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A new method for classification of ECG arrhythmias using neural network with adaptive activation function

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ABSTRACT

In this study, new neural network models with adaptive activation function (NNAAF) were implemented to classify ECG arrhythmias. Our NNAAF models included three types named as NNAAF-1, NNAAF-2 and NNAAf-3. Activation functions with adjustable free parameters were used in hidden neurons of these models to improve classical MLP network. In addition, these three NNAAF models were compared with the MLP model implemented in similar conditions. Ten different types of ECG arrhythmias were selected from MIT–BIH ECG Arrhythmias Database to train NNAAFs and MLP models. Moreover, all models tested by the ECG signals of 92 patients (40 males and 52 females, average age is 39.75 ± 19.06). The average accuracy rate of all models in the training processing was found as 99.92%. The average accuracy rate of the all models in the test phases was obtained as 98.19.

1. Introduction

Electrocardiography is commonly used by the physicians in cardiology since it consists of effective, functioning, simple, noninvasive, and low-cost tool to the diagnosis of cardiovascular diseases. For this purpose, electrocardiogram (ECG) record is made to examine and observe a patient. ECG expresses electrical activity of the heart and according to its shape and features, diseases could be diagnosed. Early detection and treatment of the heart diseases can rescue the patient's life or prevent permanent damages on tissues of the heart.

Abnormality of the ECG shape is usually called arrhythmia. Arrhythmia is a common term for any cardiac rhythm that differs from normal sinus rhythm [1]. Automatic arrhythmia detection and classification of arrhythmias are important in clinical cardiology, especially when performed in real time. This is achieved through the analysis of ECG and its extracted features [2]. Up to now, several research and various methods of automatic arrhythmia detection have been developed, such as use of neural network [3–5], neuro fuzzy [6–9], feature extraction [10–12].

Übeyli classified four types of ECG signals in two studies [13,14] by using Support Vector Machine (SVM) and achieved 98.6% and 98.33% classification accuracy, respectively. In other study with two ECG signal classes [15], Übeyli reached 99.44% accuracy. In addition, Polat ve Güneş obtained the best result on two classes ECG signal classes using SVM [16]. These studies were conducted on maximum four ECG signal classes but in our study, we used ten ECG signal classes.

Artificial neural network (ANN) has played an important role in a wide variety of applications, such as pattern recognition and classification tasks. In traditional ANN model such as multi-layered perceptron (MLP) network, each neuron computes the weighted sum of its inputs and applies to sum a nonlinear function called activation functions [17,18]. In general the performance of MLP depends on the number of hidden layers, the number of hidden neurons, the learning algorithm and the

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activation function for each neuron [19]. MLP have the ability to perform tasks involving nonlinear relationships, in which all the neurons may perform the same type of activation function or different layers of neurons may realize different kinds of activation functions [17]. The commonly investigated activation functions in literature are sigmoid function, generalized sigmoid functions, the radial basis function, and so on. These functions which are all fixed and cannot be adjusted to adapt to different problems represent a relation between a single input, the weighted sum, and a single output, the neuron response. One common characteristic of these activation functions is that they are critical as the behavior performance of MLP depends on it [20–22].

Some researchers have tried to define special activation functions, such as adaptive activation function (AAF) with free parameters, to simplify the network structure through a reduction in the network's size, and to shorten the training time; however, limited studies, emphasize in setting activation function with a few free parameters [17–22]. In Liu [23], real variables, node offset(s) and slope of the sigmoid function(s) in sigmoid activation function were adjusted during learning process. Yu at al. [17], established an adaptive activation function for MLP to solve N-Parity and two spiral problems. Vecci at al. [24] and Solazzi and Uncini [18] studied with adaptive spline activation function neural networks. Zhang at al. [25, 26] and Xu and Zhang [19–22,27], studied adaptive higher feed-forward neural networks for financial analysis. Networks with such activation functions called neural network with adaptive activation functions (NNAAF), seems to provide better performance than classical architectures with fixed activation function neurons.

Until now, to our knowledge, there is no study in literature analyzing to ECG signals using the method of neural network with adaptive activation function (NNAAF). In this paper, we presented traditional multilayer neural network (MLP) and three models of the new neural network with different activation functions with free parameters (NNAAF-1, NNAAF-2 and NNAAF-3) for classification of ECG arrhythmias. These networks (MLP, NNAAF-1, NNAAF-2 and NNAAF-3) are implemented using MATLAB software package without Neural Network Toolbox. All of these networks presented in this study were trained to classify ECG signals with ten different arrhythmias. Then, the best structures of these NNs were tested by ECG signals recorded from patients.

2. Methods

In this study, three NNAFF models were used as a new approach in determining of ECG arrhythmias. MLP and NNAAF models were trained for ECG signals including ten arrhythmias taken from MIT–BIH ECG Arrhythmias Database. These networks were tested using ECG signals recorded from 92 patients for the best architectures obtained in training phase. Thus, the training and test achievements of NNAAF models were compared with MLP.

2.1. Architecture of neural network with adaptive activation function (NNAAF)

The improved neural network with adaptive activation function (NNAAF) has three layers (an input layer, one hidden layer and output layer) as in traditional MLP. The net input of hidden and output layers is weighted sum of its inputs. In the input neurons of the input layer, any activation function is not used. Sigmoid activation function with fixed parameters is used in the output neurons of the output layer, while an adaptive activation functions with free parameters are used as the activation function in the hidden nodes of the hidden layer. The developed NNAAF is depicted in Fig. 1 [28]. Three NNAAF models defined as NNAAF-1, NNAAF-2 and NNAAF-3 were improved. The models were implemented with MATLAB software package without Neural Network Toolbox. In this study, the training algorithms of the designed three different NNAAF models, whose architecture is depicted in Fig. 1, are not very different from each other except for the activation functions in hidden layer.

ψ_1 function, which is used as AAF in hidden layer neurons of NNAAF-1 model, has been characterized by Eq. (1) with two free parameters (a, b). In literature, in most of the studies dealing with adaptive activation functions, sigmoid function with free parameter (Eq. (1)) has been used [17,23,29,30].

In hidden layer neurons of NNAAF-2, ψ_2 function that includes four free parameters characterized by Eq. (2) is used as AAF. In literature, this function has been used as AAF in previously reported studies implementing single output, noncomplex network structures for financial modeling purposes [21,22,25]. ψ_3 Morlet wavelet function that includes two free parameters (b_1 and b_2) characterized by Eq. (3) is chosen as AAF for the hidden layer neurons of NNAAF-3 model. Until now, to our knowledge, the use of Morlet wavelet function with free parameter as AAF of neural networks has not been reported. In literature, Morlet wavelet function with fixed parameters was used as activation function in hidden layer's neurons of NN. Because of this, in this study, Morlet wavelet function with free parameters was selected as AAF in the model of NNAAF-3 [31–33].

The sigmoid function with fixed parameter (ψ_4) characterized by Eq. (4) is widely utilized in studies reported in literature. In present study, it has been used as activation function of both hidden and output layers of conventional MLP model. The activation function of output layer neurons of NNAAF-1, NNAAF-2 and NNAAF-3 models is also chosen as ψ_4 function.

In a previous study of ours [34], various architectures and configurations for NNAAF-1 and NNAAF-2 have been tried and tested with records from 10 patients. Differing from that, in present study, architectures of NNAAF-1 and NNAAF-2 have been altered to obtain smaller error values. In other words, in this study, NNAAF-1, NNAAF-2 and NNAAF-3 models have been used to classify ECG signals and tests of these models were implemented with the ECG data obtained from 92 patients. These three models have been compared with the MLP model implemented in similar conditions.

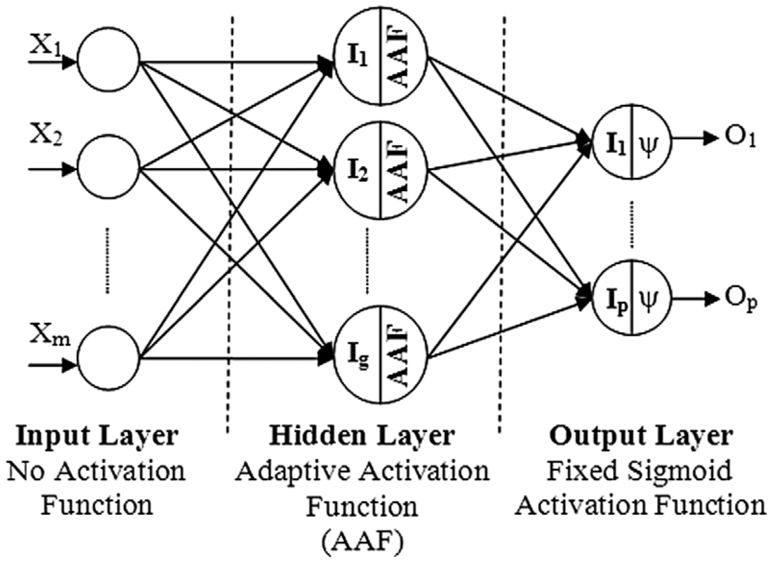

Fig. 1. Typical NNAAF model with adaptive activation function.

$$\psi_1(x) = \frac{a}{1 + e^{-bx}} \tag{1}$$

$$\psi_2(x) = a_1 \operatorname{Sin}(b_1 x) + \frac{a_2}{1 + e^{-b_2 x}} \tag{2}$$

$$\psi_3(x) = e^{-b_1 x^2}\big(\operatorname{Cos}(b_2 x)\big) \tag{3}$$

$$\psi_4(x) = \frac{1}{1 + e^{-x}} \tag{4}$$

where a, b, a_1, a_2, b_1, b_2 are real variables which will be tuned during training as weights between neurons. To describe the training algorithm in NNAAF models, following notations are adopted.

Notations

$I_{i,k}(u)$: The input of ith neuron in the kth layer,
$w_{i,j}$: The weight between jth neuron in the layer $(k-1)$ and ith neuron in the layer k,
$o_{i,k}(u)$: The value of output from ith neuron in the kth layer,
$\theta_{i,k}$: The threshold value of ith neuron in the kth layer,
β: Learning rate,
$d_j(u)$: The desired value of jth output neuron,
m: Total number of neurons in the output layer,
p: Total number of neurons in the hidden layer,
l: Total number of network layers,
r: The iteration number.

2.2. Learning algorithm for NNAAF models

In the NNAAF models, we developed a learning algorithm which is not very different from traditional back propagation algorithm. Although, generally the activation function with fixed parameter is used in the MLP model with back propagation algorithm, we used adaptive activation function with free parameters in the hidden layer of the NNAAF models. Similar to the adjustment of the weights between neurons, the free parameters in adaptive activation functions are adjusted with this learning algorithm that is based on steepest descent rule. There are two phases, feed forward and error back propagation in the NNAAF models as in MLP [17,22].

All the weights and biases are initialized to small real random values in feed forward phase [35,36]. The choice of initial weights will influence whether the network reaches a global minimum of the error and if so, how quickly it converges. Nguyen–Widrow initialization method [35] gives much faster learning performance and depends on the number of input neurons and hidden neurons. Because of these advantages, Nguyen–Widrow method was used in this study.

After the initializing process, training pair (input vector and corresponding desired responses) is presented to the network inputs. Each hidden unit sums weighted signals according to Eq. (5), applies its selected activation function (ψ_1, ψ_2 or ψ_3) as in Eq. (6) to compute its neuron output signal in the hidden layer. Then each output neuron in the output layer sums its weighted output signal of each hidden neuron according to Eq. (5) and applies fixed sigmoid activation function given by Eq. (4) in feed forward phase.

The input of ith neuron in the kth layer is defined as:

$$I_{i,k}(u) = \sum_j \left[w_{i,j,k} o_{j,k-1}(u) \right] + \theta_{i,k} \tag{5}$$

where j is neuron number in the layer $(k-1)$, the value of output from ith neuron in the kth layer for first activation function;

$$o_{i,k}(u) = \psi_1\left(I_{i,k}(u)\right) = \frac{a_{i,k}}{1 + e^{-b_{i,k}.I_{i,k}(u)}} \tag{6}$$

To train NNAAF models, an error function given by Eq. (7) is used, which is sum of the squared error between the actual network and the desired output for all input patterns. The proposed learning algorithm specifies how to reduce the mean squared error for all patterns through an adjustment of weights between neurons and thresholds and free parameters in backpropagation phase [22].

$$E = \frac{1}{2} \sum_{j=1}^{m} \left(d_j(u) - o_{j,l}\right)^2 \tag{7}$$

It is suggested to use gradient descent to perform steepest descent in which the adjustment of weight is proportional to the first derivative of the output function in each neuron (Eqs. (8) and (9)). Similarly, the adjustment of free parameters in each activation function is proportional to the first derivative of the output function in each neuron (Eqs. (10) and (11)) [17,19,20].

The network is trained to minimize the error function by adjusting the weight, threshold and free parameters in the activation functions in backpropagation phase as follows:

$$w_{i,j,k}^{r} = w_{i,j,k}^{r-1} + \beta \frac{\partial E}{\partial w_{i,j,k}} \tag{8}$$

$$\theta_{i,k}^{r} = \theta_{i,k}^{r-1} + \beta \frac{\partial E}{\partial \theta_{i,k}} \tag{9}$$

$$a_{i,k}^{r} = a_{i,k}^{r-1} + \beta \frac{\partial E}{\partial a_{i,k}} \tag{10}$$

$$b_{i,k}^{r} = b_{i,k}^{r-1} + \beta \frac{\partial E}{\partial b_{i,k}} \tag{11}$$

To derive the gradient information of E with respect to adjustable parameter in Eqs. (8)–(11), we define,

$$\frac{\partial E}{\partial I_{i,k}(u)} = \delta_{i,k} \tag{12}$$

$$\frac{\partial E}{\partial O_{i,k}(u)} = \lambda_{i,k} \tag{13}$$

Now, using Eqs. (6), (7), (12) and (13), we have the partial derivatives of E with respect to adjustable parameters as follows:

$$\frac{\partial E}{\partial w_{i,k}(u)} = \frac{\partial E}{\partial I_{i,k}(u)} \frac{\partial I_{i,k}(u)}{\partial w_{i,k}(u)} = \delta_{i,k} O_{j,k-1}(u) \tag{14}$$

$$\frac{\partial E}{\partial \theta_{i,k}(u)} = \frac{\partial E}{\partial I_{i,k}(u)} \frac{\partial I_{i,k}(u)}{\partial \theta_{i,k}(u)} = \delta_{i,k} \tag{15}$$

$$\frac{\partial E}{\partial a_{i,k}(u)} = \frac{\partial E}{\partial O_{i,k}(u)} \frac{\partial O_{i,k}(u)}{\partial a_{i,k}(u)} = \lambda_{i,k} \frac{1}{1 + e^{-b_{i,k} I_{i,k}}} \tag{16}$$

$$\frac{\partial E}{\partial b_{i,k}(u)} = \frac{\partial E}{\partial O_{i,k}(u)} \frac{\partial O_{i,k}(u)}{\partial b_{i,k}(u)} = \lambda_{i,k} \frac{a_{i,k} I_{i,k}(u) e^{-b_{i,k} I_{i,k}}}{(1 + e^{-b_{i,k} I_{i,k}})^2} \tag{17}$$

And for Eqs. (12) and (13) the following equations can be computed:

$$\delta_{i,k} = \frac{\partial E}{\partial I_{i,k}(u)} = \frac{\partial E}{\partial O_{i,k}(u)} \frac{\partial O_{i,k}(u)}{\partial I_{i,k}(u)} = \lambda_{i,k} \frac{\partial O_{i,k}(u)}{\partial I_{i,k}(u)} \tag{18}$$

$$\frac{\partial O_{i,k}(u)}{\partial I_{i,k}(u)} = \frac{a_{i,k} b_{i,k} e^{-b_{i,k} I_{i,k}}}{(1 + e^{-b_{i,k} I_{i,k}})^2} \tag{19}$$

These equations from Eqs. (14) to (19) are computed for the model of NNAAF-1. The other parameters (a_1, a_2, b_1, b_2) and weights and threshold in the other model of NNAAF-2 and NNAAF-3 can be adjusted in the similar way for Eqs. (2) and (3).

In these NNAAF algorithms, the weights are updated after each training pattern was presented. An epoch is one cycle through the entire set of training vectors. At the end of the every epoch, free parameters ($[a, b]$ for ψ_1 in as Eq. (1), $[a_1, b_1, a_2, b_2]$ for ψ_2 in Eq. (2) and $[b_1, b_2]$ for ψ_3 in Eq. (3)) are adjusted like weights. After completing the training procedure of the neural network, values of the weights and free parameters of NNAAF-1, NNAAF-2 and NNAAF-3 are frozen and ready for use in the testing mode as suggested by Fauset [35] and Haykin [36].

Summary of NNAAF algorithm

Step 1: Determine the number of hidden units for the network.
Step 2: Set all the weights and free parameters of hidden neurons' activation function to small random values and then apply Nguyen–Widrow method to the weights [21].
Step 3: Presentation of input vector from training data and calculate the actual outputs of all neurons using the presented parameter values, according to Eqs. (5) and (11).
Step 4: Evaluate the parameters of $\delta_{i,k}$ and $\lambda_{i,k}$ according to Eqs. (12), (13), (18) and (19).
Step 5: Adjust the weight and threshold values according to the iterative formulas, Eqs. (8)–(9).
Step 6: Input another learning pattern, go to Step 3.
Step 7: At the end of every epoch, adjust free parameters by using Eqs. (10)–(11).

The training segments are presented cyclically until all parameters are stabilized, until the error function E for the entire training set is acceptably low and the network converges [37].

3. Experimental results

In this study, three NNAAF models were proposed for classification of ECG signal which belongs to ten different arrhythmias using MATLAB software package without Neural Network Toolbox. These models were developed with a new learning algorithm which is derived for adjusting the free parameters of hidden neurons' activation function as well as connecting weights between neurons. The sigmoid activation function with free parameters is used in the first model called NNAAF-1. In the second model called NNAAF-2, activation function is sum of sigmoid function with free parameters and sinusoidal function with free parameters. The activation function of hidden neuron is Morlet Wavelet function with free parameters in the model of NNAAF-3. Furthermore, sigmoid function is selected as activation function in the hidden and output layer of MLP model, which was also implemented with MATLAB software package without Neural Network Toolbox to compare with NNAAF models.

3.1. Training results

Training data of ECG arrhythmias used in this study was taken from MIT–BIH ECG Arrhythmias Database [38]. Selected types of arrhythmias are normal sinus rhythm (N; 15 segments), sinus bradycardia (Br; 15 segments), ventricular tachycardia (VT; 6 segments), sinus arrhythmia (SA; 15 segments), atrial premature contraction (APC; 6 segments), paced beat (P; 10 segments), right bundle branch block (R; 10 segments), left bundle branch block (L; 10 segments), atrial fibrillation (A.Fib; 10 segments) and atrial flutter (A.Fl; 9 segments). Training patterns had been sampled at 360 Hz, so they were arranged as 200 samples in the intervals of R–R for all arrhythmias, which are called as a segment. Training patterns were formed in mixed order from the arrhythmias pre-processed by the order given above. The size of the training patterns is 106 segments $\cdot$ 200 samples, i.e. 106 segments each including 200 samples are present. The combination of these training patterns was called as training set.

The optimum number of hidden nodes and learning rate were experimentally determined for each NN structure.

After the proposed structures were trained by the training set, they were firstly tested for normal sinus rhythm (N; 15 segments). For the stopping criterion of all the networks, maximum number of iterations was set to 10 000 and the desired error value (MSE) was set to 0.001. Table 1 shows the training and test performance of MLP and proposed structures (NNAAFs) for optimum number of hidden nodes and learning rate. As shown in Table 1, the training process was completed in lowest number of iterations (6960 iterations) for NNAAF-1 model. In addition, as a result of the test process implemented using normal sinus rhythm ECG data, the lowest error value of 0.033% has been obtained for NNAAF-1 model. In Table 1, the best training performance was obtained with NNAAF-2 structure. However, as a result of the test process implemented using normal sinus rhythm ECG data for NNAAF-2 model, the error and number of iterations was higher than that of NNAAF-1 model. Table 1 shows training error and test error values calculated using Eqs. (20)–(23) which were given in Section 3.3. Architecture of NNAAF-2 model is depicted in Fig. 2.

Table 1
Optimum results of MLP, NNAAF-1, NNAAF-2 and NNAAF-3 structures.

Structure	Optimum architecture	Learning rate	Training error (%)	Test error with N (%)	Time (s)	Maximum iteration
MLP	200:12:10	0.9	0.097	0.077	674	10 000
NNAAF-1	200:35:10	0.9	0.063	0.033	2739	6960
NNAAF-2	200:20:10	0.9	0.058	0.045	2080	8232
NNAAF-3	200:25:10	0.2	0.116	0.097	3046	10 000

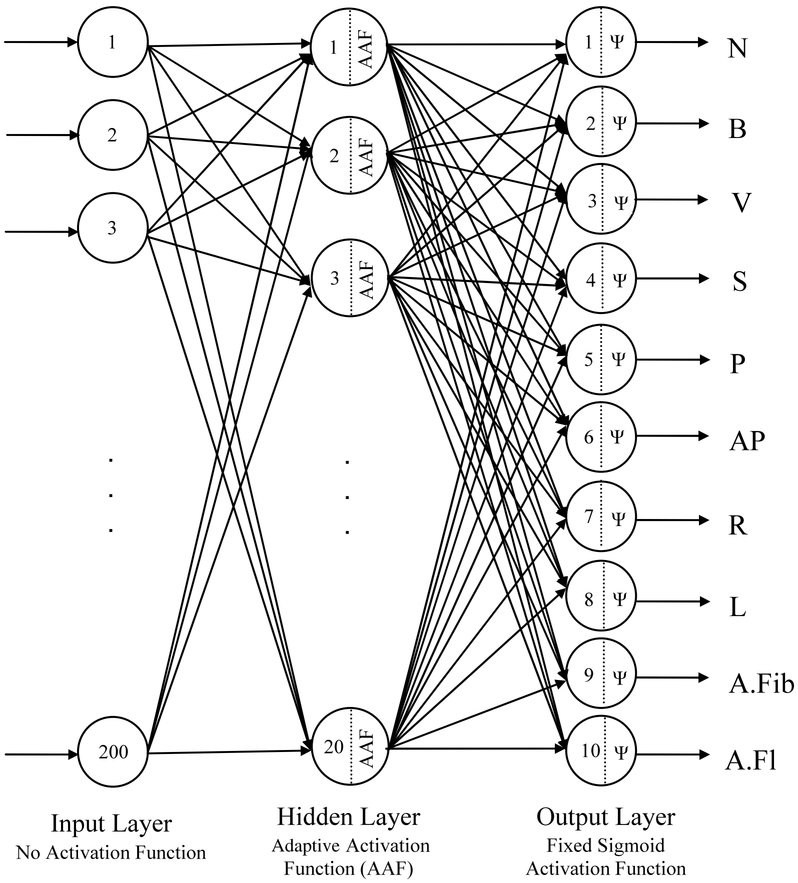

Fig. 2. Architecture of NNAAF-2 model.

3.2. Test results

MLP and NNAAF models shown in Table 1 have been trained with the training data including a number of 106 segments, and the architectures that can produce best results have been determined with trial and error. The test was implemented using ECG records taken from 92 patients (40 males and 52 females, average age is 39.75 ± 19.06).

The ECG records were taken in the Cardiology Department, Faculty of Medicine at Selcuk University in Konya, Turkey. The sampling frequency of these recorded ECG signals of patients is 360 Hz. These recorded patterns are normalized between 0 and 1 and are arranged as 200 samples in the intervals of R–R.

The detailed classification results for test data that were recorded from 92 patients can be seen in Tables 2–5. As shown in these tables, test data recorded from 92 patients are consisted of a total of 5342 segments. In Tables 2–5, the first five columns provide descriptive information about the patient. This information includes patient number, gender, age, total number of samples belonging to the patient, and number of segments that is consisted of 200 samples. The other columns provide values obtained from the test results. The columns between Q_1 and Q_{10} provide the number of segments of the class belonging to the arrhythmia obtained from the test results. For unclassified number of segments that do not belong to any arrhythmia at the end of the test process, i.e. those cannot be classified, (?) symbol has been used to denote unknown class. In these tables, the last column provides classification error, which is calculated using Eqs. (21)–(23) given in Section 3.3. The undermost line in Tables 2–5 provides the total number of segments obtained for each arrhythmia class of 92 patients. The last cell of the undermost line gives the average value of test errors, i.e. the average of the last column.

Table 2
The test results classified by MLP for 92 patients' ECG records.

No	M/F	Age	Samples	Number of segments	Q_1 N	Q_2 Br	Q_3 VT	Q_4 S	Q_5 Apc	Q_6 P	Q_7 R	Q_8 L	Q_9 Afib	Q_{10} Aflt	?	Error %
1	M	23	11 200	56	22	0	0	16	0	0	0	0	0	0	18	3.116
2	M	23	3600	18	0	18	0	0	0	0	0	0	0	0	0	0.098
3	M	23	18 600	93	32	18	0	11	0	0	0	0	0	0	32	2.959
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
90	F	16	13 800	69	0	0	0	69	0	0	0	0	0	0	0	6.162
91	F	16	14 400	72	0	0	0	72	0	0	0	0	0	0	0	4.962
92	F	16	17 400	87	0	0	0	0	0	0	0	0	0	0	87	5.961
				5342	916	452	251	1501	84	51	824	56	542	104	561	1.902

Table 3
The test results classified by NNAAF-1 for 92 patients' ECG records.

No	M/F	Age	Samples	Number of segments	Q_1 N	Q_2 Br	Q_3 VT	Q_4 S	Q_5 Apc	Q_6 P	Q_7 R	Q_8 L	Q_9 Afib	Q_{10} Aflt	?	Error %
1	M	23	11 200	56	33	0	0	8	0	0	0	0	3	0	12	2.987
2	M	23	3600	18	0	18	0	0	0	0	0	0	0	0	0	0.315
3	M	23	18 600	93	55	16	0	7	0	0	0	0	3	0	12	3.341
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
90	F	16	13 800	69	0	0	0	69	0	0	0	0	0	0	0	5.363
91	F	16	14 400	72	0	0	0	72	0	0	0	0	0	0	0	3.454
92	F	16	17 400	87	0	0	0	0	0	0	0	0	0	0	87	4.483
				5342	942	490	274	1365	95	42	763	56	555	105	655	1.543

Table 4
The test results classified by NNAAF-2 for 92 patients' ECG records.

No	M/F	Age	Samples	Number of segments	Q_1 N	Q_2 Br	Q_3 VT	Q_4 S	Q_5 Apc	Q_6 P	Q_7 R	Q_8 L	Q_9 Afib	Q_{10} Aflt	?	Error %
1	M	23	11 200	56	55	0	0	1	0	0	0	0	0	0	0	2.259
2	M	23	3600	18	0	0	0	0	0	0	8	0	0	0	10	2.148
3	M	23	18 600	93	75	1	0	2	0	0	5	0	0	0	10	1.970
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
90	F	16	13 800	69	0	0	0	69	0	0	0	0	0	0	0	6.564
91	F	16	14 400	72	35	0	0	18	0	0	0	0	0	0	19	7.285
92	F	16	17 400	87	0	0	0	0	0	0	87	0	0	0	0	0.109
				5342	1226	334	427	1204	100	59	902	68	465	105	452	1.780

Table 5
The test results classified by NNAAF-5 for 92 patients' ECG records.

No	M/F	Age	Samples	Number of segments	Q_1 N	Q_2 Br	Q_3 VT	Q_4 S	Q_5 Apc	Q_6 P	Q_7 R	Q_8 L	Q_9 Afib	Q_{10} Aflt	?	Error %
1	M	23	11 200	56	25	0	0	18	0	0	0	0	0	0	13	3.646
2	M	23	3600	18	0	18	0	0	0	0	0	0	0	0	0	0.768
3	M	23	18 600	93	41	17	0	8	0	0	0	0	0	0	27	3.687
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
90	F	16	13 800	69	0	0	0	0	0	0	0	0	0	0	69	5.549
91	F	16	14 400	72	0	0	0	72	0	0	0	0	0	0	0	2.424
92	F	16	17 400	87	0	0	0	0	0	0	0	0	0	0	87	3.834
				5342	971	464	262	1225	95	61	695	56	553	93	867	2.028

The results obtained in Tables 1–5 are summarized in Table 6. In this table, NN structures, training errors, average test errors for 92 patients and the number of segments obtained for each class is shown. Using Table 6, we calculated training and test accuracies of the study in Table 7.

Comparing the results given in Table 6, at the end of test process implemented with 92 patients, the minimum test error of 1.543% has been obtained for NNAAF-1 model. Moreover, the minimum number of unclassified segments (452 segments) has been obtained for NNAAF-2 model. In terms of both test error and number of unclassified segments, the performance of NNAAF-3 has been obtained very close to the other models. Our efforts to improve the performance of the NNAAF-3 are continuing.

Table 6
Summary results of training and test for optimum structures of MLP, NNAAF-1, NNAAF-2 and NNAAF-3.

Structure	Optimum architecture	TrE (%)	TstE (%)	Q_1 N	Q_2 Br	Q_3 VT	Q_4 S	Q_5 Apc	Q_6 P	Q_7 R	Q_8 L	Q_9 Afib	Q_{10} Aflt	?
MLP	200:12:10	0.097	1.902	916	452	251	1501	84	51	824	56	542	104	561
NNAAF-1	200:35:10	0.063	1.543	942	490	274	1365	95	42	763	56	555	105	655
NNAAF-2	200:20:10	0.058	1.780	1226	334	427	1204	100	59	902	68	465	105	452
NNAAF-3	200:25:10	0.116	2.028	971	464	262	1225	95	61	695	56	553	93	867

TrE: training error, TstE: averaged test error of the ECG signals of 92 patients.

Table 7
Training and test accuracies of the study.

Structure	Training accuracy (%)	Test accuracy (%)
MLP	99.90	98.10
NNAAF-1	99.94	98.46
NNAAF-2	99.94	98.22
NNAAF-3	99.88	97.97
Average	99.92	98.19

3.3. Calculation of training and test errors

We calculated training error according to Eq. (20) [6,10,39].

$$\text{Training Error}(\%) = \left(\frac{\sum_{i=1}^{k} |t(i) - a(i)|}{m \times n}\right) \times 100 \tag{20}$$

where $t(i)$ is desired output, $a(i)$ is output of neural network, k is the number of samples in training data, m is the number of segments in training data and n is the number of outputs of the neural network.

We used previously developed algorithm [6,10,39] for evaluation of test results. Desired values of node outputs of the output layer are logic-1 or logic-0 in the training pattern. Node outputs are varied between 0–1. If one of the node outputs of the output layer is greater than or equal to 0.5 i.e. $y(i) \geqslant 0.5$, we used $h(i) = |1 - y(i)|$ in the error calculation according to Eq. (21). Furthermore, in case $y(i) \geqslant 0.5$ and $y(i) >$ (other node outputs), we interpreted this as arrhythmia for the corresponding node. If $y(i) < 0.5$, we interpreted that there is no arrhythmia, and we used $h(i) = |0 - y(i)|$ according to Eq. (22). If all of the node outputs are $y(i) < 0.5$, then an unknown state occurs. ANN does not classify this test pattern since similar pattern was not taught to the ANN beforehand. The unknown state is represented as "?" in Tables 1–5 [6,10,39].

$$y(i) \geqslant 0.5 \to h = \sum_{i=1}^{k} \bigl|1 - y(i)\bigr| \tag{21}$$

$$y(i) < 0.5 \to h = \sum_{i=1}^{k} \bigl|0 - y(i)\bigr| \tag{22}$$

where k is the number of samples in test data. Then, average test errors given in tables are found according to Eq. (23) by using calculated errors (h) [6,10,39].

$$\text{Test Error}(\%) = \left(\frac{\sum_{j=1}^{n} h(j)}{m \times n}\right) \times 100 \tag{23}$$

where m is the number of segments in test data and n is the number of outputs of neural network.

4. Conclusion

In this study, we implemented new NNAAF models and traditional MLP to classify ECG signals. We used different functions as activation function of hidden layer in these models: (1) sigmoid function with free parameters in NNAAF-1, (2) sum of sigmoid function with free parameters and sinusoidal function with free parameters in NNAAF-2 and (3) Morlet Wavelet function with free parameters as activation function in the model of NNAAF-3. Sigmoid function with fixed parameters was used as activation function in the hidden layer and output layer of MLP. In addition, sigmoid function with fixed parameters was used in the output layers of NNAAF-1, NNAAF-2 and NNAAF-3 models. These developed models and MLP were implemented with MATLAB Software Package without Neural Network Toolbox. The proposed models were trained by the training data set (106 segments) and tested by the test data set recorded from 92 patients to prove robustness of these models and to find the best model.

At the end of training, a training accuracy of 99.8% (100% – training error %) for NNAAF-3, and approximately 99.9% (100% – training error %) training accuracy for other structures has been reached. From the test results reached using a test set from 92 patients, the best classification accuracy of 98.46% (100% – test error %) has been obtained for NNAAF-1 model and the lowest classification accuracy of 97.97% (100% – test error %) was obtained for NNAAF-3 model. Moreover, in terms of the number of segments that does not belong to any arrhythmia class, the best results have been obtained for NNAAF-2 model. In addition, for NNAAF-1 and NNAAF-2 models, the training process has been completed in less number of iterations than that of the MLP and NNAAF-3 models.

The use of neural network models utilizing adaptive activation function with free parameter is a novel idea in biomedical data particularly in classification of ECG arrhythmias. In this study, NNAAF-1, NNAAF-2 and NNAAF-3 models have been used in classification of ECG arrhythmias. To our knowledge, NNAAF-3 model has been applied for the first time in literature and also its performance in terms of the classification accuracy was nearly same with the other models. Moreover efforts to improve the performance of the NNAAF-3 model are aimed in our future work.

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