Emergency diagnosis of Myocardial infarction (MI) by artificial neural network

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Abstract: - Myocardial infarction is one of the most common diseases with high mortality and morbidity in human beings. Iranian health ministry official statistical analyses show that the most frequent cause of death in the country after accidents is Myocardial infarction (MI). Inappropriately long patient time delay is the main cause for undesirable pre-hospitalization delay. We decided to apply artificial neural network to decrease the pre-hospitalization phase time.
We used clinical and medicinal parameters taken for 267 persons from ekbatan hospital of Hamadan.
We carried out Chi square test with SPSS software for 56 parameters. With regard to the results of this analysis we selected 7 parameters that had the lowest sig for ANN analysis (among parameters, whose sig were less than 0.05). Selected parameters of 267 persons were applied for training network with Levenberg-Marquardt Learning Algorithm. Learning rate was 0.1.
The training process finished at around 46 epochs; assembling and training of artificial neural network was done by Matlab software r2009a. Best validation performance was$9.06 * 10^{-15}$. After plotting the ROC curve, the area under ROC curve was measured to estimate the diagnostic performance; area under roc curve for this analysis was 1.We plotted relation between target value and output of trained neural network for training, validation & test dataset statistically; R value for all of them was 1.
Physical examination and accurate ECG interpretations, cardiac biomarkers are equally valuable in the initial evaluation of patients with non-traumatic chest pain. Because quick detection of MI is very vital for patient and these evaluation need more time, we decided to apply ANN for quick and reliable detection of MI. Therefore by using trained ANN we can predict MI quantitatively without requirement of much time.

Key-Words: - myocardial infarction, diagnosis, heart disease, Artificial Neural Network

1 Introduction

Immediately after an acute coronary occlusion, blood flow ceases in the coronary vessels beyond the occlusion except for small amounts of collateral flow from surrounding vessels. The area of muscle that has either zero flow or so little flow that it cannot sustain cardiac muscle function is said to be *infarcted*. The overall process is called a *myocardial infarction [1]* .

It is one of the most common diseases with high mortality and morbidity in human being. There are many known risk factors in Coronary Artery Disease (CAD) like: age, gender, cigarette smoking, hypertension, diabetes mellitus and hyperlipidemia[2].

Diagnosis of an AMI in the past, during the early 1990s, utilized the World Health Organization (WHO) criteria defining MI as the presence of two out of three characteristics: symptoms of acute ischemia (chest pain), development of Q waves in ECG, elevation of traditional enzyme activities in serum, total CK, CK-MB, ASAT and LDH. Creatine kinase (CK) emerged as the primary indicator of MI. Total CK starts to rise within 3 to 8 hours after MI, peaks at 10 – 24 hours and returns to normal by 3 – 4 days. Myoglobin has potential utility as test for excluding early AMI in patients presenting with chest pain at the emergency department [3-6].

Inappropriately long patient time delay is the main cause for undesirable pre-hospitalization delay. General awareness of basic symptomatology and the importance of time factor for further curse of the disease may substantially influence the duration of AMI (Acute myocardial infarction) Pre-hospitalization phase .Therefore, prompt diagnosis of

all patients with myocardial infarction (MI) is an elusive goal[3, 7].
In summary, reliable diagnosis of myocardial infarction needs many laboratories and clinical features. Therefore, more time is needed and it causes patient pain and irrecoverable hurt; thus for quantitative and quick diagnosis of MI we use artificial neural network technique (ANN). Artificial neural network represents one machine learning tool that has turned out to be useful for complex pattern recognition problem [8-17].

2 Methods

We reviewed medical records of 267 patients who admitted to Ecbatan hospital of Hamedan up to 2008 . 149 of them were diagnosed as myocardial infarction (MI) and others without MI (they may have other disease or may be normal) 56 clinical and laboratory features of these patients were selected from patients' documents .
These features were : sex, age, genetic, smoking, opium, high bp, low bp, HDL , LDL, TG , CHOL , CPK , CPKMB, INR, MCV , MCH, MCHC , BUN , CR, Na, K, CRP ,HB, HCT, ESR, DM , DH , AH , PR, RR , PMH, PT , PTT, JVP, WBC, RBC, FBS , chest pain, SHOULDERPAINE, cold sweat, headache, NAUSEA, VOMIT , HTN, HLP, DISPENEA, ASTHMA, HEARTVOICE, EDEM, RAL, ECO, ANGIO and EXPIRED.

2.1 Feature analysis

After primary statistical analysis, Chi square test was used to determine the statistical significance of the difference between the two groups (patients with and without MI). Seven out of 56 features which showed more significant difference between MI and healthy group were used as inputs for ANN analysis (statistical analysis was completed by SPSS-15 software). These features were: Age , sex , crp, dm, high blood pressure, pmh, chest pain.

2.2 Artificial neural network (ANN)

In order to train neural network, selected features were normalized; this normalization was necessary to prevent non-uniform learning, in which the weight associated with some features converge faster than others.

After normalization a randomly chosen sample was divided into training (80%), cross validation (10%) and testing datasets (10%). The training data set was presented to the network for learning. Cross-validation dataset was used to measure the training performance during training or stop training if necessary. The testing dataset wasn't used in any way during training and hence, provided an independent measure of training performance.

Multilayer perceptron model of the ANN was used. The network consists of an input layer, a hidden layer and an output layer. The input layer contained 7 neurons corresponding to eight input features; the hidden layer contained 11 neurons transforming the input features from input layer to hidden layer. Finally, the output layer had only 1 neuron, representing two possible diagnosis states MI or healthy. Then the neural network was trained with the data on hand; learning function was LM (Levenberg-Marquardt back-propagation) a learning rate was 0.1.

Training neural network is essentially a non-linear least squares problem, and thus can be solved by a class of non-linear least squares algorithms. Among them, the Levenberg-Marquardt is a trust region based method with hyper-spherical trust region. This method work extremely well in practice, and is considered the most efficient algorithm for training median sized artificial neural networks.

Like Quasi-Newton methods, the Levenberg-Marquardt algorithm was designed to approach second order training speed without having to compute Hessian matrix [14, 18]. When the performance function has the form of a sum of squares then the Hessian matrix can be approximated as

$$H = J^T J \tag{1}$$

And the gradient can be computed as

$$G = J^T e \tag{2}$$

The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$W_{K+1=}W_K - [J^T + \mu I]^{-1} J^T e \tag{3}$$

3 Results

The training process of the created neural network was performed with LM algorithm. The training process finished at around 46 epochs as seen in fig. 1; assembling and training of artificial neural network was done by Matlab software r2009a. Best validation performance was$9.06 * 10^{-15}$(fig.1).

In order to evaluate the test outputs, the ROC (receiver operating characteristic) and regression analysis between real results and outputs of the trained neural network was performed[19]. The ROC plot is merely the graph of points defined by sensitivity and (1 – specificity). Customarily, sensitivity takes the y axis and (1 – specificity) takes the x axis. The sensitivity is how good the test is at picking out patients with sepsis. It is simply the True Positive Fraction. In other words, sensitivity gives us the proportion of cases picked out by the test, relative to all cases that actually have the disease. Specificity is the ability of the test to pick out patients who do NOT have the disease. It is simply the True Negative Fraction.

After plotting the ROC curve (fig. 2) the area under ROC curve was measured to estimate the diagnostic performance; area under roc curve for this analysis was 1.We plot relation between target value and output of trained neural network for training, validation & test dataset statistically (fig. 3); R value for all of them was 1. We also perform Chi square test to analyze Relation between target value and output of trained neural network for test dataset statistically (table 1); Phi coefficient value was 1 and its sig was 0.

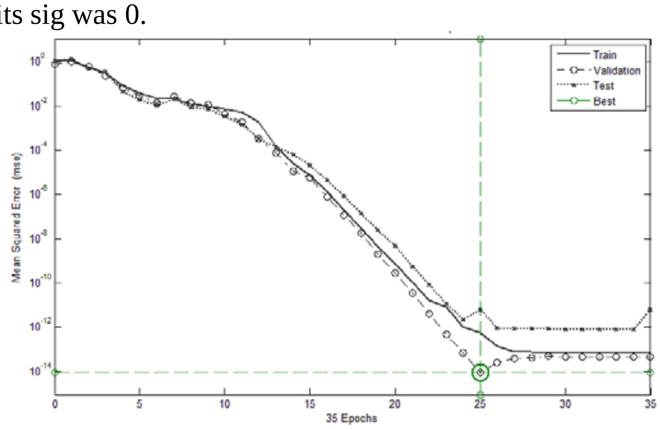

Fig.1 :training plots of the assembled ANN. The training error was minimized at around 25 epochs.

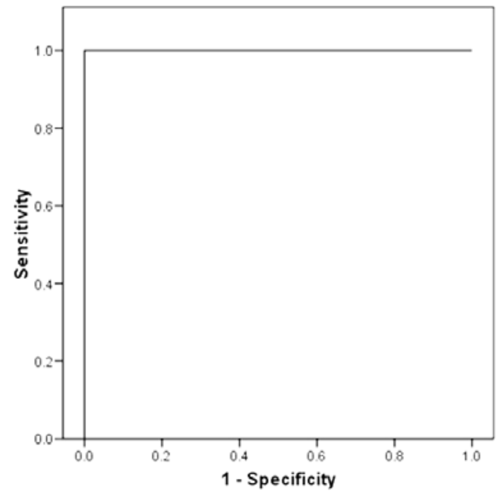

Fig. 2 : *plot of sensitivity against (1-specificity).* The area under ROC curve used to measure the accuracy of trained ANN results.

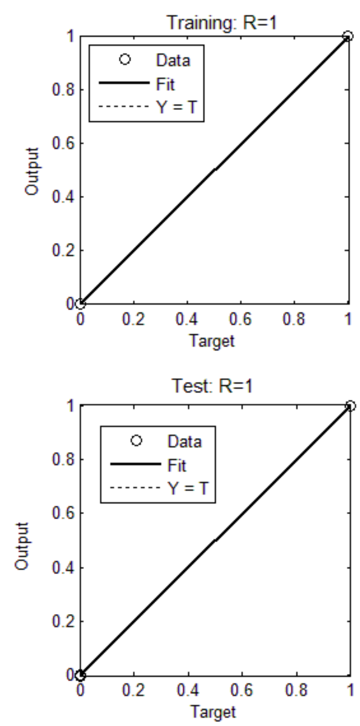

Fig. 3 : *plot of regression between output of designed ANN and target value for training, validating and test data set.* The regression value for all data set was 1.

Table 1: target value * Output of trained ANN Cross-tabulation

This table show the Relation between target value and output of trained neural network for test dataset.

		target value		Total
		Without MI	With MI	
Output of trained ANN	Without MI	11	0	11
	With MI	0	15	15
Total		11	15	26

4 Discussion

Recently ANNs have become popular in medical diagnosis. Although ANN architectures and training algorithms vary, they share one basic function: all networks accept a set of inputs and generate corresponding outputs. ANNs are particularly attractive for diagnostic problems without a linear solution such as MI relation with clinical and laboratory parameter.

Physical examination and accurate ECG interpretations, cardiac biomarkers are equally valuable in the initial evaluation of patients with non-traumatic chest pain. Because quick detection of MI is very vital for patient and these evaluation need more time; therefore we decided to apply ANN for quick and reliable detection of MI.

By using trained ANN we can predict MI quantitatively without requirement of much time. Accuracy of the detection of MI by the assembled artificial neural network was analyzed by ROC and regression analysis. Outputs of trained ANN for testing data were used to plot ROC curve; area under ROC curve was 1. Phi coefficient between known results of testing data set and output of trained ANN was 1 with sig = 0 ; This coefficient illustrated a good relation between trained ANN output and real target for test data set including high performance of training of ANN too. In sum, area under the ROC curve, performance of training and regression coefficient value, all, demonstrate the good learning process of ANN and accurate diagnosis of MI. Best validation performance was$9.06 * 10^{-15}$. All these results was better than our same researches such as Quick and reliable diagnosis of stomach cancer by artificial neural network [15] and Recognition and prediction of leukemia with Artificial Neural Network (ANN) [20].

5 Conclusion

Diagnosis of myocardial infarction mainly depend on Biochemical markers of myocardial necrosis such as such as cardiac troponin and the MB fraction of creatine kinase (CK-MB) and abnormal electrocardiogram (S-T segment elevation and pathological Q wave). In some situation patient with myocardial infarction may have a normal S-T segment .

myocardial infarction relation with different markers is nonlinear and therefore use of artificial neural network overcome this problem ; artificial neural network can be used to classify patient to myocardial infarction or not by nonlinear function. Finally we will use the weight and bias matrix value of trained network and assembled ANN structure to program the software for quick and accurate detection of MI qualitatively. And we can apply the designed software for emergency detection of MI and decreasing the pre-hospitalization phase time. On the other hand we can use ANN for other cardiac disease diagnosis too.

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References:

[1] A. C. Guyton and J. E. Hall, "TEXT BOOK of Medical Physiology," pp. 137-159, 2006.

[2] B. Azimzade-Sarwar, G. Yousefzade, and S. Narooey, "A Case-Control Study of Effect of Opium Addiction on Myocardial Infarction " *American Journal of Applied Science,* vol. 2, pp. 1134-1135, 2005.

[3] J. E. Madias, "Acute Myocardial Infarction : Shifting Paradigms of Diagnosis and Care in a Cost-Conscious Environment," *Chest,* vol. 108, pp. 1483-1486, 1995.

[4] E. B. Sgarbossa, Y. Birnbaum, and J. E. Parrillo, "Electrocardiographic diagnosis of acute myocardial infarction: Current

concepts for the clinician," *American Heart Journal,* vol. 141, pp. 507-517, 2001.

[5] C. Higgins, "Laboratory diagnosis of acute myocardial infarction.," *Nursing times,* vol. 92, pp. 36-37, 2005.

[6] M. Klain, J. L. Coulehan, V. C. Arena, and R. Janett, "More frequent diagnosis of acute myocardial infarction among Navajo Indians," *American Journal of Public Health,* vol. 78, pp. 1351-1352, 1988.

[7] Y. Rozenman and M. S. Gotsman, "The earliest diagnosis of acute myocardial infarction.," *Annual review of medicine,* vol. 45, pp. 31-44, 1994.

[8] J. H. Song, S. S. Venkatesh, E. F. Conant, T. W. Cary, P. H. Arger, and C. M. Sehgal, "Artificial Neural Network to aid differentiation of malignant and benign breast masses by ultrasound imaging," *University of Pennsylvania,* pp. 148-152, 2005.

[9] T. Anagnostou, M. Remzi, M. Lykourinas, and B. Djavan, "Artificial neural networks for decision-making in urologic oncology.," *European urology,* vol. 43, pp. 596-603, 2003.

[10] r. N. G. Naghuib and G. V. Sherbet, "Artificial Neural Networks in Cancer Diagnosis, Prognosis, and Patient Management," pp. 1-183, 2001.

[11] R. Dybowski, V. Gant, S. S. Cross, M. E. Boon, L. P. Kok, L. Tarassenko*, et al.*, "Clinical Applications of Artificial Neural Networks," p. 368, 2001.

[12] Z. H. Zhou, Y. Jiang, Y. B. Yang, and S. F. Chen, "Lung cancer cell identification based on artificial neural network ensembles.," *Artificial intelligence in medicine,* vol. 24, pp. 25-36, 2002.

[13] S. S. Haykin, "Neural Networks: A Comprehensive Foundation," p. 842, 1999.

[14] G. Srečnik, Ž. Debeljak, Š. Cerjan-Stefanović, M. Novič, and T. Bolanča, "Optimization of artificial neural networks used for retention modelling in ion chromatography," *Journal of Chromatography A,* vol. 973, pp. 47-59, 2002.

[15] S. Afshar, F. Abdolrahmani, M. Zohdi, and K. Taheri, "Quick and reliable diagnosis of stomach cancer by artificial neural network," in *Proceedings of the 10th WSEAS International Conference on MATHEMATICS and COMPUTERS in BIOLOGY and CHEMISTRY*, ed, 2009, pp. 30-35.

[16] H. Wang, Y. Shen, T. Huang, and Z. Zeng, "The Sixth International Symposium on Neural Networks (ISNN 2009)," p. 932, 2009.

[17] R. K. Orr, "Use of an artificial neural network to quantitate risk of malignancy for abnormal mammograms.," *Surgery,* vol. 129, pp. 459-466, 2001.

[18] S. Muhammad, A. Burney, T. A. Jilani, and C. Ardil, "Levenberg-Marquardt Algorithm for Karachi Stock Exchange Share Rates Forecasting," *Computational Intelligence,* vol. 1, pp. 168-173, 2004.

[19] M. Gönen, "Receiver Operating Characteristic (ROC) Curves," *Sugi 31,* pp. 1-18, 2001.

[20] S. Afshar, F. Abdolrahmani, F. V. Tanha, and M. Z. Seif, "Recognition and prediction of leukemia with Artificial Neural Network (ANN)," *Medical Journal of Islamic Republic of Iran,* vol. 25, pp. 35-39, 2011.