# Performance Evaluation of Generalized Feedforward Neural Network Based ECG Arrhythmia Classifier

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**Abstract**

Evaluation is the key to making real progress in machine learning. In this paper we have evaluated performance of our proposed approach for cardiac arrhythmia disease classification from standard 12 lead ECG recordings data, using a Generalized Feedforward Neural Network (GFNN) model. The proposed classifier is trained using static backpropagation algorithm to classify arrhythmia patient cases into normal and abnormal classes. In this study, we are mainly interested in producing high confident arrhythmia classification results to be applicable in medical diagnostic decision support systems. In arrhythmia analysis, it is unavoidable that some attribute values of a patient would be missing. Therefore we have replaced these missing attributes by closest column value of the concern class. Network models are trained and tested on UCI ECG arrhythmia data set. This data set is a good environment to test classifiers as it is incomplete and ambiguous bio-signal data collected from total 452 patient cases. The classification performance is evaluated using six measures; sensitivity, specificity, classification accuracy, mean squared error (MSE), receiver operating characteristics (ROC) and area under curve (AUC). The experimental results presented in this paper show that up to 82.35% testing classification accuracy can be obtained.

***Keywords:*** *Accuracy, ECG arrhythmia, generalized feedforward neural network model, machine learning, momentum learning rule, sensitivity, specificity.*

## 1. Introduction

Cardiac arrhythmia, disorders of cardiac rhythm, may indicate the susceptibility of serious heart disease, stroke or sudden cardiac death. Early diagnosis of cardiac arrhythmia makes it possible to choose appropriate anti-arrhythmic drugs, and is thus very important for improving arrhythmia therapy. Various machine learning and data mining methods have been applied to improve the accuracy for the detection of ECG arrhythmia. Once a data mining task is identified, appropriate methods have to be selected for execution of this task. Method selection depends highly on the application context as given by initial task analysis, on the properties of the data on which the analysis is being performed [1]. Electrocardiogram records the electronic activities of the heart, and has been widely adapted for diagnosing cardiac arrhythmia [2]. By far, a number of signal processing [3], pattern recognition [4, 5], and machine learning [6] methods had been proposed. The publications of several generally available arrhythmia data sets also played an important role in stimulating research on cardiac arrhythmia diagnosis [7, 8].

In this paper, we proposed an artificial neural network (AAN) based system, which can classify ECG arrhythmia into normal and abnormal classes i.e. distinguish between presence and absence of cardiac arrhythmia. We used generalized feedforward neural network (GFNN) model with static backpropagation algorithm. The proposed approach first cleans the data set by replacing missing values by closest column values of the concern class. To evaluate the performance of GFNN, we used the UCI cardiac arrhythmia database which contains 452 instances with 245 normal and 207 arrhythmia (abnormal) instances.

## 2. Related Research Work

Gao and Madden [1] developed an arrhythmia detection system with ECG signals based on a Bayesian ANN Classifier and its performance is compared with that of other classifiers, specifically Naive Bayes, Decision Trees, Logistic Regression and RBF Networks. Zuo et al. [2] proposed a kernel difference weighted k-nearest neighbor classifier (KDF-WKNN) for the diagnosis of cardiac arrhythmia based on the standard 12 lead ECG recordings. They have used a modified principal component analysis (PCA) approach to cope with the missing attribute values. The approach [2] is different from classical K-nearest neighbor (KNN) classifier. Several methods for automated arrhythmia detection have been developed in the past few decades to attempt to simplify the monitoring task [9]. These include Wavelet transformation [10-12], Radial Basis Function (RBF) Neural Networks [13], Slf- Organizing Map (SOM) [14] and fuzzy c-means clustering techniques [15]. Multilayer neural networks are used to classify arrhythmia QRS complexes, and for ischemia detection [16-17]. A review of classification methods suitable for ECG signals can be found in [19-21]. Similar work using multilayer perceptron and modular neural network is available in [22] and [25] respectively. Issac Niwas et. al. [23] presented a method capable of distinguishing the normal beat and nine different arrhythmias. An Artificial immune recognition system (AIRS) with fuzzy weighted pre-processing [26] is also used for arrhythmia classification. ECG arrhythmia classification and Fetal state classification using ANN models is also available in [27-32]. In this paper we are using another alternative neural network model which is GFNN.

## 3. Methods

### 3.1 Description of data set

The Cardiac Arrhythmia Database from the UCI Machine Learning Repository [8] is used. This data set is a good environment to test classifiers as it is incomplete and ambiguous bio-signal data collected from total 452 patient cases. The first class is “Normal”, and the other 15 classes are 15 kinds of arrhythmia. These 15 classes are merged into a single class called Abnormal class a representative of 15 arrhythmia classes. For each sample, there are 279 attributes, where the first four attributes age, sex, height, and weight are the general description of the patient and other 276 attributes are extracted from the standard 12 lead ECG recordings. For the details of the data set, please refer to [4, 6]. The entire database is first preprocessed to replace missing attributes. We have used closest column value of the concern class. And later all the records are randomized.

### 3.2 Data set groups

The original data set grouped into different data sets as shown in the table 1 and each group is partitioned into two subsets viz. training set and testing set except the last group labeled as DSMains in which all 452 instances are used for training purpose only.

Table 1: Data Set Group Partitions

| *Data Set (Group) Name* | *Training % age* | *Testing % age* | *Training instances* | *Testing Instances* |
|---|---|---|---|---|
| Data set 1 (DS1) | 80 | 20 | 362 | 90 |
| Data set 2 (DS2) | 75 | 25 | 339 | 113 |
| Data set 3 (DS3) | 70 | 30 | 316 | 136 |
| Data set 4 (DS4) | 85 | 15 | 384 | 68 |
| Data set 5 (DS5) | 90 | 10 | 407 | 45 |
| Main Data set (DSMains) | Training set itself all 452 instances for Training only. | | | |

### 3.3 Selection of neural network model

Generalized feedforward networks are a generalization of the Multilayer perceptron (MLP) such that connections can jump over one or more layers. In theory, a MLP can solve any problem that a generalized feedforward network can solve. In practice, however, generalized feedforward networks often solve the problem much more efficiently. A classic example of this is the two spiral problem. Without describing the problem, it suffices to say that a standard MLP requires hundreds of times more training epochs than the generalized feedforward network containing the same number of processing elements. Figure 1 illustrates architecture of a simple generalized feedforward neural network model with two hidden layers [18]. The circles are processing elements (PEs) and are arranged in layers. The left column is the input layer, the middle columns are hidden layers and the rightmost column is the output layer. The lines represent weighted connections (i.e., a scaling factor) between PEs. By adapting its weights, the neural network works towards an optimal solution based on a measurement of its performance. GFNNs are normally trained with the backpropagation algorithm. In fact the renewed interest in ANNs was in part triggered by the existence of backpropagation. The backpropagation rule propagates the errors through the network and allows adaptation of the hidden PEs.

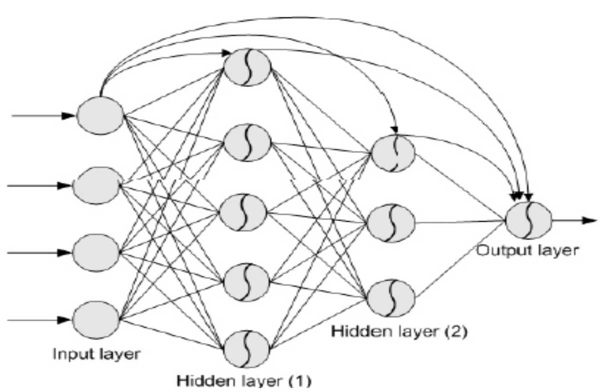


Fig. 1: Generalized Feedforward Neural Network Model

## 4. Performance Measures

Classification efficiency has been widely used as the main criterion for comparing the classification quality of classifiers [21]. First if class distribution is skewed rather than constant and relatively balanced in the real world, then the evaluation based on accuracy breaks down, second, classification accuracy assumes equal misclassification costs (for false positive and false negative errors), which is problematic because for real-world problems one type of classification error is much more expensive than another, e.g., classifying a healthy patient to have arrhythmia and classifying a arrhythmia patient to be healthy will have different misclassification cost, since the latter may cost the patient's life. We have evaluated the performance of the classification algorithms using six measures; sensitivity, specificity, classification accuracy, mean squared error (MSE), receiver operating characteristics (ROC) and area under ROC curve (AUC). These measures are defined using True Positive (*TP*), True Negative (*TN*), False Positive (*FP*) and False Negative (*FN*). *TP* decision occurs when an arrhythmia detection of the classifier coincided with a decision of the physician. *TN* decision occurs when both the classifier and the physician suggested the absence of arrhythmia. *FP* occurs when the system labels a healthy case as an arrhythmia one. Finally, *FN* occurs when the system labels an arrhythmia case as healthy.

### 4.1 Classification Accuracy

Classification accuracy is defined as the ratio of the number of correctly classified cases and is equal to the sum of *TP* and *TN* divided by the total number of cases *N*.

$$Accuracy = (TP + TN)/N \qquad (1)$$

### 4.2 Classification Sensitivity

Sensitivity refers to the rate of correctly classified positive and is equal to *TP* divided by the sum of *TP* and *FN*. Sensitivity may be referred as a *True Positive Rate.*

$$Sensitivity = TP/(TP + FN) \qquad (2)$$

### 4.3 Classification Specificity

Specificity refers to the rate of correctly classified negative and is equal to the ratio of TN to the sum of TN and FP. False Positive Rate equals (100-specificity).

$$Specificity = TN/(FP + TN) \qquad (3)$$

### 4.4 Mean Squared Error (MSE)

The mean squared error is simply two times the average cost. The formula for the mean squared error is:

$$MSE = \frac{\sum_{j=0}^{P}\sum_{i=0}^{N}(d_{ij} - y_{ij})^2}{NP} \qquad (4)$$

where,
P = number of output processing elements (PEs)
N = number of exemplars (instances) in the data set
$y_{ij}$ = Network output for exemplar i at processing element j
$d_{ij}$ = desired output for exemplar i at processing element j

### 4.5 ROC Matrix

Receiver Operating Characteristic (ROC) analysis originated in electrical engineering in the early 1950's where the technique was developed to assess the performance of signal detection devices (receivers). From there it spread into other fields, finding useful applications in both psychology and medical diagnosis. The receiver constantly sees small amounts of noise, so a threshold must be set to distinguish between an actual signal and background noise. Anything below the threshold will be classified as "noise", while anything above the threshold will be classified as "signal". ROC matrices are used to show how changing the detection threshold affects detections versus false alarms. If the threshold is set too high then the system will miss too much detection. Conversely, if the threshold is set too low then there will be too many false alarms [21].

### 4.6 Area under ROC Curve (AUC)

Area under curve has been recently used as an alternative measure for machine learning algorithms [20]. AUC has many advantages such as its independence to the decision sensitivity in analysis of variance tests, its independence to the decision threshold, and its invariance to a priori class probability (recognized in advance as equally probable) distribution etc. Since the AUC is a portion of the area of the unit square, its value will always be between 0 and 1 [21].

## 5. Experimental Results

Experiments are performed on Neuro Solutions (version 5.0) software simulation tool [24]. Neural network model used is GFNN model with static backpropagation with momentum learning rule. We have varied number of hidden layers (HL) from one to three on each data set. Training Accuracy, Sensitivity, and Specificity is a calculated using equation 1, 2, and 3 respectively from entries of confusion matrix. Training classification results for one to three numbers of hidden layers are given in figure 2. Testing classification results for all data sets are shown in given in table 2.

Table 2: Arrhythmia Classification Results

| *Data Set Name* | *No. of HLs* | *Sensitivity (%)* | *Specificity (%)* | *Classification Accuracy (%)* |
|---|---|---|---|---|
| DS1 | 1 | 73.681 | 80.769 | 77.778 |
| | 2 | 65.789 | 86.538 | 77.778 |
| | 3 | 60.526 | 84.615 | 74.444 |
| DS2 | 1 | 76.471 | 83.871 | 80.531 |
| | 2 | 68.627 | 77.419 | 73.451 |
| | 3 | 60.784 | 87.097 | 75.221 |
| DS3 | 1 | 67.188 | 80.556 | 74.265 |
| | 2 | 68.75 | 80.556 | 75 |
| | 3 | 64.063 | 84.722 | 75 |
| DS4 | 1 | 68.182 | 82.609 | 77.941 |
| | 2 | 68.182 | 89.13 | **82.353** |
| | 3 | 72.727 | 80.435 | 77.941 |
| DS5 | 1 | 60 | 88 | 75.556 |
| | 2 | 75 | 80 | 77.778 |
| | 3 | 60 | 92 | 77.778 |
| DS-Mains | 1 | 97.825 | 92.265 | 94.873 |
| | 2 | 98.689 | 92.743 | 95.523 |
| | 3 | 98.709 | 94.022 | 96.248 |

These performance measures for testing are computed as per equation 1, 2, and 3. MSE is computed using equation 4 and average MSE for all data sets is shown in figure 3. Results shown in table 2 against data set DSMains are obtained using all 452 instances for training only. Observing classification results it is clear that the data set 4 gives better performance in terms of training sensitivity, specificity and accuracy. This is supported by other performance evaluation approach, the average MSE for training which is also lowest for this data set. Figure 4 gives performance against testing for all the data sets. ROC matrix is used to show how changing the detection threshold affects detections versus false alarms. Data set DS4 has given best classification results therefore for this data set ROC matrix is graphed as an ROC curve as shown in Figure 5 for network models with 1 to 3 no. of hidden layers. From table 3 it is proved that proposed work have given the best classification accuracy with 2 numbers of hidden layers for data set 4 and it is **82.35** %. Therefore area under ROC curve is also higher as compared with NN model with 1 and 3 numbers of hidden layers as shown in Figure 6 for this data set 4.

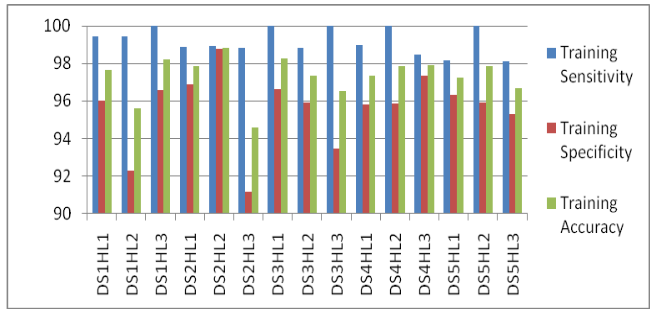


Fig. 2 Sensitivity, Specificity and Accuracy for Training Data Sets

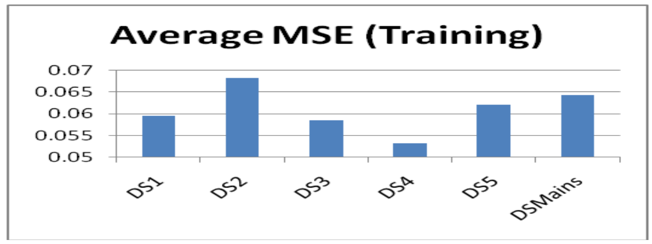


Fig. 3 Average Mean Squared Error (Training)

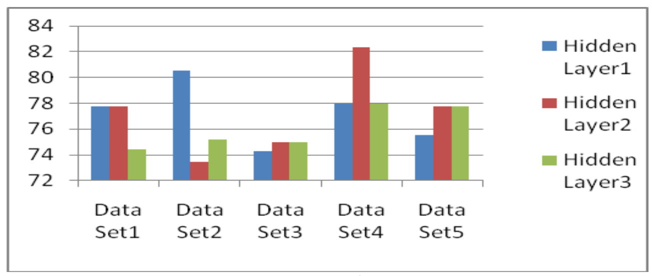


Fig. 4 Testing Accuracy for all Data Sets

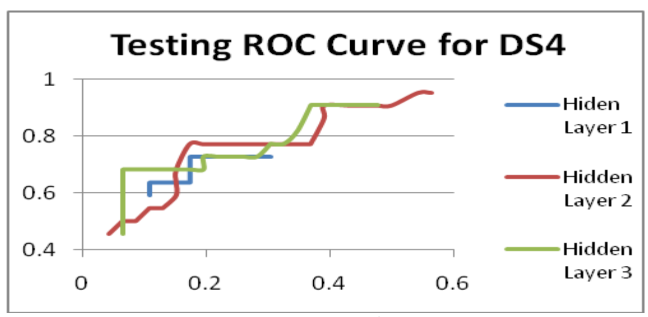


Fig. 5 Testing ROC Curve for Data Set 4

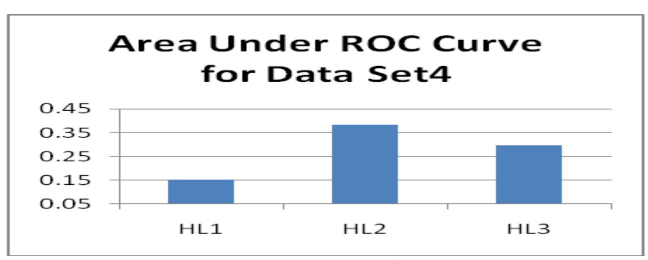


Fig. 6 Area under ROC Curve for Data Set 4

Table 3: GFFNN model's classification accuracy for ECG classification problem with classification accuracies obtained by other methods in literature

| *VF 15 [26]* | *VF 15 FW [26]* | *KDF-WKNN [2]* | *J4.8 [26]* | *Naïve Bayes [26]* | *Fuzzy weighted AIRS [26]* | *GFFNN Model (our work)* |
|---|---|---|---|---|---|---|
| 62% | 68% | 70.66% | 74.26% | 75% | 80.71% | **82.35%** |

## 6. CONCLUSION

This paper presents an effective GFNN based approach for cardiac arrhythmia classification using ECG signal data. From the comparative analysis of results obtained, it is clear that the GFNN is better classifier to classify given cardiac arrhythmia ECG data. From exhaustive and careful experimentation with two numbers of hidden layers we reached to the conclusion that proposed classifier system ensures better estimation of the complex decision boundaries. Our experimental results on the UCI cardiac arrhythmia database show classification accuracy of **82.35%** for data set 4. It is also proved that to evaluate the performance of classifier almost all different performance measures are required to evaluate the performance of neural network based classifiers.

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