



Examination of the ECG signal classification technique DEA-ELM using deep convolutional neural network features

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Received: 31 March 2020 / Revised: 15 October 2020 / Accepted: 5 January 2021 /

Published online: 12 April 2021

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Abstract

The accurate separation of ECG signals has become crucial to identify heart diseases. Machine learning methods are widely used to separate ECG signals. The aim of this study was to obtain optimal number of hidden neurons of the Extreme Learning Machine (ELM) using the differential evolution algorithm (DEA) and increase the accuracy rate of ECG classification. In this study, a public database on PhysioNet was used for ECG signal classification. A deep feature method using convolutional neural network was used to extract the major features of the ECG samples. Then, a conventional ELM was applied to the ECG signals. Subsequently, the ECG signals with deep properties were shared with the MATLAB classifier toolbox (k-NN, SVM, Decision Trees). In addition, the ECG signals in the dataset were tested using the Genetic Algorithm Wavelet Kernel-ELM (GAWK-ELM). Finally, the DEA-ELM was improved for the determination of the number of hidden neurons. This study optimized the hidden neuron numbers of traditional ELM with DEA using deep learning capabilities in the feature extraction. The aim of was to maximize the best cost of the DEA and achieve the optimal number of hidden neurons in ELM. Accuracy (Acc), sensitivity (Se), specificity (Spe) and F-measure were used as the performance metrics for the classifier performances. The classification results were 80.60%, 81.50%, and 83.12% with SVM, ELM and DEA-ELM, respectively. Thus, the best classification scores were accomplished with an accuracy of **83.12%** with the algorithm supported by the DEA.

Keywords Convolutional neural network · Deep features · Differential evolution algorithm · Electrocardiogram · Extreme learning machine

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1 Introduction

Electrocardiogram (ECG) is the signal that represents the activity of the human heart. ECGs are comprised of various important sections. Figure 1 shows a typical ECG signal [17, 47, 54, 58]. During atrial depolarization, the P wave occurs. Subsequently, the QRS wave occurs in the heart [17, 58]. The movement of the ECG signal has become a significant parameter for defining heart diseases. [22, 38]. The diagnosis of heart diseases at the right time is a very important issue in treating cardiovascular diseases [43]. In particular, attempts have been made to develop powerful computer based algorithms to identify heart disorders using ECG recording classification [50]. Scientists have developed many methods to classify ECG signals. Some of these methods include wavelet transform [52], radial basis function [37], multi-layer perceptron (MLP), support vector machine (SVM) [35], extreme learning machine (ELM) [33] and deep feature learning based method [55]. Deep learning is a new method that has been used in many studies in the literature for Image classification [41], biomedicine applications [8, 20] and agriculture [30]. Deep learning structures are multi-layered and include many parameters. The most commonly used architectures in the literature are automatic encoders and convolutional neural networks (CNNs) [48]. CNNs are well-known deep learning structures and are comprise of two parts. In the initial section of CNN, feature subtraction is applied to

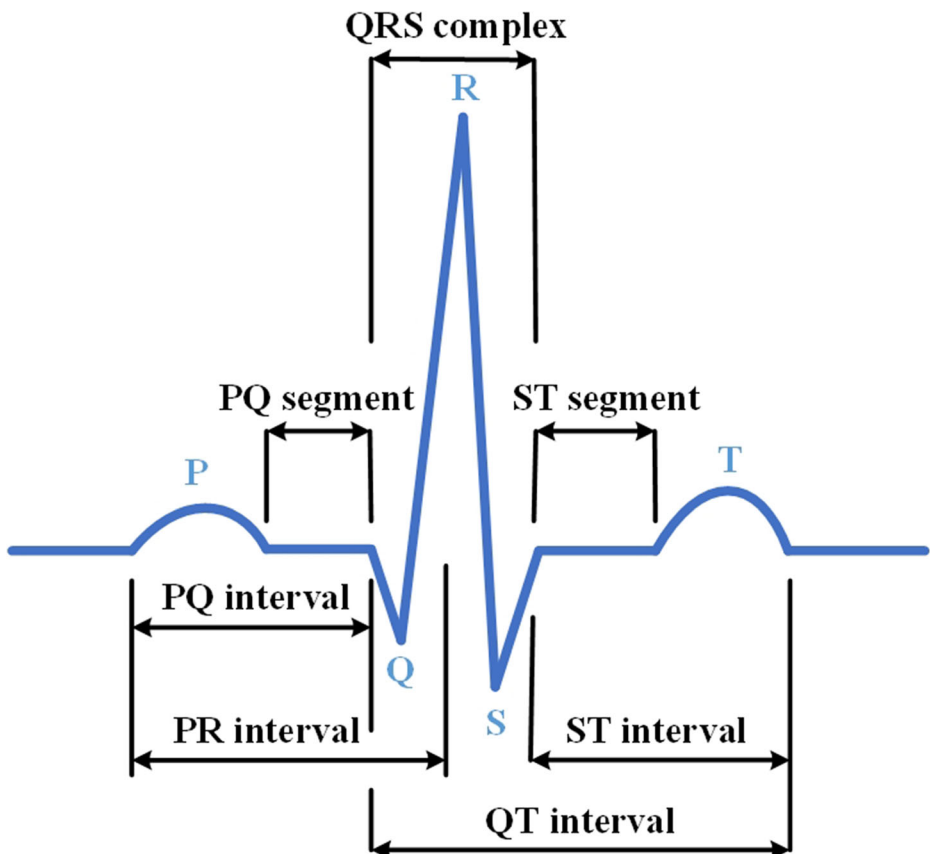


Fig. 1 A typical ECG signal and important sections

the input data [48, 19]. CNN is principally successful in image processing applications [25, 59, 62].

ELM's have been used in many areas including ECG signal classification and EEG signal classification owing to their impeccable properties such as quick learning and generalization [6, 28, 29, 57]. However, they have several problems including the presence of local minima's, indefinite learning rate, selection of the number of hidden neurons (NHN) and overfitting [56]. To solve these problems diverse methods with global search capabilities such as differential evolutionary (DE) [26, 61], PSO algorithm (classification performance of ECG signals accuracy of 89.72%) [44], GA algorithm (classification performance of radar signals accuracy of 95.50%) [4], ACO algorithm [9] and ABC algorithm [23] have been developed. Clustering Algorithm [11], Intuitionistic Fuzzy Rough Set Technique [10], Segmentation and Feature Extraction method in medical imaging [13], Intuitionistic Possibilistic Fuzzy C-Mean Clustering Algorithm [12], Digital Mammography [14], Heart Disease Diagnosis Using Rough Set and Cuckoo Search Technique [1], Formal Concept Analysis [60] can be added to these publications. ECG signals, which can be normal or abnormal, are very critical in making an accurate diagnosis. Thereby, computer-aided ECG analysis has a considerable role in detecting heart disorders. In this study, the impact of the differential evolutionary extreme learning machine based (DEA-ELM) technique was examined to determine ECG signals as normal and abnormal.

The novelty of the technique proposed in this study is that it uses the most appropriate NHN values, which are determined using the DEA optimization technique to overcome the setbacks of ECG classification (e.g. election of the NHN) with ELM. In addition, as accurate attribute extraction is required to determine the signals as normal and abnormal. In this study, CNN, which is based on the deep learning techniques of the ECG samples, was used for attribute extraction. Moreover, in this study, the efficiencies of several machine learning techniques were examined. The principal objective of this study was to ensure the enhancement of classification efficiency and decrease the mentioned problems of ELM to accurately separate the ECG signals as normal and abnormal using DEA. In this study, a method offering the following advantages was proposed to be used instead of traditional ELM:

- a) The DEA-ELM, which is used in a process to separate normal and abnormal samples, has a better classification accuracy than the ELM owing to the improved NHN.
- b) This process, which is carried out using DEA, is used to adjust the most optimal efficiency separating the samples as normal and abnormal.

The paper is organized as follows: in Section 1 the collection of the ECG signals is presented. In Section 3 the results of the ELM and DEA-ELM studies used in ECG classification are given. In Sections 4 and 5 the discussions and conclusion are presented.

2 Data collection and techniques

The diagram of the proposed classification method is presented in Fig. 2. This technique can be separated into four parts. Primarily, ECG samples are attained through the PhysioNet. This step is consists of two parts, as baseline-wandering and remove 60 Hz interference. After preprocessing steps, ECG signals which are acquired from Physionet were converted to image

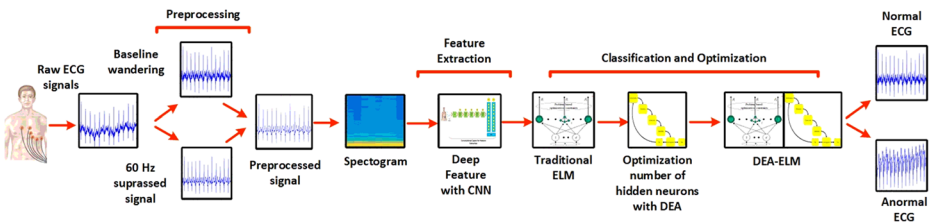


Fig. 2 The block schema of the recommended system

using a spectrogram. The next process of the schema is attribute extraction that deep features are attained from CNN. The other step of the recommended system is an improvement that is optimized of a NHN of ELM and, is the last stage which is samples separated as normal and abnormal.

2.1 Dataset

In this study, to determine the adequacy of ELM, PTBDB heart records, which were available on the Physionet, were utilized [24]. A total of 549 ECG samples and samples of signals records were collected from 294 contributors. Roughly 20% of the contributors comprised the healthy samples. The record samples include healthy and different abnormal varieties as indicated in Fig. 3.

A preliminary study was conducted on healthy and MI signals. As a result, 112 MI and 48 healthy signals were selected. Furthermore, in this study, all of the ECG samples were achieved through lead II on the database as shown in Fig. 4.

2.2 Pre-processing

Noise and interference, which increase waves, are unwanted in applications. ECGs have a significant number of interferences, thus the preprocessing stage is important for the classification operation in computer-aided methods [15, 18]. In addition, a normal analysis is carried out with many applications by achieving noiseless clean samples. ECGs contain different kinds of disorderliness including a fundament origin period and device parasites. Using the symlet filter wavelet transformation and denoising operation baseline navigation was adjusted. On the other hand, line parasites and system parasites were decreased in this step. Then, the

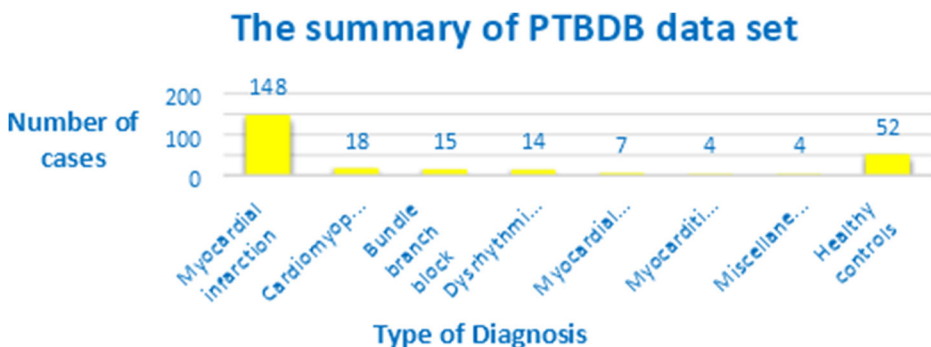


Fig. 3 Cases of the PTB dataset

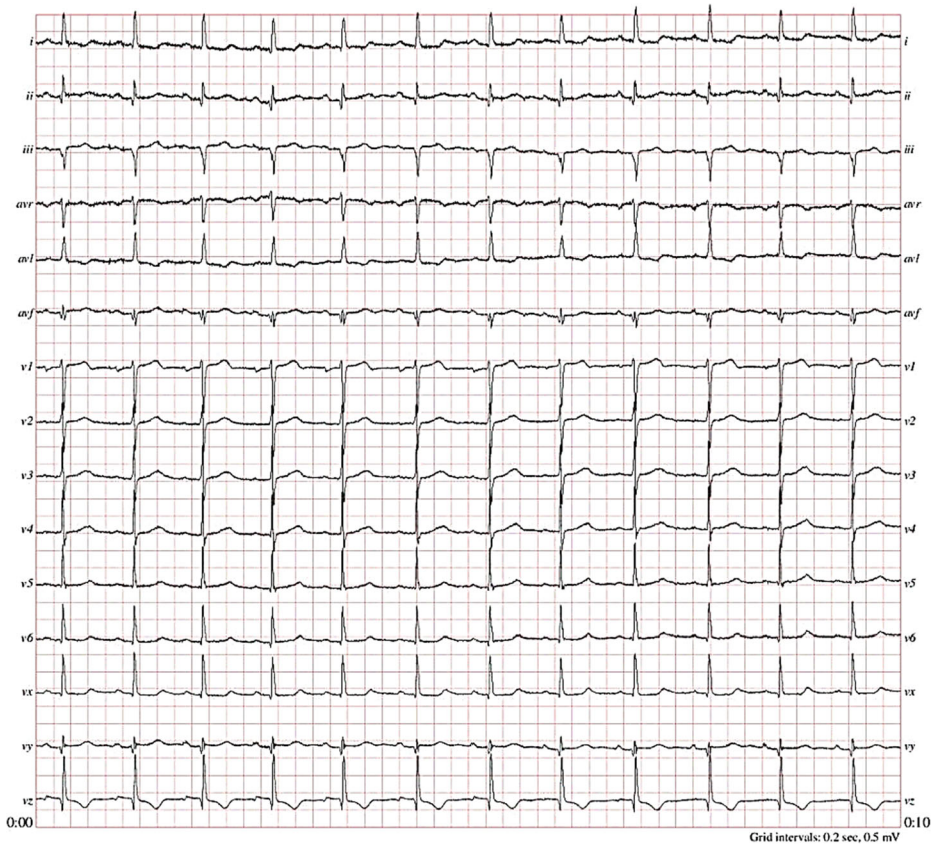


Fig. 4 Heart recording withal number s0001_re

parasites proceedings on the ECG samples were appeased by employing the Savitzky-Golay filter, which is given in Fig. 5.

2.3 Feature extraction

Feature extraction is a major operation in the classification process. After the pre-processing, it is required to take out the attributes of the ECG samples. In this study, the deep features were obtained by using CNN. Within this context, AlexNet, a CNN structure, was used.

2.3.1 Convolutional neural network structure

CNNs are type of multi-layer sensors [48]. CNN, which is considered to operate data in multiple arrays, has become a popular technique because of its working dexterity in image attribute subtraction [49]. CNNs are comprised of a lot of layers as shown in Fig. 6. All layers consisted of three layers, namely characteristic pooling layer, the filter bank layer, and the non-linear layer. There are a lot of kernels in the filter bank on account of other attribute subtractions.

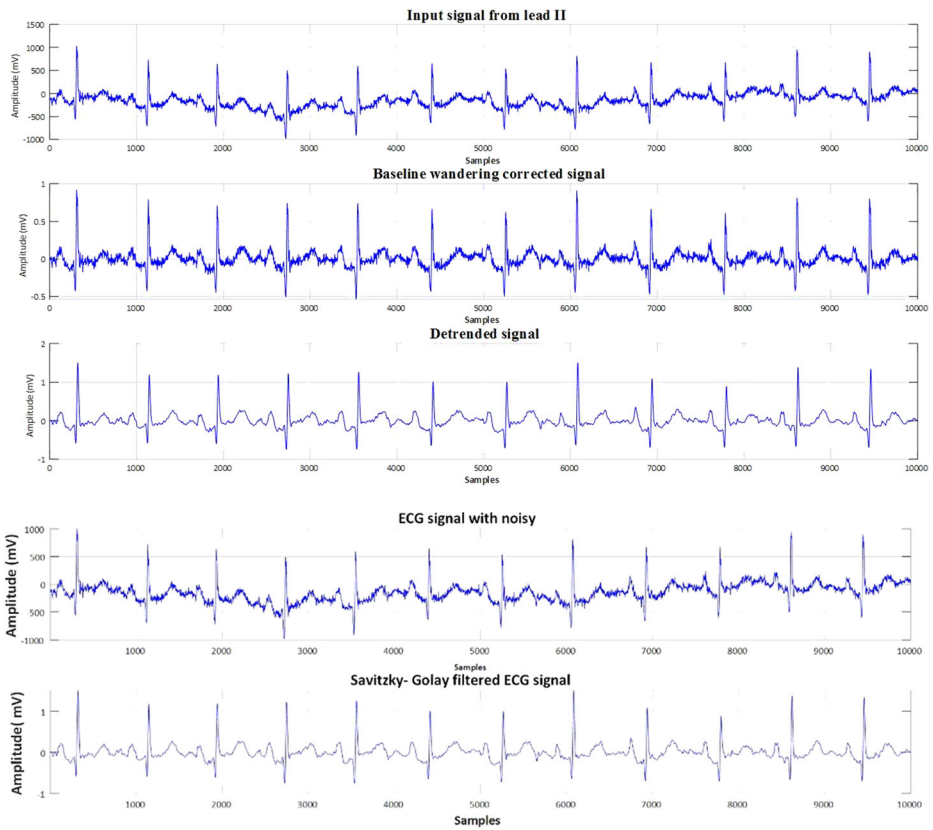


Fig. 5 (i) Preprocessed ECG sample (ii) Savitzky-Golay performed ECG sample

In the pooling layer, all attribute maps are operated one by one. Every map ensures the mean or maximum value of the contiguous value [48].

2.3.2 Layers used in CNN structure

In this study, AlexNet, which is a CNN architecture, was used to take out the features. The convolution layers in the AlexNet embody the Input-Convolution-ReLu-Pooling-Fully connected layers. The Rectified linear unit (ReLU) used in the AlexNet architecture is the activation function that has a very fast learning speed. ReLU has a higher performance than sigmoid and tanh, both of which are other activation functions. The ReLU activation function fulfills a threshold process to each input element where values less than zero are set to zero thus the ReLU is calculated using Eqs. 1.

$$f(x) = \max(0, x) = \begin{cases} x_i, & \text{if } x_i \geq 0 \\ 0, & \text{if } x_i < 0 \end{cases} \quad (1)$$

ReLU verifies the values of inputs less than zero and forces them to zero and eliminates the vanishing gradient disadvantage observed in previous activation function types [45, 49]. The CNN structure used to take out the attributes of the ECG samples achieved from the ECG spectrograms is presented in Fig. 7.

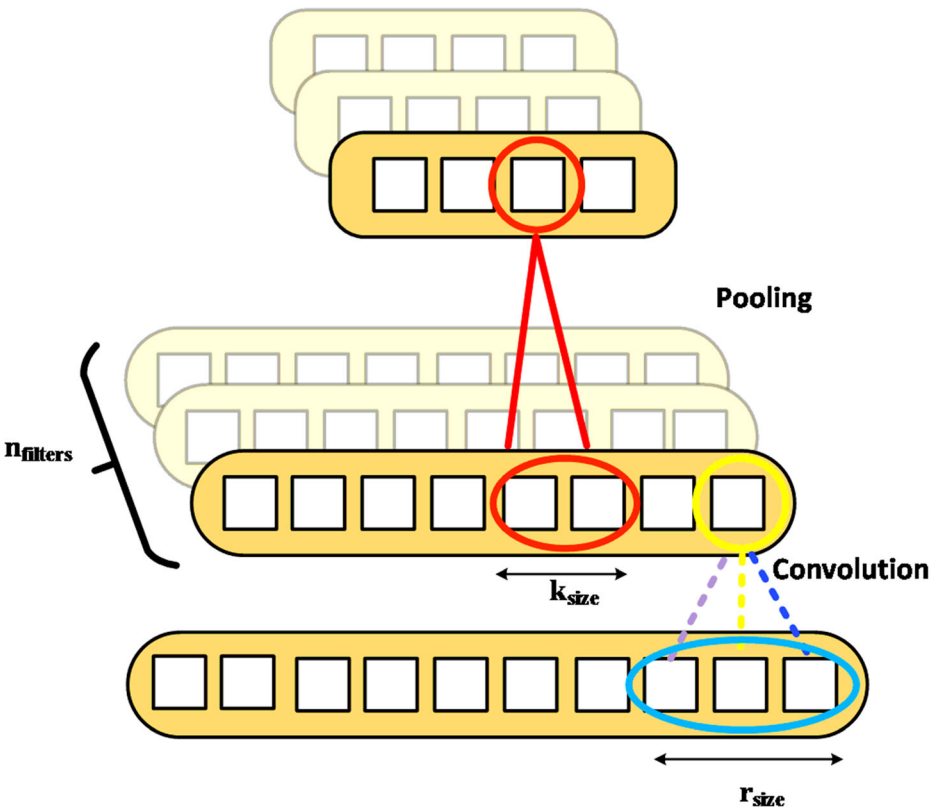


Fig. 6 CNN structure

CNN structure used in the study was comprised five convolutional strata (C1 to C5 scheme) that included two fully connected strata (FC6 and FC7). The output attributes achieved from the FC7 layer were given as input to the ELM and DEA-ELM classifiers.

2.4 Extreme learning machine

It has been suggested by ref. [28] that ELM can only determine the expiration step weights in the course of training [6, 28, 29]. ELM is a universalized SLFN and as can be seen in Fig. 8 it is not essential to regulate the hidden layer.

For N casually distinct instances (x_i, t_i) , ELM with H hidden nodes and the activation coefficient $h(x)$ is designated by $x_i = [x_{i1}, x_{i2}, \dots, x_{iD}]^T \in R^D$ and $t_i = [t_{i1}, x_{i2}, \dots, x_{iK}]^T \in R^K$. SLFNs are described as shown in Eq. 2:

$$\sum_{i=1}^L \beta_i h_i(x_j) = \sum_{i=1}^L \beta_i h_i(w_i \cdot x_j + b_i) = o_j, \quad j \in 1, N \text{###} \tag{2}$$

The ELM is shown in Fig. 9.

Different from standard learning procedures the ELM technique can casually produce hidden node parameters. $w_i = [w_{i1}, w_{i2}, \dots, w_{iD}]^T$, is the weight vector connected to the hidden

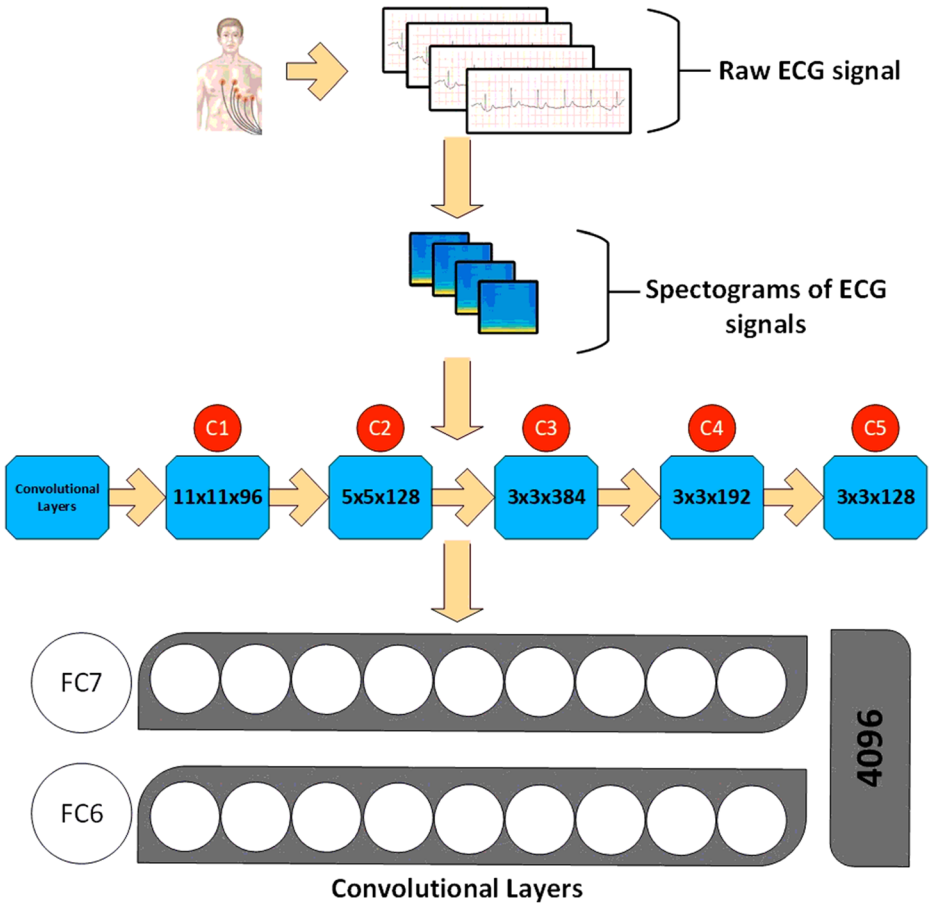


Fig. 7 CNN structure used in this work

node and the input nodes, $\beta_i = [\beta_{i1}, \beta_{i2}, \dots, w_{iK}]^K$ is the weight vector and b_i is the i th node. The $h(x)$ activation function and hidden nodes L are shown in Eqs. 3, 4 and 5.

$$H\beta = T \tag{3}$$

$$H = \begin{bmatrix} h_1(w_1x_1 + b_1) & \cdots & h_L(Lx_1 + b_L) \\ \vdots & \ddots & \vdots \\ h_1(w_1x_N + b_1) & \cdots & h_L(w_Lx_N + b_L) \end{bmatrix}_{N \times M} \tag{4}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{M \times 1} \quad \text{and} \quad T = \begin{bmatrix} t_1^T \\ \vdots \\ t_L^T \end{bmatrix}_{N \times 1} \tag{5}$$

Besides, ELM has represented as in Eq. 6, conversely SLFNs.

$$\beta = H^\dagger T \tag{6}$$

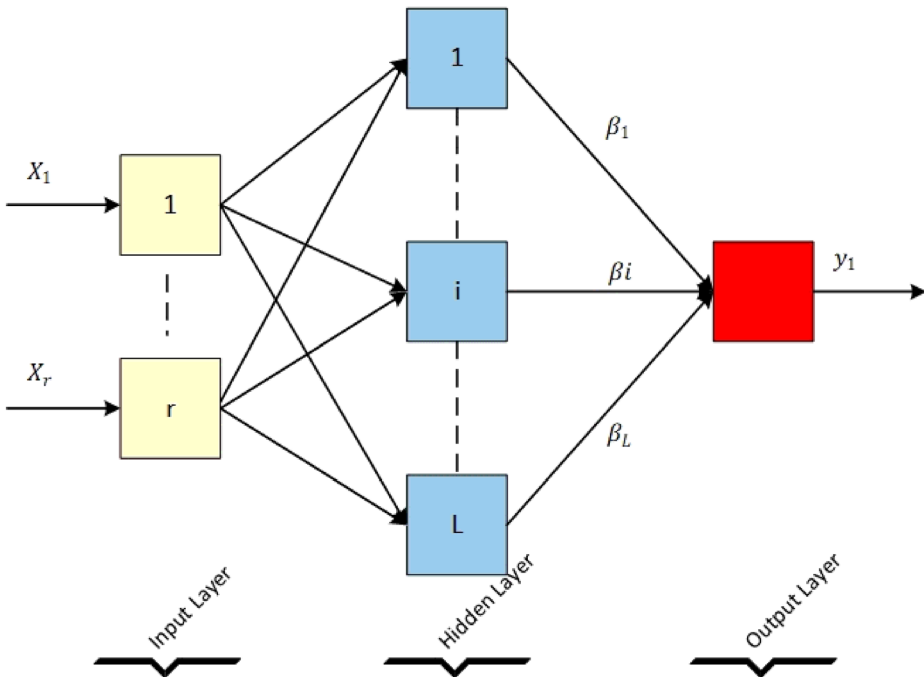


Fig. 8 SLFN structure

H^\dagger characterize Moore-Penrose, the universalize reverse of H matrix to attain a least-square solve [28], [7, 27, 36, 42].

2.5 Differential evolution algorithm

The DEA, which is an advanced technique used for working out the problems of constant parameters, was put forward by Price and Storm [34]. DEA is an inhabitants-dependent empirical procedure that is inspired by GA related processing and operators. In addition, DEA can particularly ensure effective results that are the disadvantages of constant data [21, 32, 51, 63]. Incidentally, DEA is exerted investigative on a lot of areas. Through the repetitions in the algorithm, superior consequences for the resolution of the disadvantage by the aid of the operators are explored. Furthermore, the goal of the algorithm is to advance the remedy efficiency of the disadvantages in which coding by constant scores is used, by certain alters in genetic operators. The crossing, mutation and election operators in GA are also used in DEA. However, in DEA not all of the operators are carried out to the all of the inhabitant in the order. Chromosomes are handled one by one and obtained by a new individual through the randim election of three other chromosomes. In the course of this procedure, mutation and crossover processors are used. The compatibility of the recent chromosome obtained using the existing chromosome are compared and the one that is more suitable is transferred to next population as a new individual. As a result, the election operative is also used. The quality of the solutions created is evaluated according to the value they come up with for the goal function [34]. The major benefits and significant parameters of the DEA procedure are presented in Table 1.

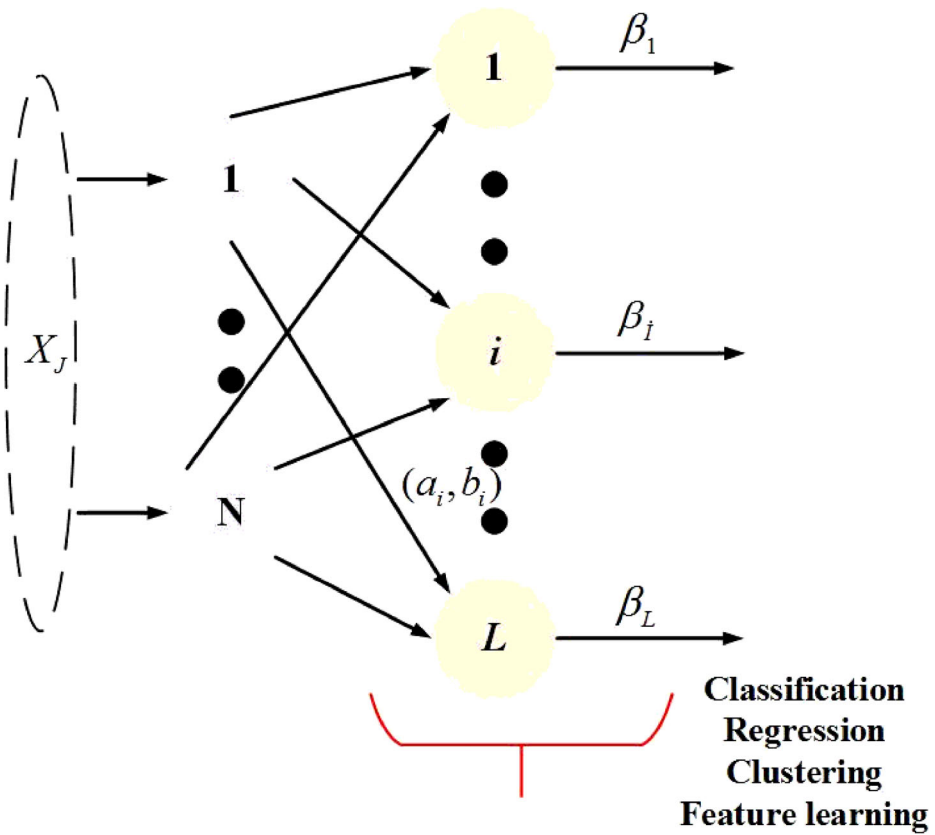


Fig. 9 ELM architecture

The D factor can be characterized by a D vector. In this algorithm, firstly an inhabitant of NP inhabitant vector is selected. This inhabitant is achieved advanced with execution mutation, crossover, and selection operators [21]. The primary steps of DEA are given in Fig. 10. The number of variables of the problem determines the number of genes for each chromosome. The population size (number of chromosomes) in DEA should always be greater than three because three chromosomes are required, excluding the existing chromosome, for the production of new chromosomes.

Mutation is to perform alters in casually decisive amounts on various sections of the genes of the actual chromosome. Three extra chromosomes are selected for mutation within the DEA. The difference of the first two selected chromosomes is obtained. Afterward, this chromosome is multiplied by the scaling parameter. This parameter mostly receives scores

Table 1 Benefits-significant factors

Benefits	<ul style="list-style-type: none"> • Basic architecture • Facilitate of handling • Rapid and powerful [31, 32].
Factors	<ul style="list-style-type: none"> • NP (Number of Population-size) • CR (Crossover Rate) • F (Scaling Factor) [51].

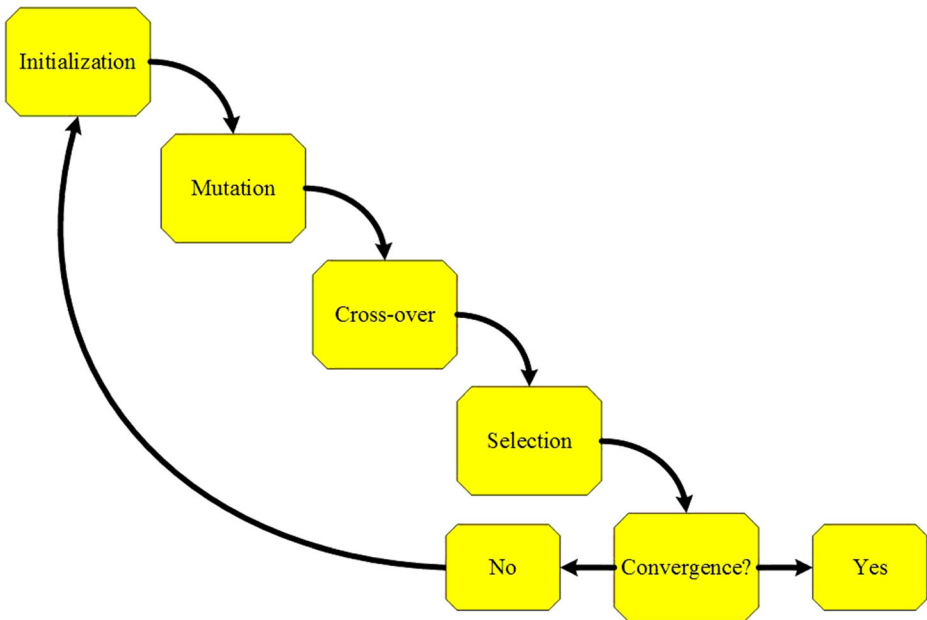


Fig. 10 Differential algorithm steps

among 0–2. The attained weighted difference chromosome is added to the third chromosome. As a result, the result of the mutation chromosome is used in the crossover [34]. The aim is to reduce costs and obtain the optimal number of hidden neurons of ELM using DEA. Table 2 presents the DEA pseudo code used in this study.

3 Classification results

In this section the classification scores for healthy and abnormal samples are presented. To determine the scores a total of 160 ECG samples comprised of 80 abnormal and 80 normal signals were selected from a public dataset. The confusion matrix was employed to appraise

Table 2 DEA-ELM used in this work

Algorithm : Differential Evolution Extreme Learning Machine (DEA-ELM)	
Input: Preprocessed ECG signals (Dataset)	
NHN :Number of Hidden Neuron	
pCR : Crossover Rate	
nPop : Number of population	
nVar: VarMin_1, VarMax_1, VarMin_2, VarMax_2	
TF, MaxIt	
Output: Best cost results	
1.	for i=1:nPop
2.	pop(i).Cost=DEA-ELM (Dataset, Elm_Type, pop(i).NHN, TF {pop(i).TF},5) // Initialization
3.	end
4.	beta=unifrnd (beta_min,beta_max,VarSize);
5.	y1=pop(a).NHN+beta.*(pop(b).NHN-pop(c).NHN)... // Mutation
6.	z1=zeros(size(x1));j0=randi([1 numel(x1)]); // Crossover
7.	BestCost(it)=BestSol.Cost; // Best cost of DEA-ELM for classification

classifier efficacy. The accuracy, sensitivity, specificity, quality index, and F-measure of the classifiers were determined using Eqs. 7–10. The true positive (TP) and true negative (TN) characterized the quantity of the normal and abnormal ECG samples, while the false positive (FP) and false-negative (FN) represented the quantity of the normal and abnormal ECG samples [16, 21].

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \quad (7)$$

$$Se = \frac{TP}{TP + FN} \quad (8)$$

$$Spe = \frac{TN}{TN + FP} \quad (9)$$

$$F\text{-measure} = \frac{2*TP}{2*TP + FP + FN} \quad (10)$$

Firstly, the preprocessing step was performed to remove the 60 Hz interference and the baseline wander of the ECG samples obtained from the PTB dataset. Then, the spectrograms to represent the frequency domain the ECG signals were obtained as can be seen in Fig. 11.

After obtaining the spectrograms of the ECG signals to extract the features of the ECG signals AlexNet, which is a CNN architecture, was used. As a result, a feature vector of 160×4097 size was obtained to be given to the classifiers.

3.1 Comparison of classifiers efficiency

In this section, the performance of the ELM, DEA-ELM, k-NN, SVM, and decision trees algorithms were compared. Within this scope, achievement consequences were achieved via the ELM's Radbas, Sin, Sig, Hardlim and Tribas activation functions (AC). All of the ECG samples were separated into two sets as training and test sets. Moreover, the ECG samples was tested with a 10-fold cross-validation method. Classifier consequences were attained by tuning the NHN of ELM to 40, 60, 80, 100, and 120 as can be seen in Figs. 12, 13, 14 and 15.

The proposed method was provided by 10-fold cross-validation via the MATLAB Classification Learner Toolbox. The results of the classifiers used in this toolbox are presented in Fig. 16.

In addition, the confusion matrix and receive operating curve (ROC) of the classifiers, namely k-NN, SVM and decision trees, are shown in Fig. 17.

The main aim of this study was to analyze the performance of the model by improving the NHN of ELM via DEA. Therefore, the classification parameters were examined via the NHN of the ELM as seen in Figs. 12, 13, 14 and 15. The classification efficiency of the ELM can be enhanced by NHN. For this, the DEA, which is a powerful meta-heuristic improvement method, was applied. The DEA was used to boost the consequences which were attained by the ECG classification using ELM. This method was carried out as can be seen from Fig. 18. The best costs as efficiency consequences were attained with 250, 500, 750, 1000, 1500, 1600,

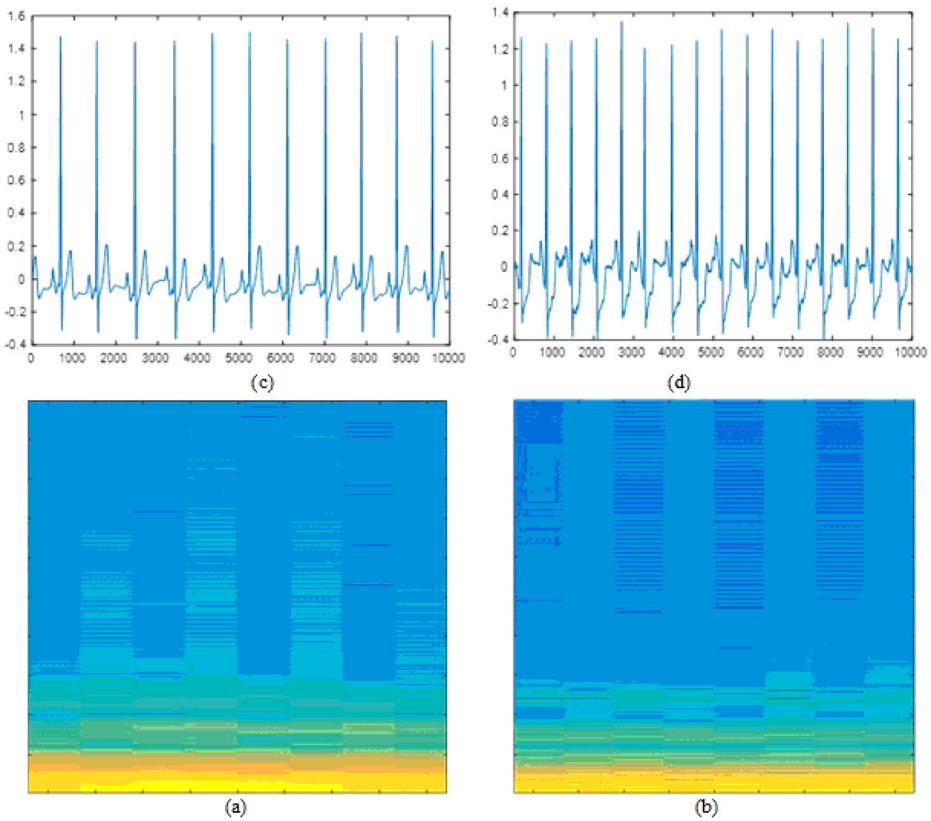


Fig. 11 (a) Spectrogram of normal ECG record with number s0292lre (b) Spectrogram of abnormal ECG record with numbers0021brem (c) Normal ECG record with number s0292lre (d) Anormal ECG record with numbers0021brem

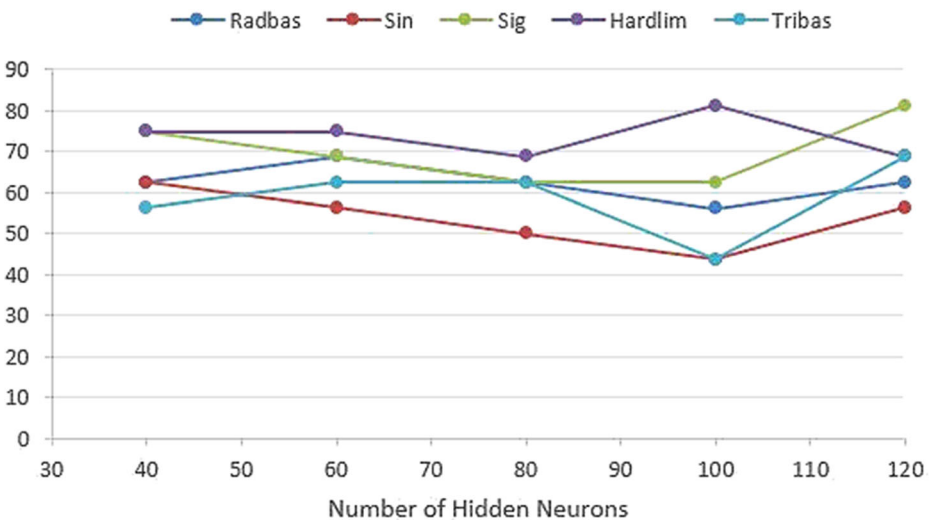


Fig. 12 Accuracy results of ELM

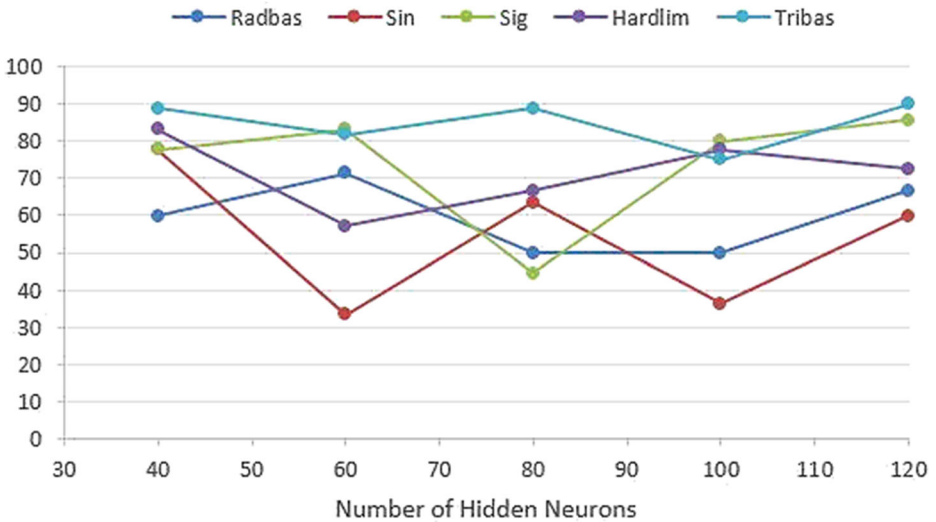


Fig. 13 Sensitivity results of ELM

1700, 1800, 1900, and 2000 repetitions with DEA-ELM (Fig. 18). Moreover, the factors attained from the DEA-ELM are presented in Table 3.

The efficiency scores for five diverse AC were attained by DEA-ELM. The NHN that improved via DEA-ELM is given in Table 3. Furthermore, the factors used in the DEA method are presented in Table 4.

In the NHN improvement applied via the DEA-ELM method the best accuracy score of 83.12% was achieved with Sigmoid AC and 89 NHN. When the highest best cost value was achieved, the number of repetitions was increased to verify this result. In addition, this dataset was tested using the Genetic Algorithm Wavelet Kernel ELM (GAWK-ELM) [5], which is

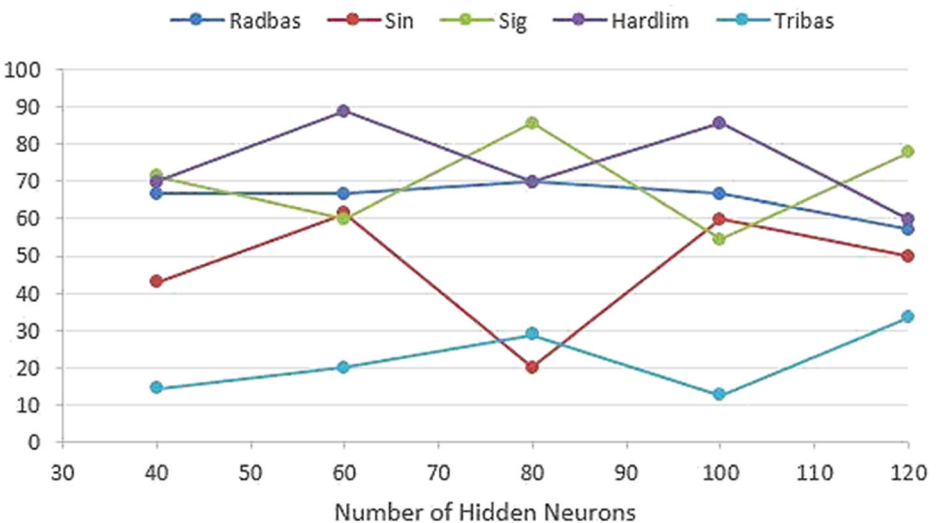


Fig. 14 Specificity results of ELM

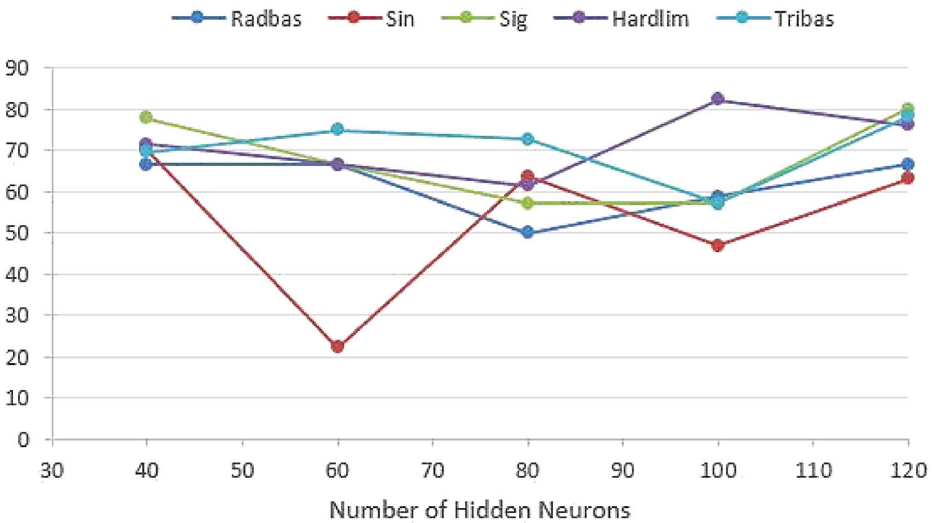


Fig. 15 F-measure results of ELM

another meta-heuristic optimization method. The parameters used in the GAWK-ELM method are given in Table 5 and the results of the method are given in Table 6.

As can be understood from the results of the GAWK-ELM method, the DEA-ELM method had higher classification accuracy. This is due to the fact that the DEA method is an iterative solution search-based heuristic search algorithm.

Whether the best cost value changed with excessive repetitions was evaluated. As a result, the best cost score accomplished was left consistent at 1900 and 2000 repetition numerals as referred in Table 3.

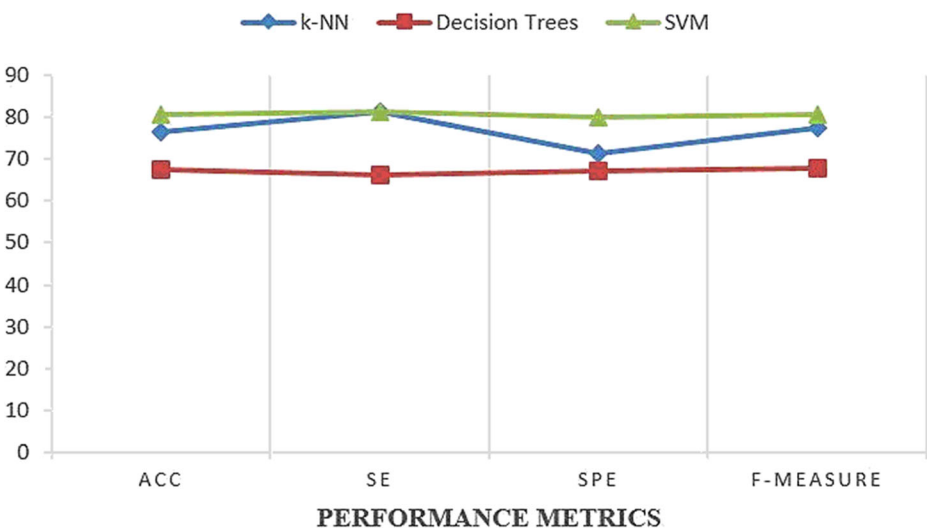


Fig. 16 The efficiency consequences of the classification learner toolbox

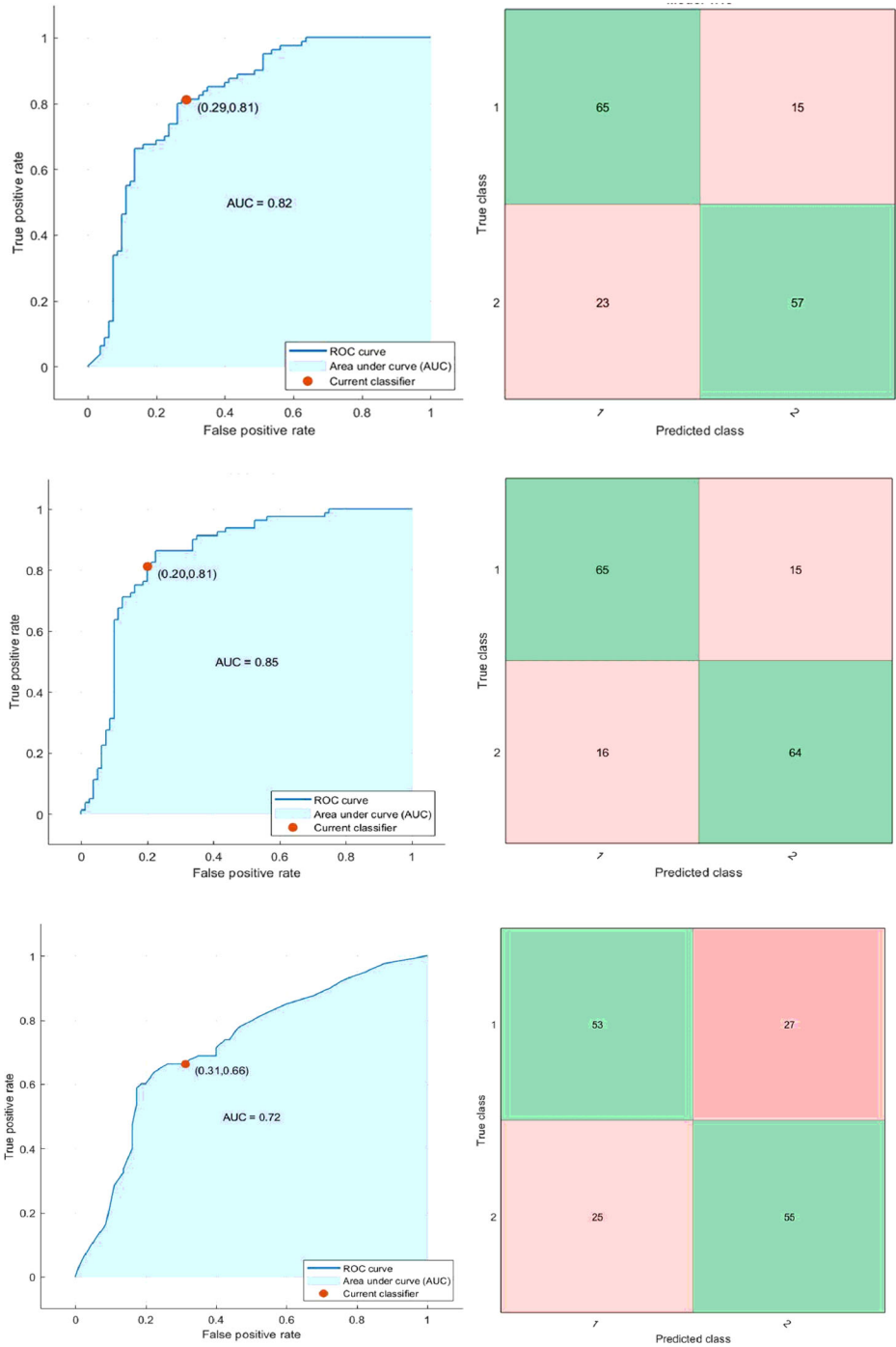


Fig. 17 (a) ROC and confusion matrix of k-NN classifier (b) ROC and confusion matrix of SVM classifier (c) ROC and confusion matrix of decision trees classifier

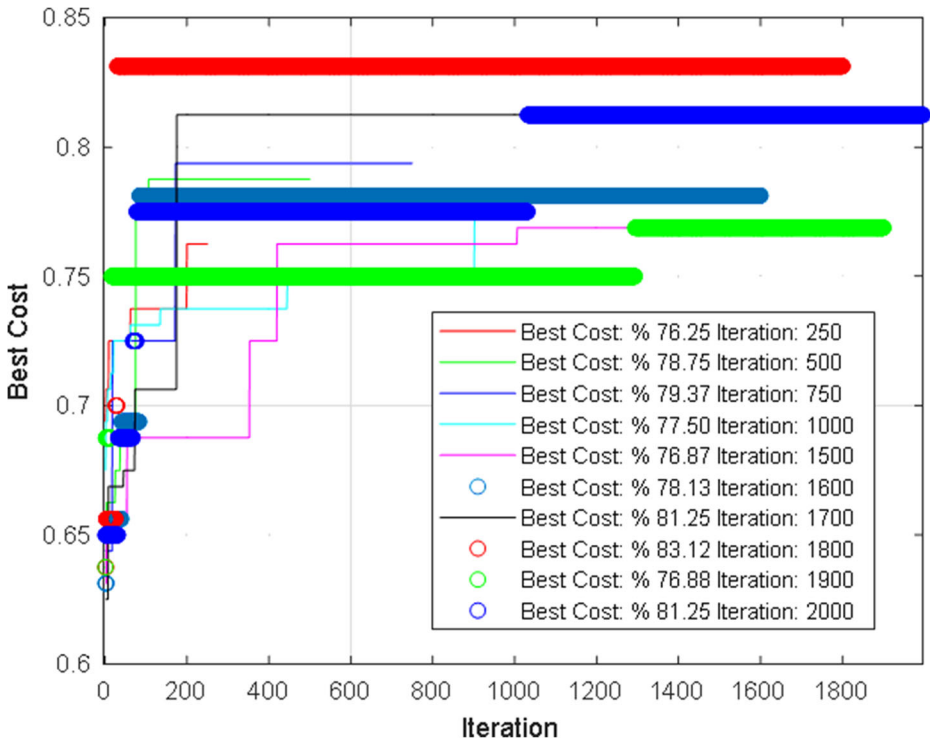


Fig. 18 Classification results of the DEA-ELM

4 Discussion

Heart failure is a fatal disease that affects both the heart and the heart vessels and is the most important cause of death worldwide. Therefore, the early detection of heart diseases is very important. As a result, ECG classification has become a critical area of study over the last 20 years [2]. In this section a benchmark regarding automated ECG analysis systems, which is shown in Table 7, among the recommended technique and the ultimately concerned works considering the prominent parameters, such as techniques, databases, classes and attributes type is discussed.

Table 3 Factors attained through DEA-ELM in work

Iteration	NHN	AC	Acc(%)
250	43	Tribas	76.25
500	56	Sin	78.75
750	25	Hardlim	79.37
1000	108	Sig	77.50
1500	79	Radbas	76.87
1600	111	Sig	78.13
1700	39	Radbas	81.25
1800	89	Sig	83.12
1900	67	Hardlim	76.88
2000	15	Tribas	81.25

Table 4 DEA important metrics used in the work

Factor	Value
Population	160
Mutation	0.1
Crossover	0.8
Factor bounds	NHN Min=1, Mak=120
Number of iteration	250,500,750,1000, 1500, 1600, 1700, 1800, 1900, 2000
Stopping criteria	Until it compasses the best cost score.

The offered DEA-ELM procedure for the improved NHN of the ELM is completely unique compared to former techniques and is an innovative method in this area. In this study, low accuracy performance was achieved due to the low number of signals used. The sensitivity and specificity values in ELM can be misleading. Therefore, accuracy should be taken into consideration in the system evaluation. Consequently, some studies have reported low accuracy values when using the DEA-ELM. When a collation is accomplished taking notice of the coefficients in Table 4, the classification performance of DEA-ELM based on deep feature may be defined promising. In Ref [65], two deep neural network architecture for the classification of arbitrary-length ECG samples were proposed and evaluated according to the atrial fibrillation (AF) classification data set provided by the PhysioNet/CinC Challenge 2017. Consequently, was found to outperform the first one, obtaining an F1 score of 82.1% on the hidden challenge testing set. In another ref. [46] a novel approach to automatically detect the MI using ECG signals was used. In the present study, a CNN algorithm was implemented for the automated detection of normal and MI ECG beats (with and without noise) and average accuracy of 93.53% and 95.22% using ECG beat with noise and noise removal respectively was obtained, respectively.

It should be emphasized that in this study only DEA-ELM was used for ECG classification yet the primary aim of this study was to advance the classification efficiency and improve NHN. Furthermore, it was determined that the classification efficiency of the ECG sample was

Table 5 The parameters for the GA design

The parameters type of GA	
Coding type	Binary encoding
Mutation rate	5%
Mutation type	Bit inversion
Crossover rate	80%
Crossover type	Two point crossover
Population size	40 chromosomes
Chromosome size	20 bits

Table 6 GAWK-ELM results

Activation Function	Acc (%)
Wavelet	71.67

Table 7 Classification performance of the proposed method and comparison with other studies

References	Class	Database	Features	Classifiers	Performance
Zühlmann et al. [65]	2	PhysioNet/CinC Challenge 2017 and PTB Diagnostic ECG Database	Deep learning- LSTM	CNN and CRNN (Softmax)	F1-Score: 82.1%
Oh et al. [46]	5 (Total 16,499 beat)	MITDB	Deep learning	LSTM and CNN	Accuracy: 98.1%, Sensitivity: 97.5%, Specificity: 98.7%
Limam and Precioso [39]	4	PhysioNet/CinC Challenge 2017	Deep learning	CRNN and CRNN-SVM	Score: 90.6%, Sensitivity: 82.5% Specificity: 98.8%
Acharya et al. [1]	2	PTB Diagnostic ECG Database	<ul style="list-style-type: none"> R-peaks detection 11-layer deep neural network No feature selection or feature reduction Denosing not required 	CNN	With noise: Accuracy: 93.53% Sensitivity: 93.71% Specificity: 92.83% Without noise: Accuracy: 95.22% Sensitivity: 95.49% Specificity: 94.19%
Cömert and Kocamaz [49]	2	CTU-UHB	Deep learning	DCNN	Accuracy: 93.32%, Sensitivity: 56.15%, Specificity: 96.51%
Sannino and Pietro [55]	2 (Total 4576 beat)	MIT-BIH	<ul style="list-style-type: none"> Pre-RR interval Post-RR interval Local average RR interval Global average RR interval 	DNN	Accuracy: 99.68%, Sensitivity: 99.48%, Specificity: 99.83%
Andersen et al. [3]	2	AFDB, MITDB, NSRDB	Deep learning	CNN and RNN	Accuracy: 89.30%, Sensitivity: 99.82%, Specificity: 87.94%
Melgani and Bazi [44]	6 (Total 45,438 beat)	MIT- BIH	ECG morphology features, ECG temporal features	PSO-SVM	Accuracy: 89.72%
Lin and Hsieh [40]	2	MIT-BIH	R peak	ECG R peak detection method and a beat-to-beat Gaussian voting AFib method	Accuracy: 94.72%, Sensitivity: 98.11%, Specificity: 97.97%

Table 7 (continued)

References	Class	Database	Features	Classifiers	Performance
Avci [5]	2	UCI	20 features (age, sex, fatigue etc.)	GAWK-ELM	Accuracy: 96.642%
The method proposed in this study	2	PTB Diagnostic ECG Database	Deep Features •7-layer deep neural network	DEA-ELM	Accuracy: 83.12%

increased via the DEA-ELM procedure as is shown in Figure 18. It must realized that system efficiency can be increased via different attributes taken by various domains such as temporal and deep learning. The experimental consequences showed that NHN is beneficial for ECG classification efficiency.

5 Conclusion

In this study, DEA-ELM, a recently improved procedure, was used for ECG classification. The proposed system was tested by operating the open access PTB Diagnostic database. Moreover, a comparison was achieved by considering major parameters from the point of the ECG analysis. The best classification scores were achieved with an accuracy of 81.50% via ELM. The best cost of 83.12% was achieved with the Sigmoid function, while the best classification results of 89 NHN were obtained with the DEA-ELM approach. The main aim of this study was to classify ECG with the DEA procedure that was optimized with ELM.

Author's contribution **Aykut Diker:** Literature analysis, Interpretation of the results, Drawing of the figures, Preparation of the manuscript. **Yasin Sönmez:** Literature analysis, Interpretation of the results, Preparation of the manuscript. **Fatih Özyurt:** Literature analysis, Drawing of the figures, Preparation of the manuscript. **Engin Avci:** Literature analysis, Interpretation of the results. **Derya Avci:** Literature analysis, Interpretation of the results, Preparation of the manuscript.

Funding This review was not supported by any external funding sources

Compliance with ethical standards

Conflict interests The authors declare no conflicts of interest.

Statements of ethical approval The authors did not carry out any work that involved human or animal participants for this study.

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