modular neural network. Neural networks are a mathematical model of data processing that include a number of elements or units that are called nodes or neurons. These nodes or neurons are arranged in layers and communicate by weight between layers. In a multilayer neural network, there is an input layer, a hidden layer, and an output layer. A forward neural network is a generalization of the multilayer neural network model in which connections have the ability to jump over one or more layers. A modular neural network is a type of neural network that is monitored using a set of independent neural networks by various mediators in which each independent neural network acts as a module and operates separately at the inputs. From three different neural network models, multilayer neural network has had acceptable results, and classification accuracy, sensitivity, and specificity have been obtained as 86.67%, 93.75%, and 93.1%, respectively [30].

Electrocardiogram signals indicate the heart's electrical activity. Important elements of this signal are P wave, QRS complex, T wave, and U wave. Any change in the electrocardiogram signal can indicate a heart disease called arrhythmic changes. It takes even a skilled person a considerable amount of time to diagnose cardiac arrhythmias, and this process is always prone to error. Therefore, the idea of automating the detection of cardiac arrhythmias was formed. Reference [31] provides a new method for

classifying cardiac arrhythmias that is founded on the conversion of violet and nerve networks. Discrete violet conversion is used to process electrocardiogram signal records and extract time and frequency features. The result is used as an input vector to train and test a nerve network. Although various algorithms for heart arrhythmias have been proposed in recent years, most of the scientists have used a limited value of data in their work, while in this research, 20 records in the standard database in the form of 420 examples have been utilized. The general steps of the present study are as follows: first the electrocardiogram signals are received and a preprocessing is performed to remove the recorded sounds and noise. Then, 5 beats of the signal are selected and discrete violet conversion and time-frequency features are extracted. Later, the input vector is normalized and finally the arrhythmia classification of the heart is performed. The simulation results show that the designed system is highly accurate using a multilayer perceptron network as a classifier and it can classify 4 arrhythmia classes with an accuracy more than 97% [31].

An electrocardiogram signal is the most efficient tool for diagnosing heart disease. It can measure the heart's electrical activity with great accuracy. Manual detection of arrhythmic electrocardiogram signals is very time-consuming. Automatic diagnosis and classification of arrhythmias is an important part of research in clinical cardiology. In Ref. [32], a multistage clustering method founded on the maximum margin clustering algorithm and the evolutionary algorithm for the diagnosis of cardiac arrhythmias are presented. The database used includes 5 different types of arrhythmias: normal sinus rhythm, premature contraction block, premature atrial contraction, ventricular fusion, and normal heart rate. The cardiac arrhythmia detection system consists of three parts, namely, preprocessing, feature extraction, and classification. In the first step, the raw electrocardiogram signal is collected before the filter and then processed to identify the waveforms. In the preprocessing step, the sound is deleted for each record. Feature extraction is the second step; this has the aim of finding the best coefficients to describe the electrocardiogram signal. The purpose of the final step is to diagnose cardiac arrhythmia using a multistage clustering algorithm. Randomly, 130 data (70% of the data) were used for training, while 55 data (30%) were used for system testing. Three methods of sensitivity, features, and accuracy were deployed to assess the system's performance. Sensitivity, features, and accuracy were 82.4%, 98.8%, and 97.4%, respectively [32].

Reference [33] presents a new approach to classification of the cardiac arrhythmias. In this study, a combined method of feature selection based on correlation and inverted neural network has been used. The aim of this study was to classify cardiac arrhythmias into two parts: arrhythmia presence and arrhythmia absence. In this regard, intelligent decision systems with reliability variables have been tested in the UCI arrhythmia database. Among the various tools deployed in this field is artificial neural network for classification. Various feature selection techniques have been put to use for better and more accurate classification. This is an attempt to correlate feature selection with forward-

looking linear selection. The classification results are evaluated according to the classification accuracy, specificity, and sensitivity. The database used contains 420 samples. The datasets used are divided into three categories: training datasets (68%), validation datasets (16%), and test data sets (16%). Feature extraction and reduction is an important stage in terms of classification, because even in the most accurate classification, the system can display poor performance if the features are not selected. Data preprocessing comprises the first stage for any development model. Conventional neural networks are not incremental in nature. In the proposed neural network, this issue is investigated through the introduction of a scaling factor that reduces all weight settings. This study basically includes two stages: feature extraction stage and reduction stage using feature selection correlation and classification by backward extended neural networks. The experimental results presented here demonstrate that a classification accuracy of 87.71% has been obtained using an average of 100 simulations [33].

In Ref. [34], a general method for automatic diagnosis of cardiac arrhythmias is presented, which uses the methods of artificial neural network, decision tree, and nearest neighbor K for accurate classification of cardiac abnormalities. In this study, two databases of arrhythmia and fibrillation were used. In the database, 1200 heart rates were examined in 360 samples. Initially, the received electrocardiogram signals are preprocessed and the useless information is removed. The Fourier transform method provides good frequency resolution but has no localization time and also includes information that occurs at different times. Such signals are separated using discrete wavelet transform. In this study, principal component analysis is deployed to decrease the dimensions of the problem. To validate the system, the 10-segment validation method has been used. The proposed method is simulated using MATLAB software. The nearest neighbor K has the highest efficiency and has reached 99.45% accuracy. Therefore, the proposed diagnostic system is highly reliable for use by physicians. This method can further be used to diagnose other cardiovascular disorders. The main advantages of the method are as follows: (1) it showed improvements to the previous methods with regard to accuracy. (2) The accuracy of the system is very high, so the system is reliable for classification. (3) The results can be retrieved as the average performance of 10 experiments. (4) The proposed method is noninvasive and fully automatic, and requires only limited communication with the doctor. (5) The proposed method can be extended to other heart disorders.

3. Materials and Methods

First, the ECG signal data are entered into the program and the extraction operation feature with the differential evolution algorithm is applied to them as an optimization technique. Parameter control and evolutionary strategy selection are the two main features of differential evolution discussed. This controls the parameter settings for the

scaling factor F, the probability of CR crossing, and the magnitude of the NP population. However, for different problems, different strategies are optimized, and the most appropriate strategy needs to be chosen. Population diversity is affected by parameter setting, the ability to develop the initial period of time, and the convergence of the next period of time. Choosing the evolutionary strategy is essential in terms of working out the balance between exploration and convergence differential evolution. Various evolutionary strategies have different polling abilities and tendencies of convergence. Combination operations simultaneously bring a range of effects to bear on the search for global optimization. The function of traditional binomial combinations plays a particular role; however, it depends more on the coordinate system of the compound and is broadly employed. Furthermore, population structure forms a significant indicator with regard to the performance of the algorithm. When the size of the population is too small, this can very easily cause a loss of the effective alleles, thus decreasing the production of competitive individuals. On the other hand, when the population is too large, the likelihood of the algorithm producing a correct search is reduced. As a result of early convergence, the control of parameters, the strategy improving, the performance of composition, and population structure lead more attention to be placed on improving the performance of differential evolutions.

Differential evolution is often thought of as a greedy evolution algorithm based on real number coding and global optimization. During the evolutionary stage, the three processes of repetition of the mutation, combination, and selection are carried out until the cessation conditions are achieved. The performance of the fit function is used for the evaluation of the quality, and the best person is noted. Assuming the population size is NP and the dimension of the solution space is practical D, x_G is used to show the evolution of the G generation population. Every individual comprises the following parameters D, which can be expressed in the following equation:

$$x_i^G = \{x_{i,1}^G, \dots, x_{i,D}^G\}, \quad i \in \{1, 2, \dots, NP\}. \quad (1)$$

In this regard, $x_{i,j}^G \in (x^L, x^H)$ and x^L and x^H represent the upper and lower limits of the independent samples, respectively. The independent sample x_i^G produces an individual type of v_i^G in the parent population using a mutation strategy. "DE/rand/1" shows that DE selects a random perturbation for the mutation. Expression (2) describes the relation.

$$v_i^G = x_{r_1}^G + F \cdot (x_{r_2}^G - x_{r_3}^G), \quad r_1, r_2, r_3 \in \{1, 2, \dots, NP\}. \quad (2)$$

In this respect, $r_1 \neq r_2 \neq r_3$ and $r_1, r_2,$ and r_3 are random mutants. The criterion of dimensions F is taken from the range [0, 1]. The primary function of blending operations is to differentiate the individuals produced to create new blends with individuals in the main population. The differential evolution algorithm supports the binomial combination scheme. Equation (3) describes the combination operation:

$$u_{i,j}^G = \begin{cases} v_{i,j}^G, & \text{if } \text{rand}_j \leq CR \text{ or } j = j_{\text{rand}}, \\ x_{i,j}^G, & \text{otherwise, } j = 1, \dots, D, \end{cases} \quad (3)$$

where $\text{rand}_j \in [0, 1]$ is selected from $\{1, 2, \dots, D\}$ and the probability of combination is $[0, 1]$. The selection operation is primarily a greedy choice of survival of the fittest and has the effect of placing the children always in a superior or equal position to parents x_i . If the new user's fit function is better than the objective person, the new user interface is taken up. Otherwise, x_i stays in the next generation population and continues to engage in mutation and combination operations as a target in the next iterative calculation. Thus, the population continues to adapt towards the optimal solution. The selection operation serves to minimize the value of the fit function, as can be seen in the following equation:

$$x_r^{G+1} = \begin{cases} u_i^G, & \text{if } f(u_i^G) \leq f(x_i^G), \\ x_i^G, & \text{otherwise,} \end{cases} \quad (4)$$

where $f(x)$ is a fitting function that must be optimized and in this study is used to diagnose coronary heart disease, which will terminate as soon as the condition is found.

Convolution neural network is to be used as a deep learning technique to diagnose and classify cardiac arrhythmias [35]. The features will be in the form of a matrix s , which includes relative frequencies with two signals, one with a gray surface value of i and the other with a value of j that is separated by a distance d and a certain angle θ that appears in the signal. Consider the input signal window as $W(x, y, c)$ for each separate value d and θ , and the input matrix as simultaneously as $s(i, j, d, \theta)$ for the convolution neural network and settings. The general definition is as follows:

- An input to the matrix s contains the number of times that the gray area i is inclined to the gray area j , so that $\mathbf{W}(x_1, y_1) = \mathbf{i}$ and $\mathbf{W}(x_2, y_2) = \mathbf{j}$ and the relation $(x_2, y_2) = (x_1, y_1) + (\mathbf{dcos}\theta, \mathbf{dsin}\theta)$.
- Features of the differential evolution optimization algorithm as inputs in the layer.
- The inputs and neurons of the neural network are convoluted.
- The convolutional neural network has three layers in its hidden or middle layer, which include the torsion layer, the fully connected layer, and the pulling layer, respectively.
- The input of the neural network in the neurons and the input layer is for features extracted features.
- In the torsion layer, a filter should be used in which the weights are set to be $w[0] * x[0] + w[1] * x[1] + w[2] * x[2]$. It should be noted that this filter is in the form of Dilation. The initial weight, which is the content of the filter, will be in the form of a $3 \times 3 \times 3$ matrix, which can be changed in the range of dimensions of the extracted features.

- The nonlinear function, which is the stimulus function applied to the torsion layer, is the sigmoid function.
- The maximum rate of pooling in the pooling layer is used as simple pooling.
- Training in the hidden layers of the convolution neural network is performed in a specific repetition cycle, and if the feature classes are identified, the classification will be performed and the condition will be terminated. Finally, the cardiac arrhythmia diagnosis will be determined from the ECG signal.

In order to apply the lattice, it is necessary to specify the torsions. There are three general methods for this, including thresholding of wavelet coefficients, adaptive filters, and thresholding of the range of action potentials. The approach of this research is to use thresholds from the range of action potentials. By using the following equation, we can find the threshold value [36]:

$$\begin{cases} \sigma_n = \text{median} \left\{ \frac{|x|}{0.6745} \right\}, \\ \text{Threshold} = 3.5\sigma_n. \end{cases} \quad (5)$$

where x represents the recorded of signal by using the microelectrode and σ_n is an estimate of the noise's standard deviation. If a standard deviation of the signal is used, a larger value for the threshold is obtained, and as a result, most torsions will be removed incorrectly. When the threshold selected, the turns are aligned based on their maximum values. Accurate alignment of torsions is a very important and decisive factor in identifying dynamic obstacles with torsions. This network, like all networks, needs training. The purpose of this tutorial is to find a mapping such as $f: R^n \rightarrow R$ in the following equation:

$$f(v) = \sum_i^n w_i \varphi(\|v - C_i\|). \quad (6)$$

Here, $v \in R^n$ is a 32-point vector for input, and the Gaussian basis function $\phi(0)$ is defined in the following equation:

$$\phi(v) = \exp\left(\frac{-v^2}{2\sigma^2}\right). \quad (7)$$

Then, it is necessary to calculate the corresponding error for each training sample from equation slope and for random initial values for weights, for each training sample as expressed in the following equation:

$$e_i = t_i - y_i = t_i \sum_{j=1}^N w_j \varphi(\|v_i - C_j\|). \quad (8)$$

Therefore, the total network error for all training input vectors or P of signal data is equal to $E = 1/2 \sum_{i=1}^P |e_i|^2$. If the error E reaches a lower value than the threshold error, the training ends. This value is set manually at the beginning of the work. Otherwise, the weights are updated using a

gradient slope. After completing the training phase with the multichannel convolution neural network, the ability of each torsion to belong to its class is obtained. It is necessary to specify the structure of the network layering. This layering contains the input layer with the different neurons, where the training operation takes place. This layer contains three internal layers of twisting, pulling, and fully connected. The final test operation is performed on the output layer. The problem of how to detect the absence or presence of coronary heart disease creates a challenge and a search space. In an optimization problem, the absence or presence of a coronary artery with the next N_{var} will be an x_{Nvar} array that indicates the current position for the torsion layer in the convolution neural network. This array is defined in the following equation:

$$\text{Convolve} = [x_1, x_2, \dots, x_{Nvar}]. \quad (9)$$

The appropriateness (or amount of gain) in the current torsion layer is reached by evaluating the coronary heart function (f_p) in the Convolve, which is given in the following equations:

$$\text{profit} = f_p(\text{Convolve}) = f_p(x_1, x_2, \dots, x_{Nvar}), \quad (10)$$

$$\begin{aligned} j(x^{(1)}, \dots, x^{(n)}, \theta^{(1)}, \dots, \theta^{(n)}) \\ = \frac{1}{2} \sum_{(i,j): r(i,j)=1} \left((\theta^{(j)})^T x^{(i)} - y^{(i,j)} \right)^2 + \frac{\lambda}{2} \sum_{i=1}^{n_m} \sum_{k=1}^n (x_k^{(i)})^2 \\ + \frac{\lambda}{2} \sum_{i=1}^{n_u} \sum_{k=1}^n (\theta_k^{(j)})^2. \end{aligned} \quad (11)$$

In fact, the function of the general goal in the part of detecting perturbations or not detecting it is described in equation (11). In general, the above function should be minimized as much as possible to detect coronary heart disease. In fact, a mode of elimination of additional sections is to accurately identify the area in question, which is to minimize the following equation:

$$\min_{\substack{x^{(1)}, \dots, x^{(n_m)} \\ \theta^{(1)}, \dots, \theta^{(n_u)}}} j(x^{(1)}, \dots, x^{(n)}, \theta^{(1)}, \dots, \theta^{(n)}). \quad (12)$$

The structure of the deep neural network used in multichannel convolution is an algorithm that maximizes the coronary heart function presence or its absence. To use a deep multichannel convolutional neural network to solve minimization problems, multiplying a negative sign by the cost function, as in this study, is adequate. For this algorithm, a Convolve matrix of size $N_{pop} * N_{var}$ is generated. A random number of pulling layers are then assigned to each of these convolves. Pooling layers are basically among 2 to 5 items. These numbers are used as the upper and lower limits of the allocation of polishing to each torsion section in the depth of training in different repetitions. Another habit of any convolutional structure based on the deep structure is that they have connected layers in a certain domain. Hence,

the maximum amplitude of the connected layers in the convolution neural network is called $\text{Max}_{\text{Connected Layer}}$. In an optimization problem, the upper limit of the variables var_{high} and the lower limit var_{low} , each depth layer will have a $\text{Max}_{\text{Connected Layer}}$ that is proportional to the total number of layers. The number of current layers of educational data and also the upper and lower limits are the problem variables. Therefore, $\text{Max}_{\text{Connected Layer}}$ is defined in the following equation:

$$\begin{aligned} \text{Max}_{\text{Connected Layer}} = \alpha \times \frac{\text{number of current layers}}{\text{total number of layers}} \\ \times (\text{Var}_{\text{high}} - \text{Var}_{\text{low}}). \end{aligned} \quad (13)$$

Here, α is the variable with which the maximum value of $\text{Max}_{\text{Connected Layer}}$ is set [36]. In equation (13), the layers are θ , and in equation (12), λ is the value of the estimator. Each torsional segment in the deep convolutional neural network travels only $\lambda\%$ of all detected regions to the current ideal target and also has a radian deflection. The data test performed in this layer goes to the output layer and displays any cardiac coronary and then creates classes to display this coronary heart. The summary of the proposed method is shown in Figure 1.

The Harris hawks optimization algorithm can be described as a meta-heuristic algorithm using a group intelligence approach that is modeled on the natural behavior of falcons. This algorithm can be considered delineating a group intelligence behavior with hunting approach. Hawks are able to detect a number of models of how to hunt that are founded on the specific dynamic characteristics of hunting situations and patterns of how their bait tends to escape.

In the proposed method, a feature vector with n components such as equation (14) indicates a member of the HHO algorithm. The values of each feature included are zero and one, which demonstrate a lack of feature selection and feature selection, respectively [9]:

$$X_i = \ll X_i^1, X_i^2, X_i^3, \dots, X_i^n \gg. \quad (14)$$

Here, X_i is a feature vector. The X_i^j is a component j of the feature vector i . Every feature vector has n components, and the feature vector is a binary vector. It is assumed that the objective function for feature selection can be calculated by

$$f = \alpha \cdot \frac{1}{n} \sum_{i=1}^n |\bar{Y}_i - Y_i| + \beta \cdot \frac{F}{A}. \quad (15)$$

Here, Y_i and \bar{Y}_i are the exact and prediction values of a sample, respectively. The parameter " n " represents the number of samples. The values F and A are the features selected and the total possible features, respectively. The coefficients α and β are two random numbers. Values of α and β are between zero and one, and their sum is equal to one. Efforts to minimize the value of the objective function or f to a feature vector are shown. In order to minimize this vector, the HHO algorithm is deployed. In

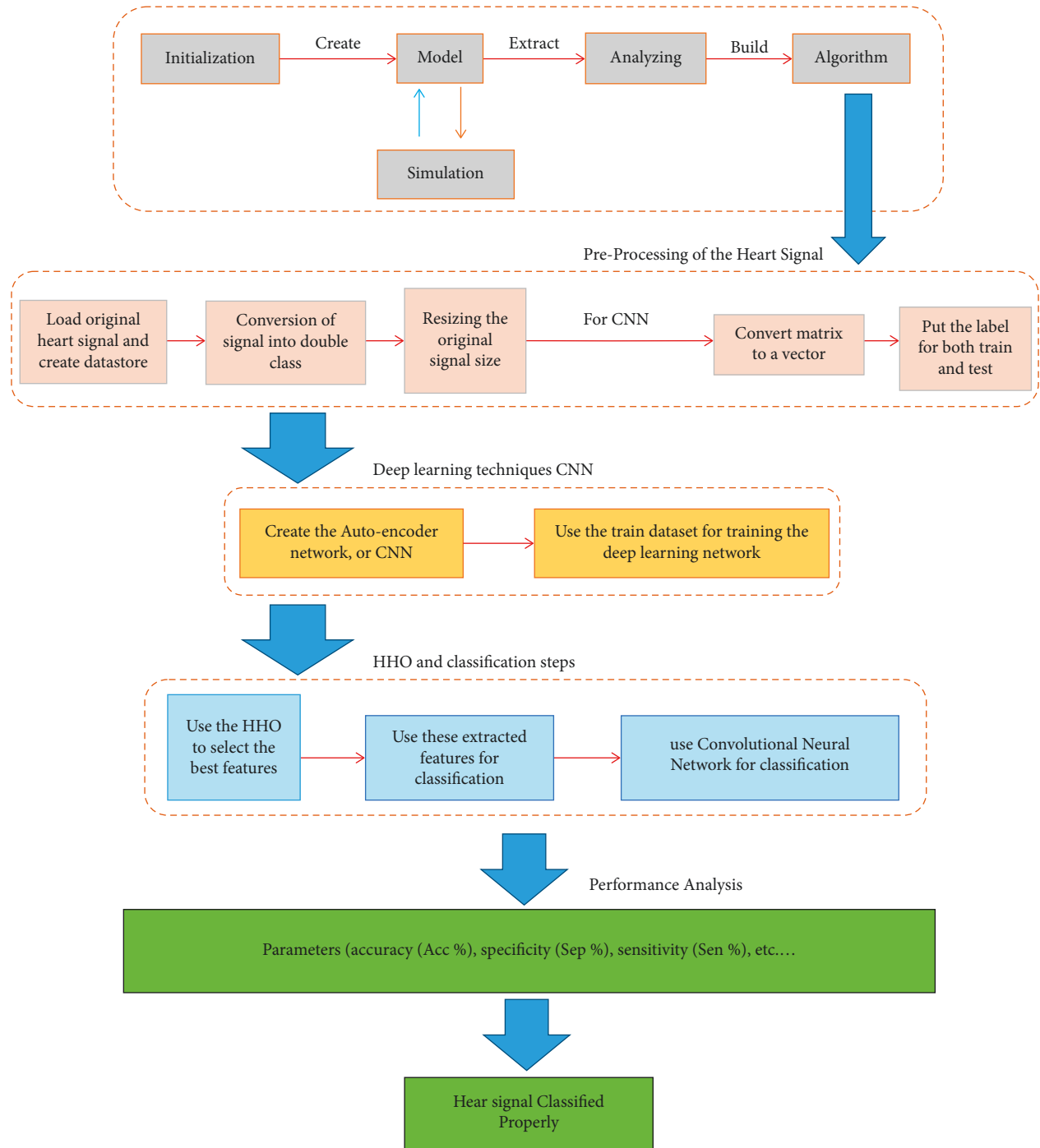


FIGURE 1: Summary of the proposed method for cardiac coronary detection of heart signal.

each iteration, the effort is made to update the feature vectors by this algorithm. After that, the HHO algorithm picks the optimal feature vector and minimizes the value of the objective function. In the method proposed, a number of random feature vectors are at first created as the population of the HHO algorithm; they are then assessed by the evaluation or objective function. The optimal feature vector is shown in each iteration with $X_{\text{rabbit}}(t)$. Equation (16) is employed to update feature vectors with random motions:

$$X(t+1) = \begin{cases} X_{\text{rand}}(t) - r_1 |X_{\text{rand}}(t) - 2r_2 \cdot X(t)|, & \text{rand} \geq 0.5, \\ (X_{\text{rabbit}}(t) - X_M(t)) - r_3 (LB + r_4 (UB - LB)), & \text{rand} < 0.5. \end{cases} \quad (16)$$

Here, $X(t)$ indicates the position of a feature vector in iteration t , while $X(t+1)$ is the position of a feature vector in the new iteration. The value of $X_{\text{rand}}(t)$ is a random position of a feature vector in the problem space. The value of $X_M(t)$ is the point of gravity and the mean of the characteristic vectors, r_1 , r_2 , r_3 , and r_4 , is uniform random

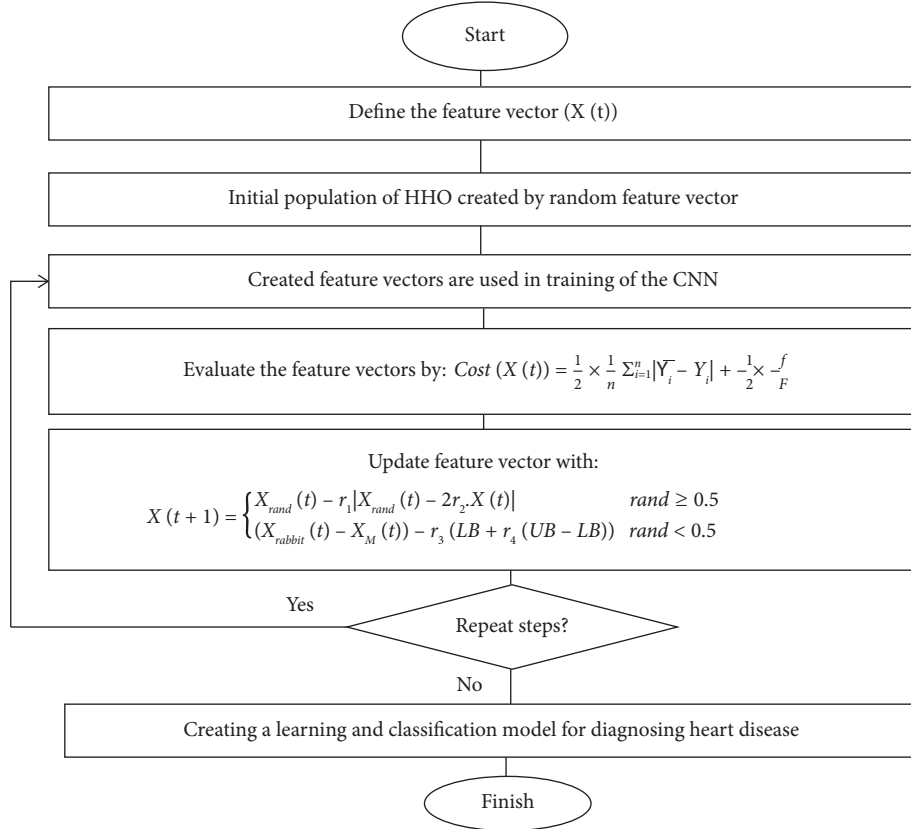


FIGURE 2: Feature selection in blockchain-related blocks.

numbers in the range of 0 and 1. The LB and UB parameters indicate the lower and upper ranges of solutions in the problem space, respectively. The values of the LB and UB parameters of the method proposed are 0 and 1, respectively. Equation (5) thus becomes the following equation:

$$X(t+1) = \begin{cases} X_{\text{rand}}(t) - r_1 |X_{\text{rand}}(t) - 2r_2 \cdot X(t)| & \text{rand} \geq 0.5, \\ X_{\text{rabbit}}(t) - X_M(t) - r_3 \cdot r_4 & \text{rand} < 0.5. \end{cases} \quad (17)$$

In updating the feature vectors under the search agent, the feature vectors are updated in subsequent iterations using a different type of search called a soft besiege, which is exhibited in the following equation:

$$X(t+1) = (X_{\text{rabbit}}(t) - X(t)) - E |J \cdot X_{\text{rabbit}}(t) - X(t)|. \quad (18)$$

Here, J is a random value between 0 and 2. The coefficient E is also a parameter. It is named the energy coefficient and is a decreasing factor in terms of iteration. Another kind of update is based on modeling Harris hawk dives and can be deployed to update feature vectors, whose modeling is shown in the following equation:

$$X(t+1) = X_{\text{rabbit}}(t) - E |X_{\text{rabbit}}(t) - X(t)|. \quad (19)$$

In HHO algorithms, it is possible to update each feature vector with regard to the average population center of gravity or population position, as in the following equation:

$$X(t+1) = X_{\text{rabbit}}(t) - E |J \cdot X_{\text{rabbit}}(t) - X_m(t)|. \quad (20)$$

Through the deployment of these relationships, the feature vectors are updated in every iteration with the aim of diagnosing the disease. In the last iteration, the most optimal feature vector is deployed to decrease diagnostic errors with regard to the disease. In the method, each Harris hawk is a feature vector and comprises components 0 and 1; these show the lack of feature selection and feature selection, respectively. The rabbit refers to the optimal feature vector. The objective function assesses each of these feature vectors, alongside errors in diagnosing the disease and the number of features. Figure 2 provides a feature selection flowchart that uses the HHO algorithm to diagnose heart disease in each treatment center.

4. Simulations and Results

In this article, the SLPDB dataset has been used. This dataset, also known as the MIT-BIH polysomnographic, is a collection of physiological signals recorded by real people in different situations. This dataset has been monitored and collected from individuals in the Israeli Idol Laboratory and Hospital in Boston, USA, to evaluate cardiac arrhythmias, coronary heart disease, sleep apnea syndrome, cardiac signals, and a number of known chronic diseases and heart problems and is used to effectively test continuous positive airway pressure. The

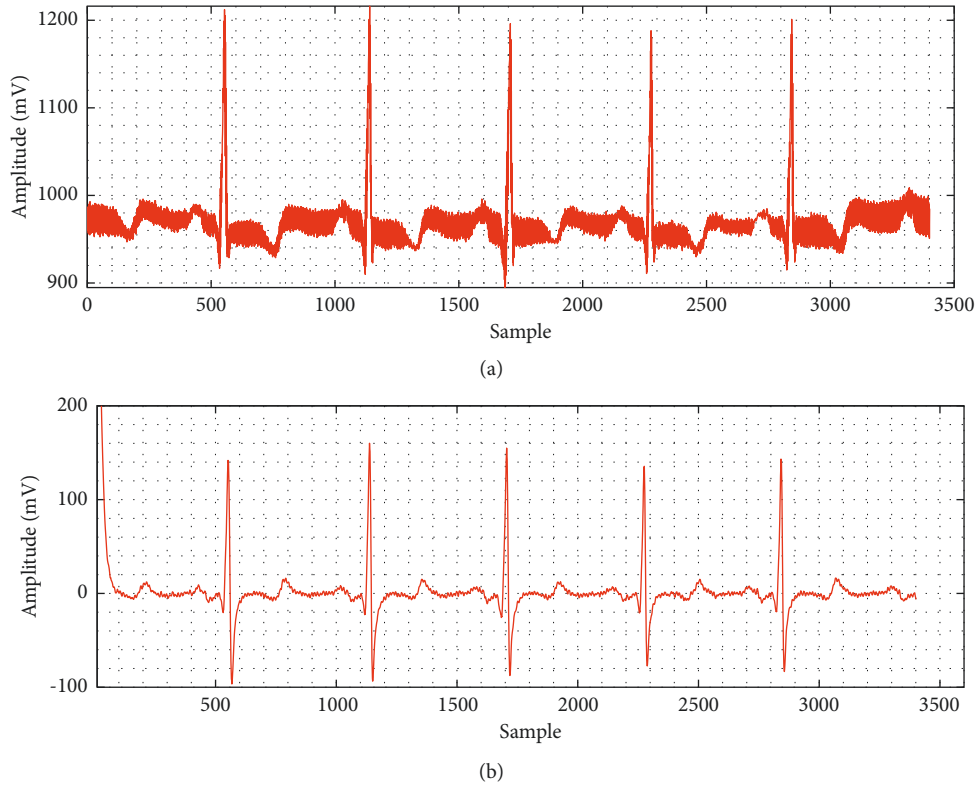


FIGURE 3: (a) Raw ECG input signal and (b) ECG signal with intermediate filter to eliminate possible noise.

dataset has 80 hours of 4-to-6 values and 7 polysomnographic channel recordings, each with an ECG and even EEG signal used to determine different purposes. This study uses ECG signals as its dataset. This dataset is used in a normalized way, which will use the ECG part of the mentioned dataset signals. The input signal is shown in Figure 3(a). Figure 3(a) shows the raw input signal, and the ratio of the amplitude to the sampling rate is displayed when the signal is displayed in full. Initially, in order to eliminate possible noise, an intermediate filter is used, which is in the form of the following equations:

$$W_1 = \frac{(1 \times 2 \times \pi)}{360}, \quad (21)$$

$$W_2 = \frac{(13 \times 2 \times \pi)}{360}. \quad (22)$$

In fact, the frequency of the input signal f is $1 < f < 13$. Figure 3(b) shows the filtered signal.

It is noteworthy that the convolutional neural network is used as the main technique for deep learning in this study. In fact, the data are trained in the neural network so that later, with the arrival of new data with common features of the same dataset used and trained, the arrhythmia diagnosis operation can be considered. For this purpose, it is necessary to identify the features simultaneously in both the training and testing phases. The convolution neural network, in addition to classification,

also of course performs feature extraction operations, but its feature extraction structure is random. Therefore, it creates a search space for the optimization of the ECG signal, which is repeated over and over again. Data training in the convolutional neural network is performed from the differential evolution optimization algorithm for the optimization of feature extraction operations in the training phase and before classification with the aim of diagnosing cardiac arrhythmias. It is noteworthy that the results of differential evolution are presented when reviewing the results of evaluation criteria as well as general comparison. Since the proposed approach is a combination of convolutional neural network and differential evolution optimization algorithm, the results are examined. The problem of detecting cardiac arrhythmias from ECG signals creates a challenge and a search space. In an optimization problem such as diagnosing a cardiac arrhythmia with two-dimensional N_{var} , an array $x_{N_{\text{var}}}$ would represent the current position for the torsion layer in the convolution neural network. It is assumed that the signal dataset is M , which represents the number of training signals, F_i mean of the signals, and L_i of each signal from the T_i vector. Initially M has a number of signals, each signal containing a $M \times N$ matrix. Each signal can be displayed in N -dimensional space, which is $A = N * N * M$. Signal averaging is calculated in equation (23), and finding standard deviation during training and testing of data in the convolutional neural network is calculated in

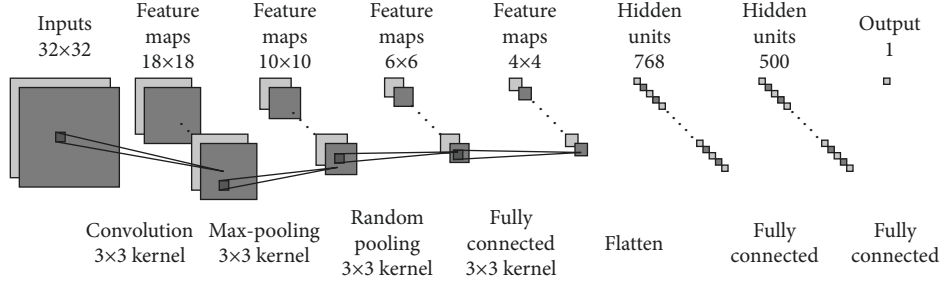


FIGURE 4: Multichannel convolution neural network architecture considered in this research after the completion of the final model.

$$Fi = \frac{1}{M} \sum_{t=1}^m Tt, \quad (23)$$

$$\text{variance} = \frac{1}{M} \sum_{t=1}^m Tt. \quad (24)$$

In the above two equations, Tt is the training part of the data that is located in the convolutional neural network. Covariance must also be calculated in signals, which is in the form of the following equation:

$$\text{Cov} = AA^T, \quad (25)$$

where $A = \text{Variance}_1, \text{Variance}_2, \dots, \text{Variance}_n$ and $\text{Cov} = N^2 * N^2$ are matrices. Because $A = N^2 * M$ is a matrix, Cov is a huge value. Now special values of Cov are obtained using the following equation:

$$U_i = AV_i. \quad (26)$$

To eliminate layers located in inappropriate areas of signals (with cardiac arrhythmia features), due to the fact that there is always a balance between layers in neural networks, a number like N_{\max} manages and limits the maximum number of layers in an environment. This balance exists as a result of the limitations of layers, torsion, and the impossibility of finding interconnected layers suitable for educational data. The convergence of the algorithm, after a number of iterations of the whole data population, achieves an optimal point with maximal similarity of the features to the signals, as well as to the location of the largest feature area. This location has the most general features, and the fewest number of connections are lost. The convergence of more than 95% of all connections at one point completes the proposed algorithm. In general, the convolutional neural network architecture considered in this research is shown in Figure 4.

Different input sizes are evaluated and tested, and the best one was 32×32 size that this scenario is shown in Figure 4. According to Figure 4 and the architecture presented for a multichannel convolution neural network in this study, the layers and their number are determined. Initially, 32 primary neurons are considered in the input layer, which includes all the features of cardiac arrhythmias. There are settings in the hidden layer section, which has three main sections in the convolutional neural network: twisting, pulling, and fully connected. The sum of

these layers is 4 items, so as to create a 3×3 torsional matrices. There is also a 3×3 matrix in each of the 4 layers. The torsion layer is a single layer, and the pulling layer consists of two layers, one part of which is considered a maximum or the so-called maxpol and the other part a random pulling that can train each of the features randomly. It is observed that there is a torsion layer, two pulling layers, and also a fully connected layer, and the output layer includes any movement based on the detection of cardiac arrhythmias that occurs in a part of the signals. There is a problem called centroid, which is considered in the principles of classification and even clustering to perform detection and tracking tasks. When windowing, the structure is basically individual, that is, 3×3 , 5×5 , 7×7 and similar values. The reason for this is that a cell or pixel is placed in the middle, and the adjacent cells are analyzed and that central pixel is considered the center or centroid. The general structure and parametric calculations in the convolutional neural network are as follows:

- The input layer has nothing to learn. At core, it provides the basic input data format. There are thus no learnable parameters here, so the number of parameters is zero.
- Conv is where the neural network learns convolution, so the matrix will certainly weigh. To calculate the learnable parameters, what needs to be done is simply to multiply the height n by the width m and to calculate this for all of these filters. The parameters of a Conv layer can be $((m \times n) + 1) \times tk$. Due to bias, one unit has been added for every filter. It is possible to write the same phrase as follows:

$$((\text{filter width shape} * \text{filter height shape} + 1) * \text{number of filters}). \quad (27)$$

- The pooling layer does not have any learnable parameters, since its only role is to calculate a specific number, without the need for diffuse learning. Therefore, the number of parameters is zero. Note that it is in this layer that the windowing operation is determined. There are also two modes in it. One is that the upper limit is equal to 1, and the lower limit is equal to zero, in which case the mechanism is maxpool, while if the upper limit is zero and the lower limit is equal to one, the mechanism is minpool. There is also a random structure in it.

TABLE 1: The values of the operators of the differential evolution algorithm.

Primitive population	360
Number of alleles	13
Combination rate	0.2
Leap rates	0.02
Selection method	Random
Core of improvement in education	Learning covariance and two-dimensional distribution of parameters
Number of repetitions	100

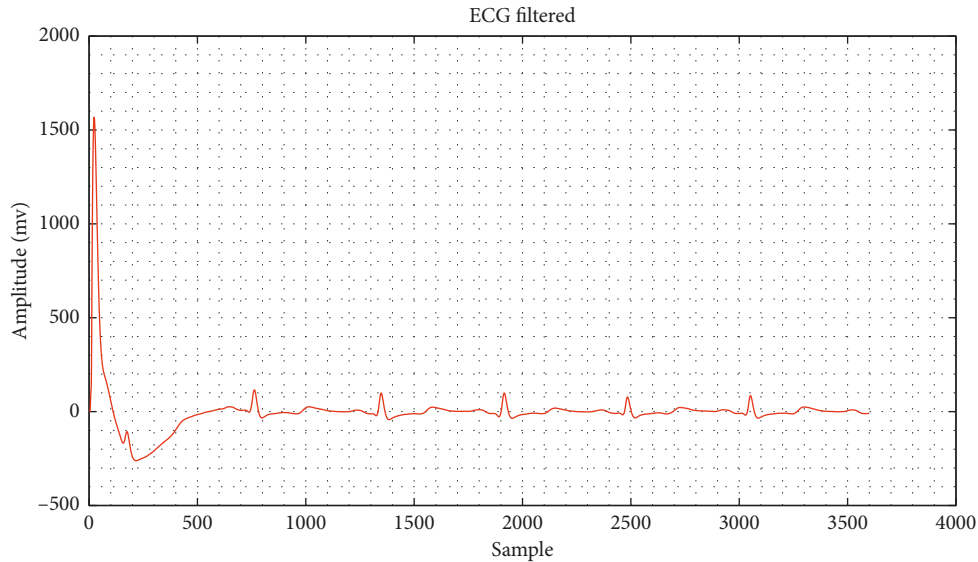


FIGURE 5: Primitive population of differential evolution on signal.

- (d) The fully connective layer definitely has learnable parameters. Compared to the other layers, these layers in fact have the greatest number of parameters, because every neuron is linked to every other neuron. The question that arises is how can the number of parameters be calculated here? The answer is clear. The product of the number of neurons in the current and previous layers must be considered. Therefore, the number of parameters here is as follows:

$$((\text{current layer } n \times \text{previous layer } n) + 1). \quad (28)$$

Plus 1 is for bias. In the first layer of training, the sigmoid or Tansig tangent transfer function is used, while in the second layer, the linear transfer function or Purelin is used. There will also be an output at the end.

The training method in the convolution neural network must also be clear. Here, the Levenberg–Marquardt method is used, which is known as `trainlm` in MATLAB. The efficiency of the neural network should also be measured and evaluated in a method during training, where the method of mean squared error is used. The method of calculation and derivation is also considered MEX, that is, additive.

The average signal limit is 56. Now the differential evolution algorithm comes into play with its operators that detect cardiac arrhythmias. In fact, the previous operation

this time occurs employing the differential evolution algorithm operators. The values of the operators of the differential evolution algorithm are given in Table 1.

Considering the values of differential evolution algorithm operators that have been set experimentally, and based on the initial explanations of the manufacturer of this algorithm, the overall goal of this algorithm is to improve the extracted features. For this purpose, the initial population of the differential evolution in the signal is shown in Figure 5.

Arrhythmia diagnosis and its characteristics are then performed according to the amplitude and middle filtration of the initial signal population. The output is indicated in Figure 6.

Then, the raw signal after the operation with the multichannel convolution neural network for classification (blue part) with the signal on which the mutation operation took place, and in fact the simultaneous filtering with the differential evolution algorithm in the feature extraction phase (red part) is shown. The output is given in Figure 7.

Figure 7 shows the amplitude in time (seconds), and this indicates that the filtered signal has a greater improvement than the raw input signal. Then, the combination operation is performed, which separates the signals and its output is Figure 8.

Finally, the differential evolution algorithm operators show that cardiac arrhythmias exist in 6 regions of the signal extracted from the multichannel convolution neural

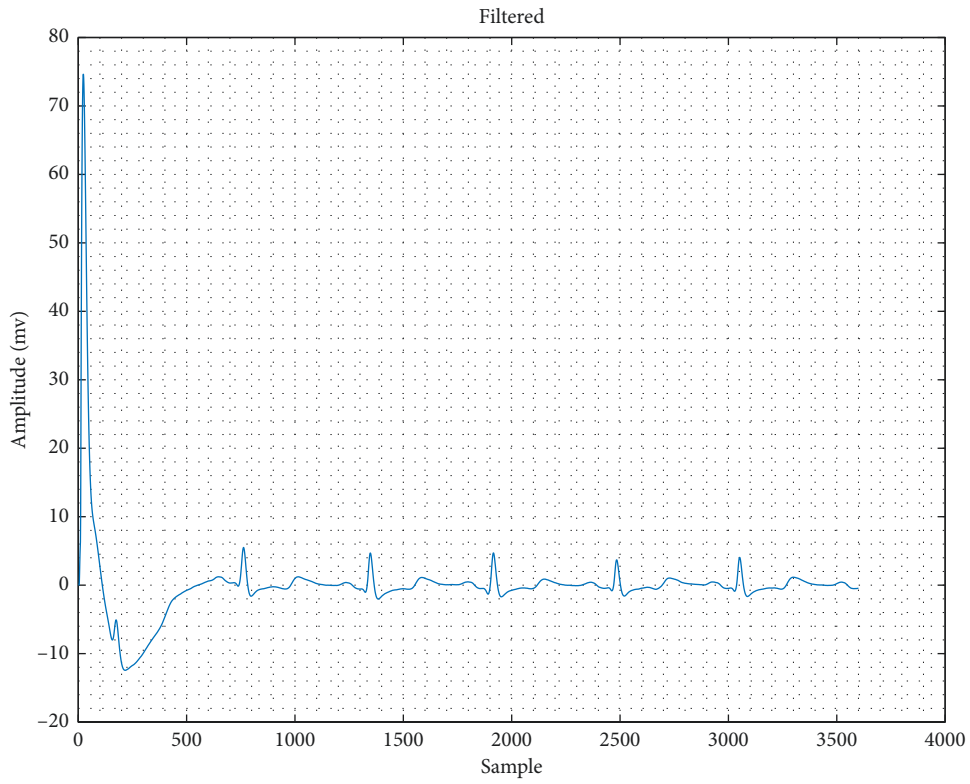


FIGURE 6: Arrhythmia detection with respect to amplitude and median filtration of the initial signal population.

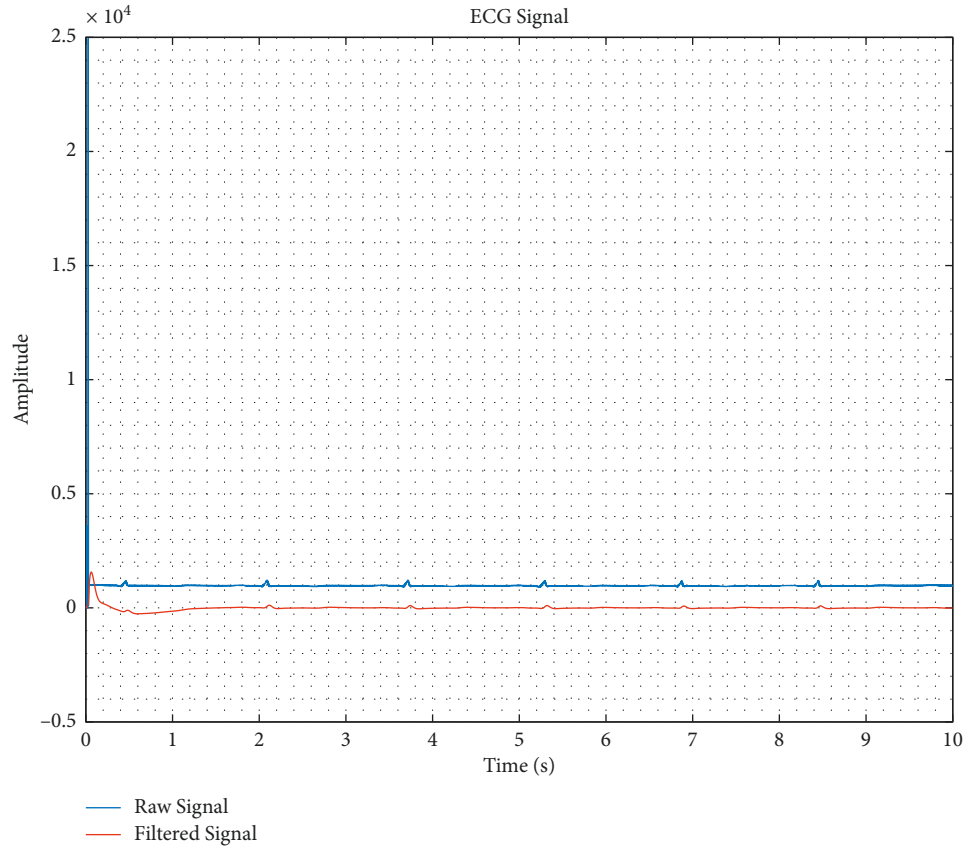


FIGURE 7: The signal from the classification and extraction of the feature (blue section) with the mutant signal.

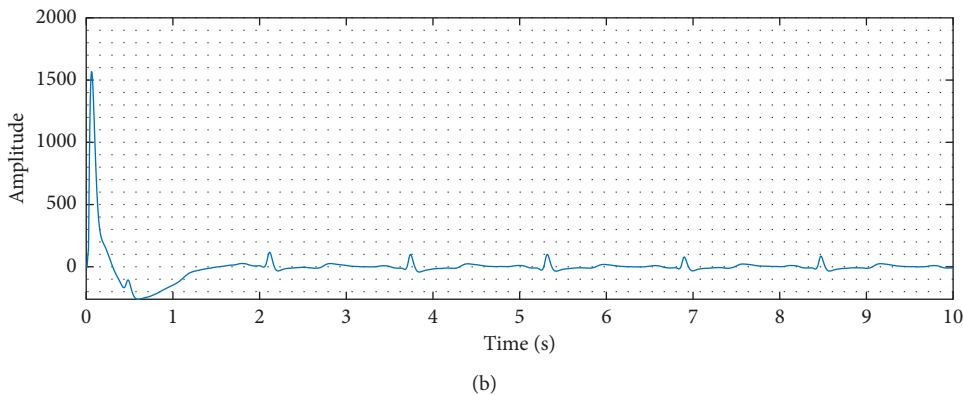
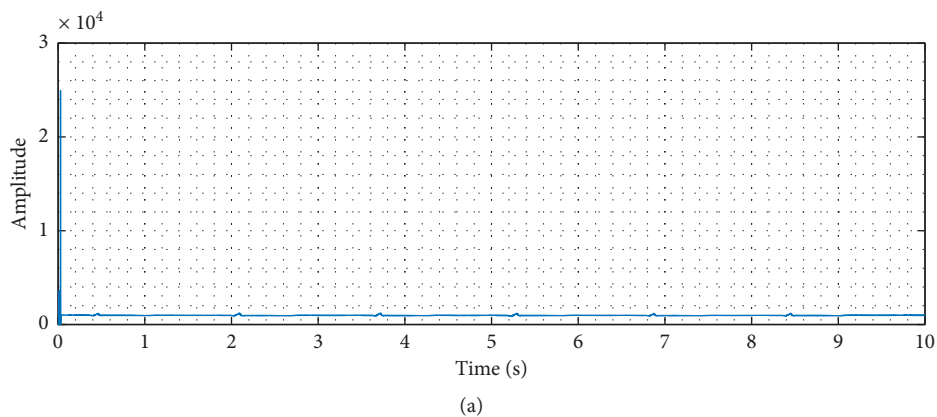


FIGURE 8: Combination operation to separate signals. (a) Raw signal and (b) filtered signal.

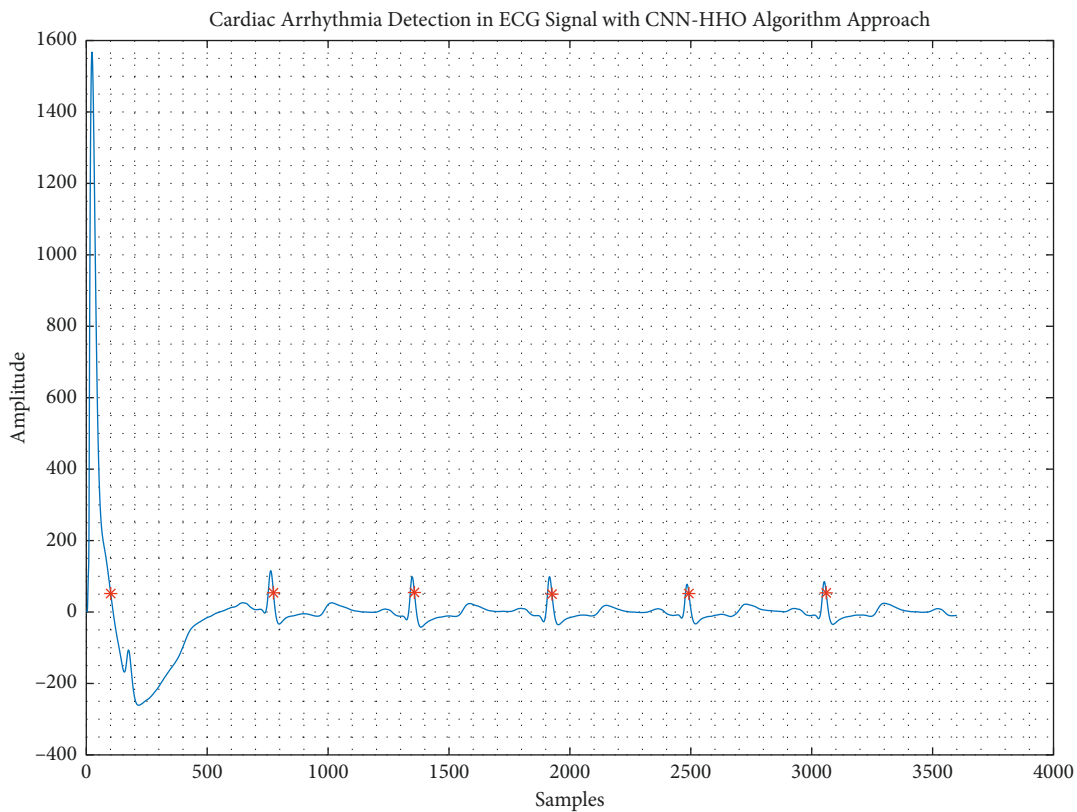


FIGURE 9: Six regions of cardiac arrhythmia.

TABLE 2: Evaluation results with different algorithms.

Method	Average squares error	Peak signal-to-noise ratio (dB)	Signal-to-noise ratio (dB)	Features rate (%)	AUC
BN	0.02	9.17	10.97	84.29	0.92
MLP	0.07	10.82	9.66	83.81	0.90
AdaBoost	0.08	13.13	7.99	81.03	0.87
SVM	0.13	15.50	6.48	82.98	0.83
Random forest	0.20	16.80	5.75	83.90	0.80
Decision tree	0.27	23.36	3.02	80.56	0.68
DL-based HHO	0.02	5.42	14.21	72.52	0.95

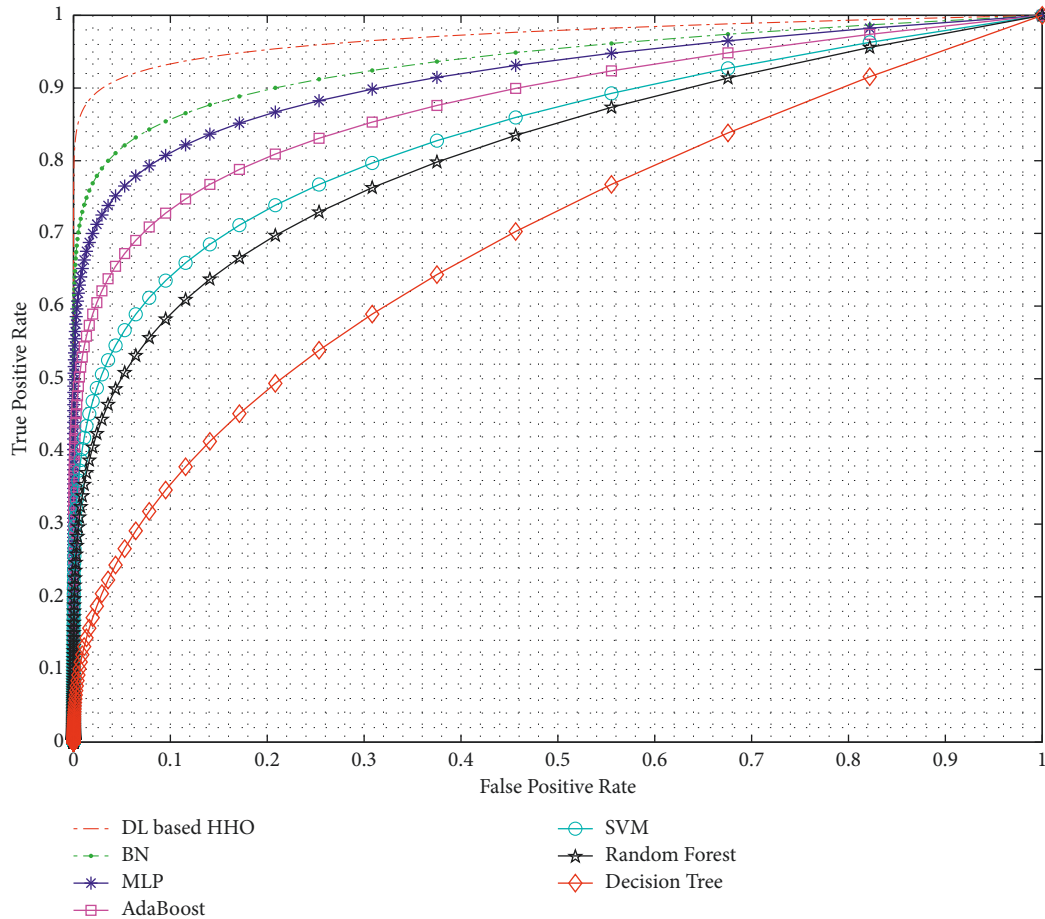


FIGURE 10: ROC diagram and observation of AUC numerical result.

TABLE 3: Results of evaluation of the method proposed with two other methods.

Reference	Accuracy (%)
Acharya et al. [29]	93.18
Yao et al. [37]	92.97
Proposed method	94.02

network test and then improve the signal tags to select the optimal features with the differential evolution algorithm and are shown in Figure 9 marked in red.

Figure 9 shows the amplitude at the sampled rate of the signal after the operation, which first shows the condition of the signal and then in a certain range, examines the

cardiac arrhythmias, and marks them in red. The fact that the signal has reached such a range in terms of sample rate is based on the differential evolution algorithm. It should be noted that the use of bpm with a value of 99.9722 was the output. In this research, several evaluation criteria have been used, which include the signal-to-noise ratio, peak signal-to-noise ratio, mean squared error, accuracy, sensitivity, feature rates, and ROC diagrams. The results of the evaluation are given in Table 2, and the ROC diagram is given in Figure 10.

In the following, a case comparison has been performed according to the accuracy evaluation criteria in terms of percentage between the present research and references [29, 37], the results of which are shown in Table 3.

TABLE 4: Comparison of accuracy, sensitivity, and precision of the proposed method and other methods in diagnosing heart disease.

Method	Accuracy	Sensitivity	Precision	Recall	F1 score
MLP	91.50	90.69	91.55	92.62	91.30
SVM	86.28	86.17	88.99	89.17	88.81
Decision tree	78.98	63.18	93.22	94.01	92.81
RF	82.32	76.12	88.12	87.13	86.29
AdaBoost	87.23	84.27	88.27	87.37	88.26
BN	93.00	91.86	94.10	92.98	93.03
DL-based HHO	95.00	96.04	93.94	94.99	95.03

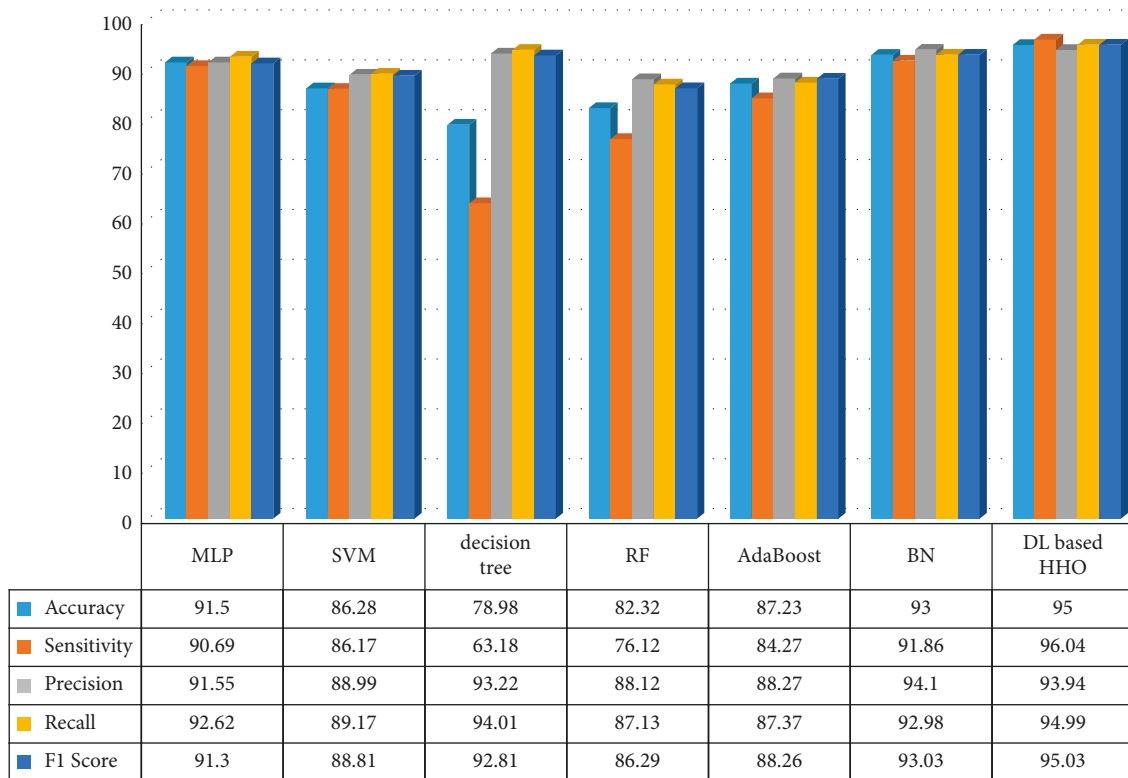


FIGURE 11: Graphical illustration of the comparison results.

The method proposed demonstrates good results in the evaluation criteria as well as the detection of points with cardiac arrhythmia from the ECG signal. It also had a better accuracy in diagnosing cardiac arrhythmias than the previous two similar methods. According to Table 3, a comparison can be considered scientific and practical if it has been done in the same conditions of data sets and the same features have been considered. This has been the case in two previous studies, [29, 37].

Table 4 compares three indicators for the diagnosis of heart disease using the proposed method and other methods, accuracy, sensitivity, and precision. The diagrams shown in Figure 11 compare the accuracy, sensitivity, and precision index of the proposed method and other methods.

The experiments demonstrated that the accuracies of the artificial neural network, support vector machine, decision tree, random forest, AdaBoost, Bayesian network, and DL-based HHO were 91.50%, 86.28%, 78.98%, 82.32%, 87.23%, 93.00%, and 95.00%, respectively. In terms of the methods compared, the DL-based HHO method was most accurate,

while when feature selection was used with the HHO algorithm, the accuracy increased to 95.00%.

5. Conclusion

There has been an extensive study of automatic arrhythmia detection using ECG in recent decades. The continuous updating and refinement of ECG databases that are openly available, such as MIT-BIH or SLPDB, has made heart rate analysis available from the ECG. There are many methods for distinguishing between heart rates in five different classes, including normal ectopic, extracerebral, ventricular ectopic, fusion, and unknown beat, identified using the AAMI standard in which the waveform of the heartbeat can be distinguished. This research has tried to provide an intelligent medical diagnosis system using valid SLPDB data. The structure of this method is that ECG signal data are first entered into the program. Then, simultaneously, the convolution neural network as a deep learning technique [38], feature extraction operations based on a differential

evolution optimization algorithm, and classification with the aim of detection were carried out. The results demonstrate that the proposed approach improves the accuracy in percentage terms in the diagnosis of cardiac arrhythmias compared to previous methods. This study considers three general algorithms for coronary heart disease detection, which include the deep convolutional neural network based on the HHO algorithm, deep convolutional neural network based on the genetic algorithm, and deep convolutional neural network based on the differential evolution algorithm. Different criteria were used to assess the accuracy of the approaches and to compare them with each other under the same conditions (using the same set of data and the same parametric rate with different operators). The most important criteria are the accuracy, sensitivity, and rate of features, which for the proposed methods include 95.00%, 96.04%, and 93.94%, respectively. For the sensitivity section, it is also equal to 96.04%, 95.54%, and 96.34%. Feature rates are 82.23%, 82.16%, and 82.41%. In addition, two main articles presenting a method that was based on artificial neural network [29] and using the deep neural network [37] have all the convulsions for diagnosing cardiac arrhythmias with the data of the same study. Their results are 93.18% and 92.97% for accuracy, respectively. The approach proposed in this research (called the deep convolution neural network based on the HHO algorithm) with 95.00% accuracy compared to the two references [37] was associated with an improvement of approximately 0.86% and 1.22%. One of the most important obstacles in front of this research is lack of more data or clinical data in the country, so the work is presented in a research context. Powerful systems are also needed for large-scale data processing called big data.

Data Availability

No data were used to support this study.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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