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MODULAR NEURAL NETWORK BASED ARRHYTHMIA CLASSIFICATION SYSTEM USING ECG SIGNAL DATA

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This research is on presenting a new approach for cardiac arrhythmia disease classification. The proposed method uses Modular neural network (MNN) model to classify arrhythmia into normal and abnormal classes. We have performed experiments on UCI Arrhythmia data set [8]. Missing attribute values of this data set are replaced by closest column value of the concern class. We have constructed neural network model by varying number of hidden layers from one to three and are trained by varying training percentage in data set partitions. In this study, we are mainly interested in producing high confident arrhythmia classification results to be applicable in diagnostic decision support systems. 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 more than 82.22% testing classification accuracy may be obtained.
Keywords: Modular Neural Network, ECG, Arrhythmia, Machine Learning, Learning Rule

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, on previous experience with similar domains, and on user-specified requirements for the results [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].

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In this paper, we proposed an intelligent system, which can classify into normal and abnormal i.e. distinguish between presence and absence of cardiac arrhythmia. We used modular neural network model to classify arrhythmia into normal and abnormal cases. The proposed method first cleans the data set by replacing missing values by closest column values of the concern class. To evaluate the performance of MNN, we use the UCI cardiac arrhythmia database which contains 452 instances with 245 normal and 207 arrhythmia (abnormal) instances.

2. Related Research Work

Several methods for automated arrhythmia detection have been developed in the past few decades to attempt simplify the monitoring task [9]. These include Wavelet transformation [10-12], RBF Neural Networks [13], self-organizing map [14] and fuzzy c-means clustering techniques [15]. Dayong Gao, Michael 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. WM Zuo, WG Lu, KQ Wang, H Zhang proposed a kernel difference weighted k-nearest neighbour classifier (KDF-WKNN) for the diagnosis of cardiac arrhythmia based on the standard 12 lead ECG recordings[2]. 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 neighbour (KNN) classifier. Their Experimental results on the UCI cardiac arrhythmia database indicate that, KDFWKNN is superior to the nearest neighbour classifier, and is very competitive while compared with several state of the art methods in terms of classification accuracy. Their results are given in Table 1.

Table 1
Results Compared in [2]

Method	NN [8]	NB [8]	VF15 [8]	VF15-FW [8]	KDF-WKNN
Accuracy (%)	53	50	62	68	70.66

A review of classification methods suitable for ECG signals can be found in [19-21]. A similar work using multilayer perceptron is available in [23] but in this work we are using MNN model. Issac Niwas, S. Shantha Selva Kumari, R. Sadasivam presented a method capable of distinguishing the normal beat and 9 different arrhythmias. The overall accuracy of classification of the proposed approach is 99.02% only for few classes [24].

3. METHODS

3.1. Description of Data Set

The Cardiac Arrhythmia Database from the UCI Machine Learning Repository [8] is used. This data set contains 452 instances of samples from 16 classes. 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 15 arrhythmia classes. For each sample, there are 279 attributes, where the first four, age, sex, height, and weight, are the general description of the participant, and the other 276 attributes are extracted from the standard 12 lead ECG recordings. For the details of the data set, please refer to [4, 6]. There are two significant characteristics which should be noted for the UCI cardiac arrhythmia database. The entire database is first pre-processed to replace missing attribute values. 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 2 and each group is partitioned into two subsets viz. training set and testing set except the last group in which all 452 instances are used for training purpose only.

3.3. Selection of Neural Network Model

The most used artificial neural networks have a monolithic structure. A lot of models work on fully connected networks or layers (Hopfield or multilayer perceptron). These networks perform well on a very small input space. However the complexity increases and the performance decreases rapidly with a growing input dimension [16]. A stock market prediction system using MNN is presented in [17]. In our work more than 152 numbers of input attributes are used. We have chosen Modular neural network model to classify arrhythmia classes into normal and abnormal cases.

Table 2
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 Dataset (DSMains)	Training set itself all 452 instances for training only			

Figure 1 illustrates modular neural network architecture. The circles are processing elements (PEs) 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. Generally speaking, for static pattern classification, the MNN with two hidden layers is a universal pattern classifier. MNNs 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. The MNN is trained with error correction learning, which means that the desired response for the system must be known. In pattern recognition this is normally the case, since we have our input and desired data labelled.

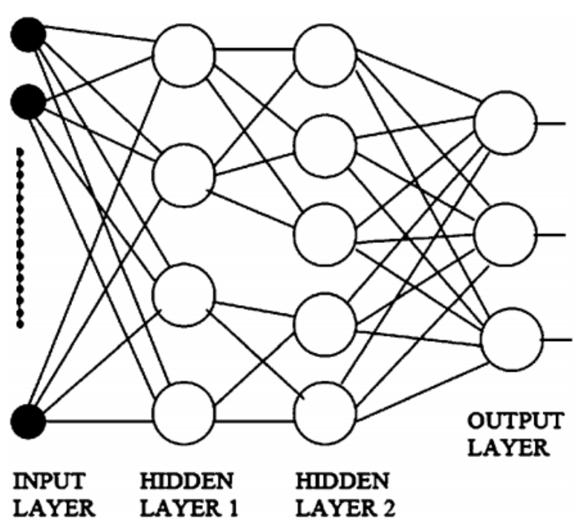

Fig. 1: Architecture of Modular Neural Network Model

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.

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

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.

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

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).

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

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. As originally conceived, receiver listens for signals, as, for example, radar searching for aircraft. 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)

AUC has been recently used as an alternative measure for machine learning algorithms [21]. AUC has many advantages such as its independence to the decision sensitivity in analysis of variance (a collection of statistical models and their associated procedures which compare means by splitting the overall observed variance into different parts) 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 [22].

Table 3
Arrhythmia Classification Results

Data Set Name	No. of Hidden Layers	Sensitivity (%)	Specificity (%)	Classification Accuracy (%)
DS1	1	73.68	82.69	78.89
	2	65.79	84.62	76.67
	3	71.05	84.62	78.89
DS2	1	68.63	82.26	76.11
	2	70.59	79.03	75.22
	3	62.75	88.71	76.99

Table 3 Contd...

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DS3	1	67.19	76.39	72.06
	2	73.44	83.33	78.68
	3	64.06	79.17	72.06
DS4	1	65.63	83.33	75
	2	75	83.33	79.41
	3	84.38	77.78	80.88
DS5	1	62.5	93.1	82.22
	2	81.25	82.76	82.22
	3	75	85.71	80
DSMains	1	97.89	94.85	96.32
	2	99.15	94.91	96.94
	3	99.54	89.57	93.95

5. Results and Discussion

Experiments are performed on Neuro Solutions (version 5.0) software simulation tool [25]. Neural network model used is modular neural network with static backpropagation. Learning rule used is momentum. We have varied number of hidden layers (HL) from 1 to 3 for each data set (data group). Fig. 2 shows sensitivity, specificity and accuracy measures for training data sets while fig. 3 shows average mean squared error for each data set grouped as shown in table 2. Table 3 gives arrhythmia classification results for six groups of data sets. In group six (DSMains) classifiers are trained using all records available and training results are given. In groups DS1, DS2, DS3, DS4 and DS5 data is partitioned into training and testing instances as shown in Table 2. It is clear from fig. 2 that all data sets give better performance in terms of training sensitivity, specificity and accuracy for hidden layer 2. Figure 4 gives performance against testing and it is clear that data set gives better results. Receiver Operating Characteristic (ROC) matrix is used to show how changing the detection threshold affects detections versus false alarms. Data set DS5 has given best classification results therefore for this data set ROC matrix is graphed as an ROC curve and is shown in fig. 5. The best classification accuracy is with 2 no. of hidden layers for data set DS5 and it is 82.22 %. Therefore area under ROC curve is higher as compared with NN models with 1 and 3 no. of hidden layers as shown in Figure 6 for this data set 5.

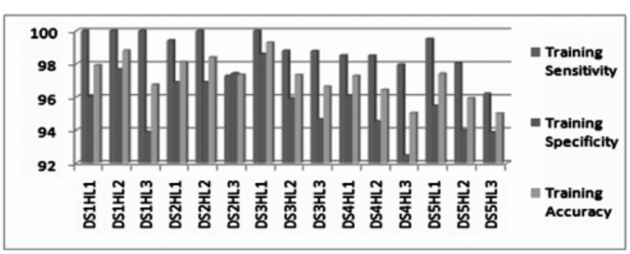

Fig. 2: Training Sensitivity, Specificity and Accuracy for all Data Set

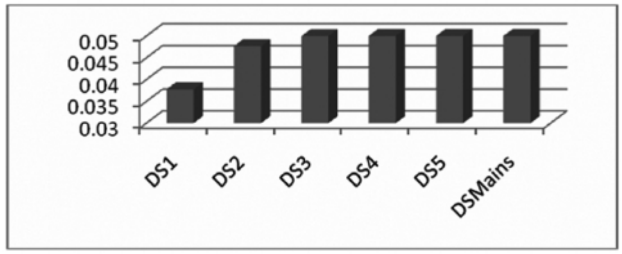

Fig. 3: Average Training Mean Squarred Error

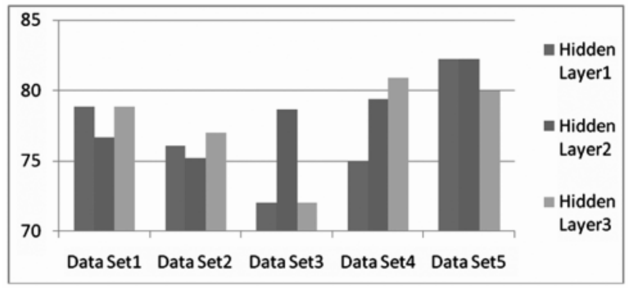

Fig. 4: Testing Classification Accuracy

6. Conclusion

In this work UCI Arrhythmia data set [8] has been used to perform experiments to classify normal and abnormal patient subjects using momentum learning rule with back propagation algorithm. Experimental results show that more than 82.22% classification accuracy may be obtained. Our future work will include the classification of other 15 classes of arrhythmia diseases.

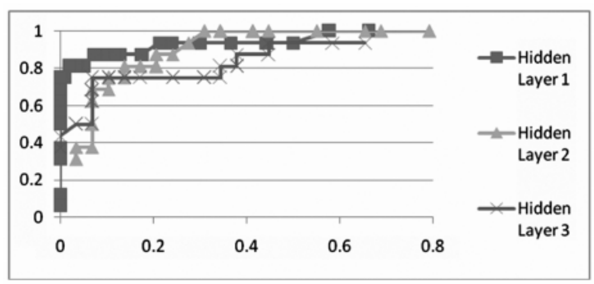

Fig. 5: ROC Curves for Data Set 5

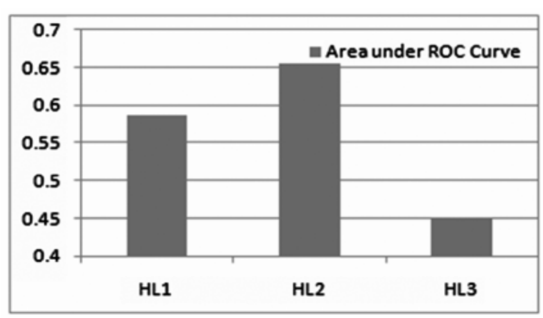

Fig. 6: Area Under ROC Curve for Data Set 5

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