Detection of Myocardial Infarction using Heart Rate Signals and Neural Networks

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ABSTRACT

Myocardial infarction (MI) is a life threatening heart disease in human beings. Early detection and treatment can save many lives. This paper presents the development of an artificial neural network, a novel non-linear soft computing tool for the detection of myocardial infarction using heart rate data derived from ECG signals of myocardial patients and healthy subjects. This heart rate data has been used to obtain a set of statistical, spectral and spatial parameters. A feedforward backpropagation artificial neural network has been trained to predict the presence or absence of myocardial infarction on the basis of these parameters. The accuracy, specificity and sensitivity of the neural network model in identifying myocardial infarction were 95.74 %, 91.67 % and 100% respectively. The results demonstrate the capability of the neural network model developed in identifying myocardial infarction with significant diagnostic accuracy. The developed system can support physicians in the diagnosis of myocardial infarction.

Keywords : Artificial Neural Networks, Backpropagation, ECG, Heart Rate Variability, Myocardial Infarction.

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1. INTRODUCTION

Myocardial infarction (MI) occurs when the blood supply to a part of the heart is interrupted. This is most commonly due to occlusion (blockage) of a coronary artery following the rupture of plaque, which is an unstable collection of lipids (like cholesterol) and white blood cells in the wall of an artery. The resulting ischemia (restriction in blood supply and therefore oxygen shortage), if left untreated for a sufficient period, can cause death (infarction) of heart muscle tissue (myocardium).

As millions of patients undergo health check up each year for evaluation of symptoms of MI, the demand for quality health care has thrown challenges to clinical decision making. Detection of myocardial infarction is especially challenging because it is a disease of low incidence yet a very high price has to be paid for its misdiagnosis. Techniques developed to aid the physician in his diagnosis need to be more accurate [1]. The detection of MI in today's medical field is based on the ECG signal and traditional symptoms which include acute pain that traverses from the heart to the entire left hand. A more reliable method is to extract the Heart Rate Variability (HRV) data from the ECG signals of various patients which describes the signal in time and frequency domain. HRV analysis is a non-invasive technique that has gained prominence in the field of cardiology for detecting heart abnormalities.

The analysis of the HRV data yields various features that prove to be a better aid in the detection of heart diseases [2,3,4] and application of artificial neural networks for disease diagnosis has yielded remarkable results [5]. This paper presents the development of a neural network based model for the detection of MI using parameters derived from HRV analysis. Subsequent sections in this paper are organized as follows: section 2 describes the Neural Network Classifier. Data for classification is dealt with in section 3, test results and discussion are presented in section 4 and the concluding remarks in section 5

2. Neural Network Classifier

Artificial neural networks are algorithms that are patterned after the structure of the human brain. They contain a series of mathematical equations that are used to simulate biological processes such as learning, storing and retrieving information. Neural networks have the ability to learn mathematical relationships between a series of input (independent, predictor) variables and the corresponding output (dependent, outcome) variables.

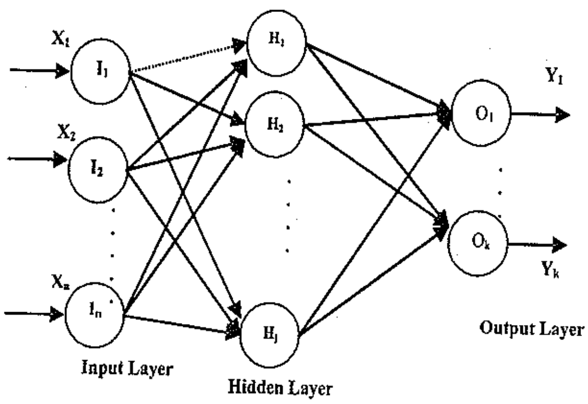

Figure 1 : Artificial Neural Network

This is achieved by training the network with a training data set consisting of predictor variables and the known outcome. These networks are programmed to adjust their internal weights based on the mathematical relationships identified between the inputs and outputs. Once the network has been trained, it can be used for classification of new input data known as testing data set [6]. A typical neural network is shown in Fig. 1

The circles in this figure represent nodes and the lines connecting different nodes represent connection weights. The network consists of a set of nodes that are arranged in three layers (input, hidden and output). The input nodes are where the values of the predictor variables are presented while the output nodes represent the predicted outputs of the network. The nodes in the hidden layer contain intermediate values that are calculated by the network. Each of the hidden and output nodes contains a function called the *activation function*. The hidden nodes allow the network to model complex nonlinear relationships between the input and the output. In a fully connected network, each node in the input layer is connected to each node in the hidden layer, and each node in the hidden layer is connected to each node in the output layer. The knowledge gained by the learning experience through training is stored in the form of connection weights, which are used to make decisions on test inputs [7].

3. Data For Classification

A. Source and Content

The data used in this work has been collected from the PTB Diagnostic ECG database as published in Physiobank, a site dedicated to data for various diseases and their study. This data has ECG signals of 184 subjects, of which 136 are of subjects with MI and 48 without MI. RR intervals (the time interval between two consecutive RR peaks in an ECG) were derived from these ECG signals. This RR interval data of each patient was analyzed using HRV analysis software [8], and the following parameters were obtained.

Statistical Parameters:

- *Mean RR*

- RR STD
- Mean HR
- HR STD
- RMSSD
- NN50
- pNN50
- RR Triindex(Triangular index)
- TINN

Spectral Parameters:

- FFT (Fast Fourier Transform) Low frequency / High Frequency ratio
- AR (Auto Regression) Low frequency / High Frequency ratio

Poincare plot parameters:

- Standard Deviation 1(SD1) / Standard Deviation 2(SD2) ratio

The details of these parameters and their significance can be found in [9,12,13]. These 12 input variables and one output variable (0 for absence and 1 for presence of MI) together is called a feature vector or an instance. The dataset used in this work therefore has 184 feature vectors corresponding to 184 subjects.

B. Data Normalization

Neural network classifiers perform well with numerical data scaled to a range between 0 and 1 [6]. The input vectors were normalized so that all the values are in the desired range (0, 1).

4. Results And Discussion

Different neural network models were developed and trained with 137 instances (75% of total 184 instances in the dataset) using Levenberg-Marquardt (LM), Bayesian Regulation backpropagation (BR) and Gradient descent with adaptive learning rate (GDA) algorithms for different combinations of number of hidden layers, number of neurons in the hidden layer and activation functions. Each of the trained models was tested with 46 instances (25% of total 184 instances in the dataset). The best performances of these neural network models measured through sensitivity, specificity and accuracy [10] are presented in Table 1.

From the experimental results presented in Table 1, the following were observed:

A. Performance with Different Training Algorithms

Three different back propagation algorithms such as Levenberg-Marquardt (LM) Gradient Descent with Adaptive learning rate (GDA) and Bayesian Regulation backpropagation (BR) algorithms were used for training the neural network. The best performances of these three algorithms are shown in Table 2. Fig. 2 clearly illustrates that among the LM, GDA and BR algorithms, the LM algorithm performs better [10,11] for the network chosen and the dataset used.

Table 1 : Performance of Different Neural Network Models

Sl No	Training Algorithm	Activation Function	No. of hidden layers	No. of neurons in hidden layers	Accuracy	Specificity	Sensitivity
1	GDA	Purelin	1	12	27.659	33.333	94.117
2	GDA	Logsig	1	12	89.361	83.333	97.058
3	GDA	Tansig	1	12	89.361	83.333	97.058
4	GDA	Tansig	2	12 12	89.361	83.333	97.058
5	LM	Purelin	1	12	40.425	25.000	94.117
6	LM	Logsig	1	12	93.617	91.666	94.117
7	LM	Logsig	1	24	95.744	91.666	100.00
8	LM	Logsig	2	24 24	95.744	91.666	100.00
9	LM	Tansig	1	12	93.617	91.666	94.117
10	LM	Tansig	2	12 12	91.489	91.666	94.117
11	LM	Tansig	2	12 24	95.744	91.666	100.00
12	BR	Purelin	1	12	38.297	33.333	97.058
13	BR	Logsig	1	24	93.617	91.666	94.117
14	BR	Tansig	2	12 24	93.617	91.666	94.117

Table 2 : Performance of Training Algorithms

Training Algorithm	Accuracy	Specificity	Sensitivity
LM	95.744	91.666	100.000
GDA	89.361	83.333	97.058
BR	93.617	91.666	94.117

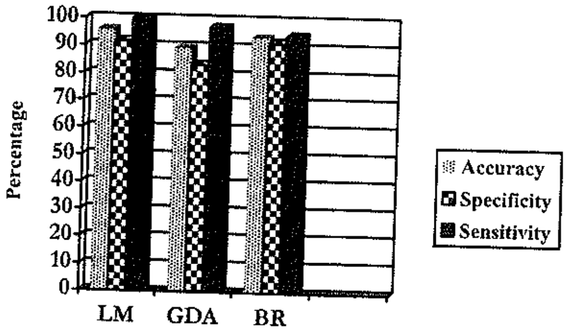

Figure 2 : Performance Comparison with Training Algorithms

Table 3 : Performance of Activation Functions

Training Algorithm	Accuracy	Specificity	Sensitivity
LM	95.744	91.666	100.000
GDA	89.361	83.333	97.058
BR	93.617	91.666	94.117

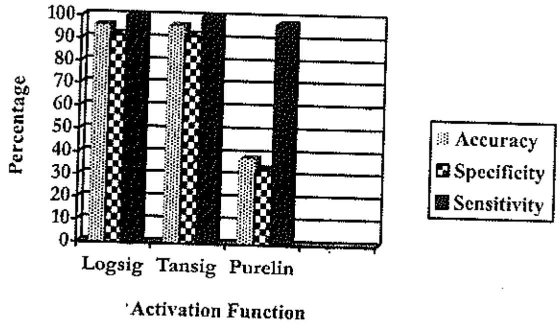

Figure 3: Performance Comparison with Activation Functions

B. Performance with Different Activation Functions

For the three training algorithms LM, GDA and BR different activation functions like logsigmoid, tansigmoid and purelin were used to train the network with varying number of hidden layers and number of neurons in each hidden layer. The same activation function was used for both the hidden and output layers in each model. The best results obtained for each activation function is shown in Table 3. The bar graph in Fig. 3 compares these results. The performance with logsigmoid and tansigmoid activation functions was found to be similar in two network models. However the architecture of the model with logsigmoid activation function is simpler with one hidden layer compared to the other with two hidden layers (Sl Nos. 7 & 11 in Table 1).

C. Inference

From the experimental results presented in Table 1, it is observed that the best performance of 95.74% accuracy, 91.67% specificity and 100% sensitivity was achieved in three network models. However, the architecture 12-24-1 (Sl No. 7 in Table 1 with 12 neurons in the input layer, 24 neurons in one hidden layer, one neuron in the output layer) trained with LM algorithm and with logsigmoid activation function for both the hidden and output layer was found to be computationally efficient in terms of number of epochs required for training. The newff function in Matlab's neural network toolbox was used for the generation of feedforward backpropagation neural network architecture. This newff function has 'learngdm' as the default learning function which chooses 'initnw' initialization function for initializing a layer's weights and biases according to the Nguyen Widow initialization algorithm. Learning occurs according to learngdm's learning parameters with their default values as 0.01 for learning rate and 0.9 for momentum constant.

The number of neurons in the hidden layer of the architecture was considered from twelve as twelve input parameters were used in the network. Increase in accuracy, specificity and sensitivity was noted until 24 above which it led to over-fitting. A maximum of 2000 epochs were considered during the training. The convergence of the error function mse meeting the error goal of 0.001 for the best architecture (Sl Nos. 7 in Table 1) is shown in Fig. 4.

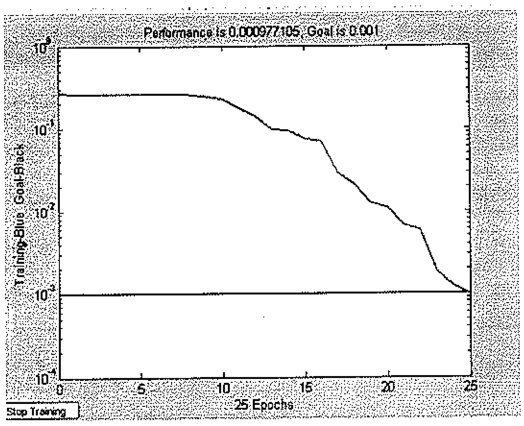

Figure 4 : Convergence of Error Function

5. Conclusions

An artificial neural network model for the detection of Myocardial Infarction has been developed. RR interval data derived from ECG signals were used with a HRV analysis software to obtain a set of parameters. These parameters were used as input to a feedforward neural network with backpropagation training algorithm to classify patients with and without myocardial infarction. The system developed does not yield results with 100% accuracy. The accuracy depends on several factors such as the size and quality of the training set, the rigor of the training imparted and also the parameters chosen to represent the input. The results presented in Table 1, indicate that the neural network classifier is effective to the tune of about 95% accuracy.

Artificial neural network techniques are initially cumbersome. It is time-intensive to collect and preprocess data and to train the networks. Once training is completed, further tasks can be carried out with relative ease. The performance of the system can be measured using real time patient data from hospitals to validate the observations. The validated system can assist physicians in the diagnosis of Myocardial Infarction.

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