Artificial Neural Networks in Medical Diagnosis

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Abstract

Artificial neural networks are finding many uses in the medical diagnosis application. The goal of this paper is to evaluate artificial neural network in disease diagnosis. Two cases are studied. The first one is acute nephritis disease; data is the disease symptoms. The second is the heart disease; data is on cardiac Single Proton Emission Computed Tomography (SPECT) images. Each patient classified into two categories: infected and non-infected. Classification is an important tool in medical diagnosis decision support. Feed-forward back propagation neural network is used as a classifier to distinguish between infected or non-infected person in both cases. The results of applying the artificial neural networks methodology to acute nephritis diagnosis based upon selected symptoms show abilities of the network to learn the patterns corresponding to symptoms of the person. In this study, the data were obtained from UCI machine learning repository in order to diagnosed diseases. The data is separated into inputs and targets. The targets for the neural network will be identified with 1's as infected and will be identified with 0's as non-infected. In the diagnosis of acute nephritis disease; the percent correctly classified in the simulation sample by the feed-forward back propagation network is 99 percent while in the diagnosis of heart disease; the percent correctly classified in the simulation sample by the feed-forward back propagation network is 95 percent.

Keywords: *Artificial Neural Networks, Medical Diagnosis, Feed-forward back propagation network, Artificial Intelligence, and Decision Support Systems.*

1. Introduction

Artificial neural networks provide a powerful tool to help doctors to analyze, model and make sense of complex clinical data across a broad range of medical applications. Most applications of artificial neural networks to medicine are classification problems; that is, the task is on the basis of the measured features to assign the patient to one of a small set of classes [1].

Er, Yumusak and Temurtas [2] presented a comparative chest disease diagnosis which was realized by using multilayer, probabilistic, learning vector optimization, and generalized regression.

Das, Turkoglu and Sengur [3] used SAS enterprise miner 5.2 to construct a neural networks ensemble based methodology for diagnosing of the heart disease. Three independent neural networks models used to construct the ensemble model. The number of neural networks node in the ensemble model was also increased but no performance improvement was obtained.

Gil, Johnsson, Garicia, Paya and Fernandez [4] evaluated the work out of some artificial neural network models as tools for support in the medical diagnosis of urological dysfunctions. They developed two types of unsupervised and one supervised neural network.

Altunay, Telatar, Erogul and Aydur [5] analyzed the uroflowmetric data and assisted physicians for their diagnosis. They introduced an expert pre-diagnosis system for automatically evaluating possible symptoms from the uroflow signals. The system used artificial neural networks (ANN) and produced a pre-diagnostic result.

Moein, Monadjemi and Moallem [6] analyzed the real procedure of medical diagnosis which usually is employed by physicians and converted to a machine implementable format. Then after selecting some symptoms of eight different diseases, a data set contains the information of a few hundreds cases was configured and applied to a MLP neural network. The results of the experiments and also the advantages of using a fuzzy approach were discussed as well. Outcomes suggest the role of effective symptoms selection and the advantages of data fuzzificaton on a neural networks-based automatic medical diagnosis system.

Heckerling, Canaris, Flach, Tape, Wigton and Gerber [7] used artificial neural networks (ANN) coupled with genetic algorithms to evolve combinations of clinical variables optimized for predicting urinary tract infection.

Francisco, Juan Manuel, Antonio and Daniel [8] developed a new system from a model based in a multi-agent system in which each neuronal centre corresponds with an agent. This system incorporates a heuristic in order to make it more robust in the presence of possible inconsistencies. The heuristic used is based on a neural network (orthogonal associative memory). Knowledge through training has been added to the system, using correct patterns of behavior of the urinary tract and behavior patterns resulting from dysfunctions in two neuronal centers as a minimum.

Monadjemi and Moallem [9] investigated application of artificial neural networks in typical disease diagnosis. The real procedure of medical diagnosis which usually is employed by physicians was analyzed and converted to a machine implementable format. The results of the experiments and also the advantages of using a fuzzy approach were discussed as well.

Lin [10] presented classification and regression tree (CART) and case-based reasoning (CBR) techniques to structure an intelligent diagnosis model aiming to provide a comprehensive analytic framework to raise the accuracy of liver disease diagnosis.

Mazurowski, Habas, Zurada, Lo, Baker and Tourassi [11] investigated the effect of class imbalance in training data when developing neural network classifiers for computer aided medical diagnosis. The investigation is performed in the presence of other characteristics that are typical among medical data, namely small training sample size, large number of features, and correlations between features.

Zhang, Yan, Zhao and Zhang [12] presented a method for developing a fully automated computer aided diagnosis system to help radiologist in detecting and diagnosing micro-calcifications in digital format mammograms.

Higuchi, Sato, Makuuchi, Furuse, Takamoto and Takeda [13] tested a three-layered artificial neural network analysis of phonocardiogram recordings to diagnose, automatically and objectively, the condition of the heart in patients with heart murmurs.

2. Artificial Neural Networks

An artificial neural network (ANN) is a computational model that attempts to account for the parallel nature of the human brain. An (ANN) is a network of highly interconnecting processing elements (neurons) operating in parallel. These elements are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. A subgroup of processing element is called a layer in the network. The first layer is the input layer and the last layer is the output layer. Between the input and output layer, there may be additional layer(s) of units, called hidden layer(s). Fig.1 represents the typical neural network. You can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements

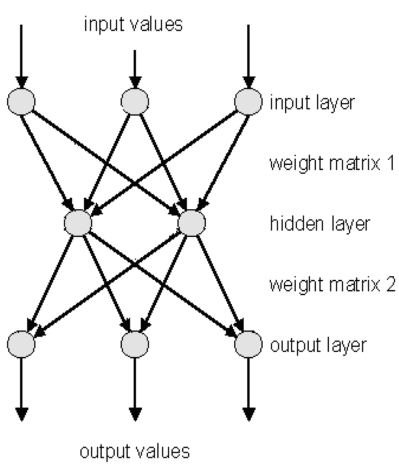

Fig.1 A typical neural network

Medical Diagnosis using Artificial Neural Networks is currently a very active research area in medicine and it is believed that it will be more widely used in biomedical systems in the next few years. This is primarily because the solution is not restricted to linear form. Neural Networks are ideal in recognizing diseases using scans since there is no need to provide a specific algorithm on how to identify the disease. Neural networks learn by example so the details of how to recognize the disease is not needed [14].

Based on the way they learn, all artificial neural networks are divided into two learning categories: supervised and unsupervised. In supervised learning, the network is trained by providing it with input and output patterns. During this phase, the neural network is able to adjust the connection weights to match its output with the actual output in an iterative process until a desirable result is reached. An ANN of the unsupervised learning type, such as the self-organizing map, the neural network is provided only with inputs, there are no known answers. The network must develop its own representation of the input stimuli by calculating the acceptable connection weights. That is self-organization by clustering the input data and find features inherent to the problem.

2.1 The Proposed Diagnosis Model

Feed-forward neural networks are widely and successfully used models for classification, forecasting and problem solving. A typical feed-forward back propagation neural network is proposed to diagnosis diseases. It consists of three layers: the input layer, a hidden layer, and the output layer. A one hidden with 20 hidden layer neurons is created and trained. The input and target samples are automatically divided into training, validation and test sets. The training set is used to teach the network. Training continues as long as the network continues improving on the validation set. The test set provides a completely independent measure of network accuracy. The information moves in only one direction, forward, from the input nodes, through the hidden nodes and to the output nodes. There are no cycles or loops in the network. The proposed neural networks are shown in Fig.2 and Fig.3.

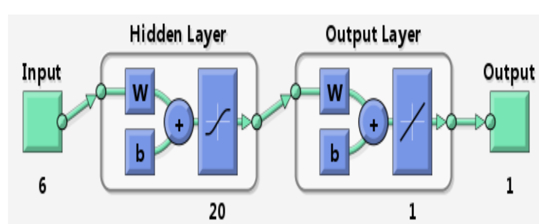

Fig.2 The proposed acute nephritis diagnosis neural network

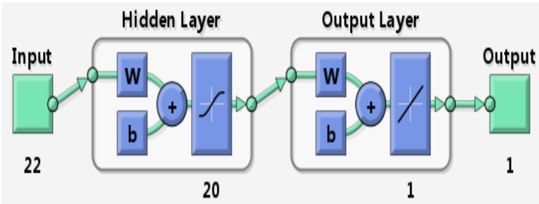

Fig.3 The proposed heart disease diagnosis neural network

Feed-forward neural network allows signals to travel one-way only; from source to destination; there is no feedback. The hidden neurons are able to learn the pattern in data during the training phase and mapping the relationship between input and output pairs. Each neuron in the hidden layer uses a transfer function to process data it receives from input layer and then transfers the processed information to the output neurons for further processing using a transfer function in each neuron.
The output of the hidden layer can be represented by

$$YNx1 = f(WNxM\ XM,1 + bN,1\ ) \qquad (1)$$

where *Y* is a vector containing the output from each of the *N* neurons in a given layer, *W* is a matrix containing the weights for each of the *M* inputs for all *N* neurons, *X* is a vector containing the inputs, *b* is a vector containing the biases and *f(·)* is the activation function [15].

3. Experimental Results

3.1 Data Analysis

Symptoms, images or signals are the data used in medical diagnosis. The data set is obtained from UCI Machine Learning Repository.

3.1.1 Acute Nephritis Diagnosis Data

The data was created by a medical expert as a data set to test the expert system, which will perform the presumptive diagnosis of one of the urinary system diseases.
The main idea of this data set is to construct the neural network model, which will perform the presumptive diagnosis of acute nephritis. Acute nephritis of renal pelvis origin occurs considerably more often at women than at men. It begins with sudden fever, which reaches, and sometimes exceeds 40C. The fever is accompanied by shivers and one- or both-side lumbar pains, which are sometimes very strong.
This dataset contains 120 patients. Table 1 presents the patient symptom data which are considered as diagnosis variables. The dataset contains 120 samples. 90 sample used in training the network while 30 samples used in testing the network.

Table 1: Diagnosis variable of datasets used in the study

Patients symptom data	
No.	Diagnosis Variable Name
1	Temperature of patient {35C-42C}
2	Occurrence of nausea {yes, no}
3	Lumbar pain {yes, no}
4	Urine pushing (Continuous need for urination) {yes, no}
5	Micturition pains {yes, no}
6	Burning of urethra, itch, swelling of urethra outlet {yes, no}

3.1.2 Heart Disease Diagnosis Data

The dataset describes diagnosing of cardiac Single Proton Emission Computed Tomography (SPECT) images. Each of the patients is classified into two categories: normal and abnormal. The database of 267 SPECT image sets (patients) was processed to extract features that summarize the original SPECT images. As a result, 44 continuous feature patterns were created for each patient. The pattern was further processed to obtain 22 binary feature patterns. SPECT data has 267 instances that are described by 23 binary attributes. The dataset contains 267 samples. 80 sample used in training the network while 187 samples used in testing the network.

3.2 Performance Evaluation

Neural network toolbox from Matlab 7.9 is used to evaluate the performance of the proposed networks.
Acute nephritis of renal pelvis origin is the first disease to be diagnosed. A two-layer feed-forward network with 6 inputs and 20 sigmoid hidden neurons and linear output neurons was created.
Such net can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer as shown in Fig.2.
Levenberg-Marquardt back propagation algorithm was used with train the network. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error (MSE) of the validation samples.
The results of applying the artificial neural networks methodology to distinguish between healthy and unhealthy person based upon selected symptoms showed very good abilities of the network to learn the patterns corresponding to symptoms of the person. The network was simulated in the testing set (i.e. cases the network has not seen before). The results were very good; the network was able to classify 99% of the cases in the testing set. Fig.4 shows the training state values.
Best validation performance is 2.8548e-007 at epoch 7 as shown in Fig.5. The mean squared error (MSE) is the average squared difference between outputs and targets. Lower values are better while zero means no error.

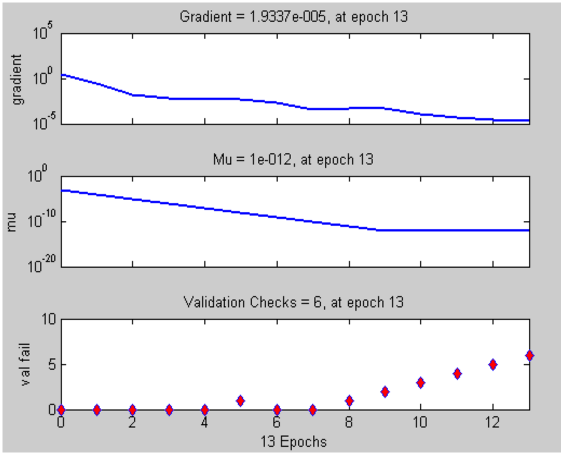

Fig.4

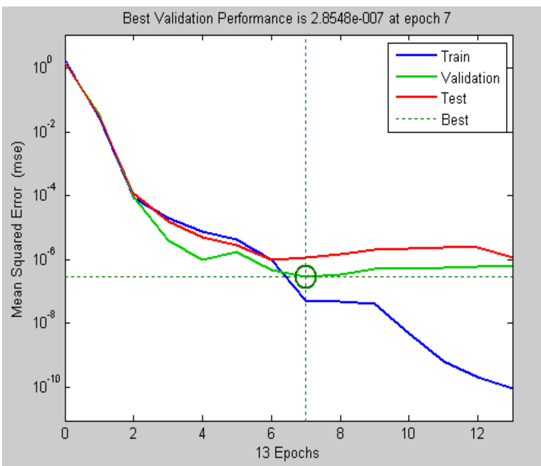

Fig.5

Table 2: The Mean Square Error (MSE) and Regression values for the training, validation and testing.

	MSE	R
Training	5.11986e-8	9.99999e-1
Validation	2.85475e-7	9.99999e-1
Testing	1.13132e-6	9.99997e-1

The percent correctly classified in the simulation sample by the feed-forward back propagation network is 99 percent. The MSE is equal to 3.96199e-5 and the regression is equal to 9.99936e-1.

Heart disease is the second disease to be diagnosed. A two-layer feed-forward network with 22 inputs and 20 sigmoid hidden neurons and linear output neurons was created.

Such net can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer as shown in Fig.3.

Levenberg-Marquardt back propagation algorithm was used with train the network. The results of applying the artificial neural networks methodology to distinguish between normal and abnormal person based upon binary feature patterns extracted from SPECT images showed very good abilities of the network to learn the patterns. The network was simulated in the testing set. The results were very good; the network was able to classify 95% of the cases in the testing set. Fig.6 shows the training state values.

Best validation performance is 0.088329 at epoch 3 as shown in Fig.7.

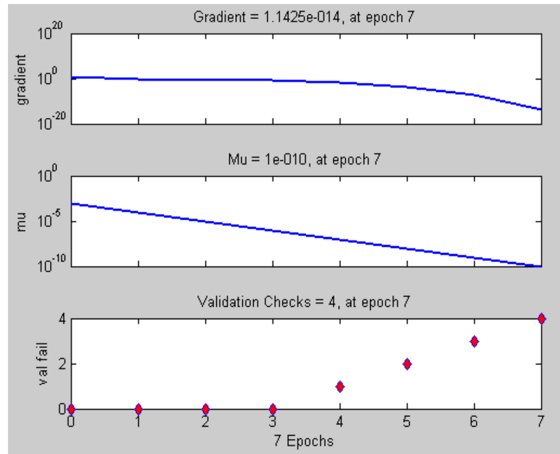

Fig.6

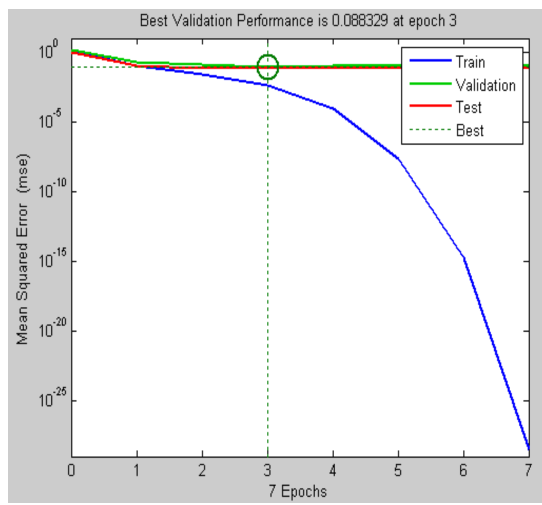

Fig.7

Table 3: The Mean Square Error (MSE) and Regression values for the training, validation and testing.

	MSE	R
Training	4.86802e-3	9.92593e-1
Validation	8.83292e-2	8.50794e-1
Testing	7.47611e-2	8.72846e-1

The percent correctly classified in the simulation sample by the feed-forward back propagation network is 95 percent. The MSE is equal to 2.78711e-2 and the regression is equal to 9.50148e-1.

4. Conclusions

This study aimed to evaluate artificial neural network in disease diagnosis. The feed-forward back propagation neural network with supervised learning is proposed to diagnose the disease. Artificial neural networks showed significant results in dealing with data represented in symptoms and images. Results showed that the proposed diagnosis neural network could be useful for identifying the infected person.

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