Arrhythmia Identification from ECG Signals with a Neural Network Classifier Based on a Bayesian Framework

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Abstract

This paper presents a diagnostic system for cardiac arrhythmias from ECG data, using an Artificial Neural Network (ANN) classifier based on a Bayesian framework. The Bayesian ANN Classifier is built by the use of a logistic regression model and the back propagation algorithm. A dual threshold method is applied to determine the diagnosis strategy and suppress false alarm signals. The experimental results presented in this paper show that more than 90% prediction accuracy may be obtained using the improved methods in the study. It is hoped that the system can be further developed and fine-tuned for practical application.

1 Introduction

The electrocardiogram (ECG) is the most important biosignal used by cardiologists for diagnostic purposes. The ECG signal provides key information about the electrical activity of the heart. Continuous ECG monitoring permits observation of cardiac variations over an extended period of time, either at the bedside or when patients are ambulatory, providing more information to physicians. Thus, continuous monitoring increases the understanding of patients' circumstances and allows more reliable diagnosis of cardiac abnormalities.

Detection of abnormal ECG signals is a critical step in administering aid to patients. Often, patients are hooked up to cardiac monitors in hospital continuously. This requires continuous monitoring by the physicians. Due to the large number of patients in intensive care units and the need for continuous observation of them, several methods for automated arrhythmia detection have been developed in the past few decades to attempt simplify the monitoring task. These include Bayesian [1] and heuristic approaches [2], expert systems [3], Markov models [4], self-organizing map [5], and Artificial Neural Networks (ANNs) [6].

According to published results, existing approaches generally tend to suffer from problems that result from high sensitivity to noise included in the data, and unreliability in dealing with new or ambiguous patterns. In clinical domains, one must to face the problem of developing classifiers that are able to deal with nonlinear discrimination between classes, incomplete or ambiguous input patterns, and suppression of false alarms. It is necessary to develop new detection schemes with a high level of accuracy, or equivalently, low false-positive and false-negative statistics, for them to be useful in practical applications. Guvenir *et. al.* [7] developed a supervised machine learning algorithm for arrhythmia analysis based on a technique called Features Interval for the UCI "Arrythmia" dataset [8] with missing features and unlabeled classes to address this problem, and achieved an accuracy of 62%. Obviously, such performance is not sufficiently good for clinical use. So far, implementations of ANN-based ECG classification schemes have, in general, been focused on problems within narrow clinical domains.

Since ANNs are inherently nonlinear, such techniques are potentially useful in the area of ECG analysis. Various techniques for ANN classification and its combination with other methods have been used to improve classification results. These include Fourier Transform Neural Networks [9], Recurrent Neural Networks [10], and Back Propagation (BP) Neural Networks [11].

The Bayesian approach has been known for some time, but only recently has it started to infiltrate different areas of science and technology systematically, with useful results [12], [13], [14], [15]. With newer knowledge available from the theory of ANNs and combination with a variety of other methods, the stage is now set for moving towards the development of practically applicable ANN-based clinical ECG interpretation systems.

This paper presents a Bayesian ANN-based arrythmia diagnostic system using ECG signals. Our system can determine the patient's current condition in real-time. The ANN is used to generate a pattern recognition model based on given {input, output} sets to classify future input sets for arrhythmia diagnosis as a system module. The logistic regression model and BP algorithm are used to build the Bayesian ANN classifier for arrhythmia detection. A dual threshold method is proposed for use in suppressing false alarm signals. Overall, the approach used in this study aims to produce a system that will perform well in practice.

The rest of this paper is organized as follows. The next section outlines the proposed system and presents the methodology for ECG diagnostic system using the Bayesian ANN classifier. The third section discusses the results of evaluation experiments. The fourth section presents a brief summary of our findings and previews potential future work.

2 System and Methodology

2.1 System Overview and Data Acquisition

The proposed system consists of three basic modules: a Server, multiple Client Machines and BAN-Hubs. The elements are as follows:

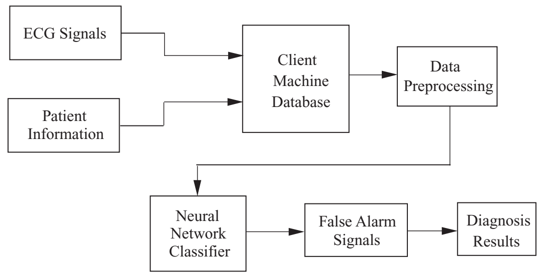

Figure 1: Block Diagram of ANN-based Arrythmia Diagnosis System using ECG Signals

- BAN-Hub
  The BAN-Hub is the core part of a wireless Body Area Network (BAN) that is used to gather key patient biosignal data in real-time. The BAN-Hub is the patient interface to this network. It is attached to the patient using either a shoulder strap, waist or other attachment form.

- Server
  The server provides the backbone of the network. It gathers patient data, sends control information to the BAN-Hub and establishes the precise location of each BAN-Hub.

- Client Machine
  The Client machine provides the medical and administrative interface to the network. It provides a patient registration mechanism for each BAN-Hub and indicates alarm conditions (relating to either a unit or patient) in each BAN-Hub.

The system is illustrated by the block diagram in Fig. 1. The ECG signals and other patient data are gathered in real-time and sent to the Client Machine. The information is transmitted using the wireless network to the server. This stored data can then be processed to detect firstly the various complexes and then detect specified arrhythmia. An ECG complex represents the electrical events occurring in one cardiac cycle. A complex consists of five waveforms labeled with the letters P, Q, R, S, and T, as shown in Fig. 2. Because the ECG is very helpful in the diagnosis of cardiac disease, only ECG signals are used at present in this project. However, our system is designed to allow other types of biosignal sensor to be attached also.

As the hardware and software for this system are still under development, this study uses 452 ECG recordings from the UCI "Arrythmia" dataset [8]. This dataset includes about 0.33% missing attribute values and 22 unclassified classes, so the prediction accuracy of any model built using it cannot be perfect. However, such characteristics make it more similar to the real-world dynamic environment in our project, when noisy data may well be acquired.

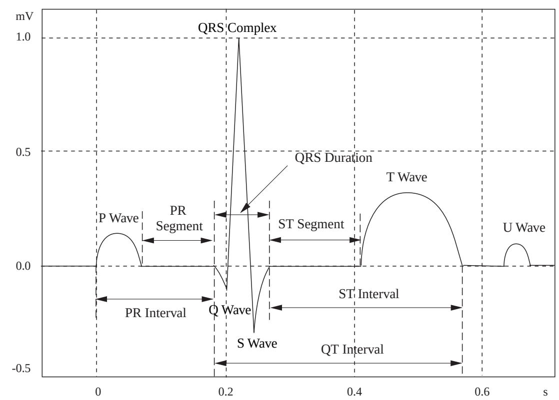

Figure 2: ECG signals. A complex of ECG signals consists of five waveforms labeled with the letters P, Q, R, S, and T.

Therefore, we believe that the results of this study should be transferable to actual ECG signals coming from our hardware. Each record consists of a set of clinical parameters measured on ECG signals and some personal information about the subjects. The dataset is divided into two groups, labeled as Normal (regular heartbeat) and Abnormal (arrhythmia). The ECG signals used as system inputs include 5 parameters: QRS duration, PR interval, QT interval, T interval and P interval. The personal information available includes age, height, weight and sex. There are 245 cases in the Normal group and 207 cases in the Abnormal group.

A sequence of extracted parameter vectors, denoted by t_n, is converted to the deviation from their mean value and scaled by a factor m to normalize their values in the range of -1 to +1, as follows:

$$x_n = \frac{t_n - \bar{t}}{m}, \qquad n = 1 \sim N \tag{1}$$

where n is input data sample index (in the training or test sets) and N is the total number of input data samples. $\bar{t}$ is the average of t_n, m is the standard deviation of input data for training and test sets, respectively.

The whole data set is divided into training and test subsets, where the training subset contains 360 ECG recordings and the testing subset contains the remaining 92.

2.2 Bayesian ANN Classifier

Since detailed descriptions of BP neural networks can be found in related literature [16] [17] [18], here we mainly focus on the description of our Bayesian ANN Classifier. Its configuration is shown schematically in Fig. 3, where i = 1, 2, $\cdots$, I is the number of input nodes, j = 1, 2, $\cdots$, J is the hidden nodes, k = 1, 2, $\cdots$, K is the class labels of the output node.

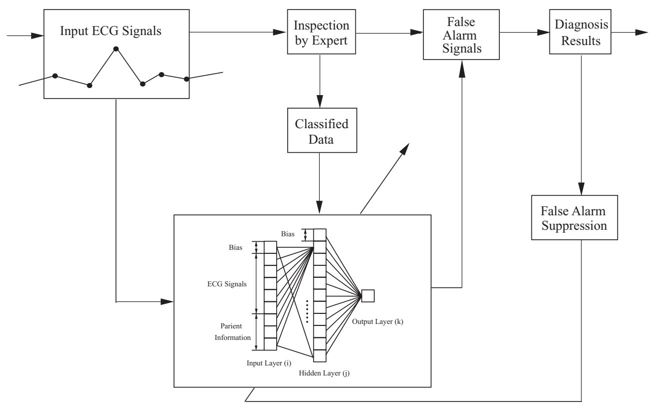

Figure 3: Block diagram of ANN-based arrhythmia diagnosis system, showing configuration of Bayesian ANN classifier with input layer ($i = 1,\ 2,\ \cdots,\ I$), hidden layer ($j = 1,\ 2,\ \cdots,\ J$) and output layer ($k = 1,\ 2,\ \cdots,\ K$)

Assume we have a training set $\mathcal{D}$, consisting of N input-output pairs:

$$\mathcal{D} = [(X^n, y^n) \mid n = 1, 2, \cdots N] \tag{2}$$

where X is an input vector consisting of I elements and y is the corresponding class label consisting of K classes. The objective is to use an ANN to model the input-output relation ($y = k \mid X$). Here, the class label is binary-valued y = (1, 0), corresponding to Normal and Abnormal, respectively.

An alternative target for our task is to use a logistic regression model based on a Bayesian method to estimate the class probability for the given input by:

$$\mathcal{P}(y = k \mid X), \qquad k = 1, 0 \tag{3}$$

Assume that the outputs for the summation operation and sigmoidal activation function in the hidden and output neurons, denoted by S_j, S_k, respectively, can be written as follows:

Input layer:

$$S_j = \tanh(\sum_i \omega_{ji} X_i + \omega_{j0}) \tag{4}$$

Output layer:

$$S_k = \sum_k \omega_{kj} S_j + \omega_{k0} \tag{5}$$

where tanh is the tangent hyperbolic function, a conventional sigmoid function. ω_{ji} denotes the weight matrix in the input layer and ω_{kj} the weight matrix in the output layer.

To ensure that the outputs can be interpreted as probabilities, logistic regression is used to model the risk (or probability) of occurrence of arrhythmia.

Let $P\ (y = k \mid X)$ be the probability of the event $y = 1$, given the input vector X. This is modeled as a function of network output y by:

$$\mathcal{P}(y = k \mid X) = \frac{1}{1 + \exp\left(-S_k\right)} \tag{6}$$

The logistic regression model is simply a non-linear transformation of the linear regression. The "logistic" distribution is an S-shaped distribution function which is similar to the standard-normal distribution (which results in a probit regression model) but easier to work with in most applications. The logit distribution constrains the estimated probabilities to lie between 0 and 1.

The final part of the system is a multi-layer perceptron neural network, trained using the BP algorithm. The network is optimized using a log-likelihood cost function, given by

$$\mathcal{C}(\omega) = -\frac{1}{k}\sum_{k}\sum_{i} y_i(k)\ln[\mathcal{P}(y = k \mid X)] \tag{7}$$

where $\omega = [\ \omega_{ji}, \omega_{kj}\ ]$ is the vector of network weights.

To minimize the cost function between the actual and desired outputs of the network, the BP algorithm passes information from the output neuron backwards to all hidden units to form error terms which are used to update the weights of the multi-layer network. In this study, a three-layer fully connected network with 10 hidden units and a single output unit is used.

2.3 Evaluation Methods

To examine how well our Bayesian ANN classifier performs in recognizing arrhythmias, the misclassification rate is used to verify that the classifier acquires the underlying dynamics of the system from the data, and the False Rate is used to measure the accuracy of the model.

The misclassification rate is defined as:

$$\mathcal{MR} = \frac{\sum i}{N}, \qquad i \subset \{K \neq O\} \tag{8}$$

where K and O are the target and output classification labels, respectively. N is the number of cases.

Let:

FP = false positives;
FN = false negatives;
TP = true positives;
TN = true negatives; and
UN = classified as "uncertain", if applicable.

Then, the False Rate for Positives, False Rate for Negatives and Overall False Rate are defined respectively as:

$$\mathcal{FR}_{\mathcal{P}} = \frac{FP}{FP + TP + UN} \tag{9}$$

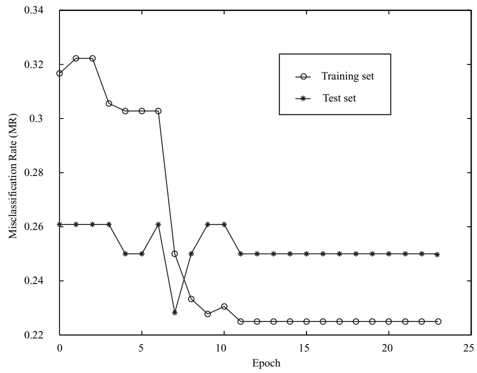

Figure 4: Misclassification Rates $\mathcal{MR}$ during training and testing.

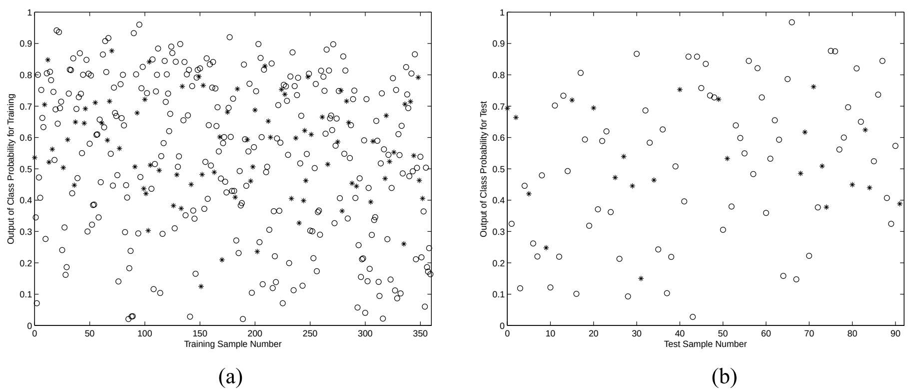

Figure 5: Scatter plot of classification results for (a) Training and (b) Test. The true and false classification results are marked by $\circ$ and $*$ respectively.

$$\mathcal{FR}_{\mathcal{N}} = \frac{FN}{FN + TN + UN} \tag{10}$$

$$\mathcal{FR} = \frac{FP + FN}{FP + TP + FN + TN + UN} \tag{11}$$

3 Empirical Results

3.1 Classification Results

To verify that the Bayesian ANN Classifier acquires the underlying dynamics of the system from the data, the misclassification rate for both training and testing phases are estimated.

Table 1: Arrhythmia Diagnosis Results for ANN-based Diagnostic System using ECG Signals. $\mathcal{FR}$: False Rate.

	Case of	Predicted Results		
	Classes	Normal	Abnormal	$\mathcal{FR}$ (%)
Training				
Normal	195	167	28	14.36
Abnormal	165	53	112	32.12
Total	360	220	140	22.50
Test				
Normal	50	39	11	22.00
Abnormal	42	12	30	28.57
Total	92	51	41	25.00

Fig. 4 shows the misclassification rate in the training and test phases respectively. Before training, synaptic connections ω_{ij} have random values and the networks yield large classification error. However, as the training processes, the misclassification rate decreases rapidly from initial values and becomes almost constant after a number of iterations, where one iteration corresponds to one round of training using all training data. After training, the misclassification rate reduces to 0.225. The corresponding misclassification rate for testing is also small enough to meet the requirements of this study.

The classification results for the training and test phases are shown in Fig. 5 (a) and (b), respectively. The output probability from the classifier is rounded to 1 or 0, depending on the classification probability threshold. Examining this figure, it may be seen that results labeled as abnormal are clustered towards higher probabilities, and conversely for results labeled as normal.

3.2 Evaluation of Classification Results

Table 1 shows arrhythmia diagnosis results. The False Rate for training and test phases is 22.50% and 25.00%, respectively. Therefore, at least 75% prediction accuracy is obtained in both phases.

Fig. 6 shows the histogram of misclassification distributions for the training and test phases, respectively. Considering Fig. 6, it may be seen that misclassifications are mainly concentrated on the area where probabilities are estimated to be between 0.4 and 0.7. We can therefore conclude that the classification results around probability = 0.5 have higher risk for misclassification. This also suggests that if the misclassifications between 0.4 and 0.7 could be ignored, the False Rate would be reduced substantially.

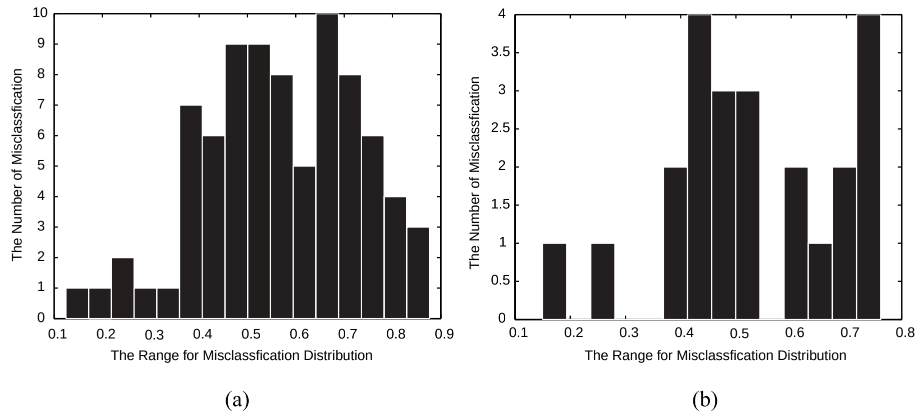

Figure 6: Histogram of Misclassification Distribution for (a) Training and (b) Testing, respectively.

3.3 False Alarm Suppression

A well-known difficulty with medical monitoring devices that raise alarms to alert the physician of problems is the "cry wolf" dilemma: such devices typically follow a conservative strategy of raising false alarms rather than risking a situation arising where a patient requires attention but no alarm is raised, but the physician may end up ignoring all alarms if many of them are false.

A dual threshold method is proposed here in an attempt to address this problem and suppress False Alarm Signals. The basic idea is to adopt a dual threshold, whereby an uncertainty criterion is introduced for high-risk classification outputs lying between Threshold 1 and Threshold 2.

IF:

Output probability > Threshold 1

THEN:

y = Classification 1 (Normal)

ELSE IF:

Output probability < Threshold 2

THEN:

y = Classification 2 (Abnormal)

ELSE:

y = uncertain class

The two thresholds used in this study are 0.4 and 0.7. These divide the outputs into three ranges where the low range corresponds to negative predictions, the middle range corresponds to questionable predictions and the high range corresponds to positive predictions. The wider the threshold band, the greater the reduction in false alarms, leading to higher prediction accuracy but also greater uncertainty.

Table 2: Arrhythmia Diagnosis Results for ANN-based Diagnosis System with ECG Signals. $\mathcal{FR}$: False Rate.

	Case of	Predicted Results			
	Classes	Normal	Abnormal	Uncertain	$\mathcal{FR}$ (%)
Training					
Normal	195	94	9	92	4.62
Abnormal	165	22	86	57	13.33
Total	360	116	95	149	8.61
Test					
Normal	50	21	5	24	10.00
Abnormal	42	3	24	15	7.14
Total	92	24	29	39	8.70

Table 2 shows diagnosis results using a dual threshold of 0.4 and 0.7. The False Rate for training and test phases is reduced to as little as 8.61% and 8.70%, respectively. Therefore, greater than 90% prediction accuracy is obtained in both phases. However, we get a classification response of "uncertain" between probabilities of 0.4 and 0.7, meaning that such cases should be reviewed manually by the supervising physician for a final decision.

When the thresholds are varied, different levels of classification accuracy and uncertainty are obtained. This can be used to control the diagnosis strategy. When suitable thresholds are chosen in building the Bayesian ANN Classifier, an optimum balance between False Rate and uncertainty may be found. The dual threshold method presented here could be applied to suppress false alarm signals and generate rules about the suppression of alarms. These rules may also be reviewed by a physician and potentially incorporated into the training phase of the system.

4 Conclusion

In this paper, an arrhythmia diagnosis system using ECG signals based on a Bayesian ANN Classifier is presented. The prediction performance of the system is evaluated by measuring the False Rate. Logistic regression and the back-propagation algorithm are used to build our Bayesian ANN Classifier. The classifier acquires arrhythmia properties from the underlying dynamics of the system, even when the dataset includes incomplete information, such as missing feature values and unclassified classes. This approach is potentially useful for generating a pattern recognition model based on given {input, output} sets to classify future input sets for arrhythmia diagnosis. The capability of uncertainty management with the dual threshold method described here could be used to control a diagnosis strategy and suppress false alarm signals.

Our future work will focus on evaluating the performance of this system on real-world data, to be gathered using the hardware under development in this project. The design of low-cost, high-performance, simple to use, and portable equipment for ECG signal monitoring, that offers a combination of diagnostic features, seems to be a goal that is highly worthwhile. We hope that this system can be further developed and fine-tuned for practical applications.

5 Acknowledgements

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