Quick and reliable diagnosis of stomach cancer by artificial neural network

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Abstract: - Approximately 90% of stomach cancers are adenocarcinoma that directly distribute from stomach wall to the neighbor tissue of stomach .this kind of cancer is more common in persons who are more than 40 and its spread in men is twice as much as women. Unfortunately, this cancer doesn't have any sign until it develops to its advanced level.
Generally biopsy, endoscopy, laparoscopy, ultra sonography, CT scan, x-ray radiography and proper clinical test are applied for cancer detection.

By advancing artificial neural network technique and due to the difficulty in detection of stomach cancer with clinical and medicinal parameters, we decided to apply ANN for quick detection of stomach cancer. To do so, we use 50 clinical and medicinal parameters taken from 126 person (90 had cancer and 36 was normal as a testifier).

We carried out independent sample T-Test with SPSS software for 50 parameters. Regard to the results of this analysis we selected 8 parameters that had lowest sig for ANN analysis (among parameters whose sig was less than 0.05).These parameters are age, anorexia, weight reduction, MCH ,MCHC, Na^+ reduction, Ca^{2+} reduction and X-ray radiography.

Selected parameters of 126 persons split to three groups with Matlab software: training group (80%), validation group (10%), and test group (10%).

Artificial neural network that we designed has three layers, 8 neurons as input, 8 neurons as hidden and 1 neuron as output. Split data are applied for training network with Levenberg-Marquardt learning algorithm. Finally, Performance of learning was 0.056, Regression coefficient between the output of trained network for test data and real results of test data was 0.927 and the area under ROC curve was 0.883. With these results we can conclude that training process was done successfully and accurately.

Key words: Cancer, stomach, ANN, Artificial Neural Network, Training, SPSS, Matlab

1 Introduction

Although the gastric cancer incidence rates have been declining in many countries, the most recent estimates show that it is the fourth most common cancer; Gastric cancer is the second commonest malignancy in the world and after lung cancer kills more people than any other malignant tumors. [1, 2, 3]

The prognosis for gastric cancer once a diagnosis has been made is poor. [2]

Physicians usually diagnose gastric cancer with clinical symptoms and laboratory technique as follow:

Gastric cancer when superficial and surgically curable, usually produce no symptoms. As the tumor becomes more extensive, patients may complain of an insidous upper abdominal discomfort varying in intensity from a vague, postprandial fullness to a severe, steady pain. Anorexia often with slight nausea is very common but is not the usual presenting compliant. Weight loss may eventually be observed, and nausea and vomiting and particularly prominent with tumors of the pylorus: dysphagia may be the major symptom caused by lesions of the cardia. The liver is the most hematogenous spread of tumor. The presence of iron-deficiency anemia in men and occult blood in the stool in both sexes mandate a search for an occult gastrointestinal tract lesion. A double-contrast radiographic examination is the simplest diagnosis procedure for evaluation of a patient with epigastric complaints. Since gastric carcinomas are difficult to distinguish clinically or radiographically from gastric lymphomas, endoscopic biopsies should be made as deep as possible, due to the submucosal location of lymphoid tumors. [4]

On the other hand reliable diagnosis by endoscopic biopsies needs more time and causes patient pain; therefore for quantitative and quick diagnosis of stomach cancer 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.[6,7,8,9,10,11,12,13]

2 Problem Formulation

After several discussions with oncologists 50 clinical and laboratory features of 126 patients who had endoscopic biopsy such as : age , sex, vomiting, nausea, hematocrit, R.B.C, W.B.C, ESR, anorexia, weight loss, M.C.H, M.C.H.C, Na^+, Ca^{2+}, K^+, PT, sonography, B.U.N, cratinin, albomin, bilirobin D, bilirobin T, S.G.O.T, S.G.P.T, X-ray radiography and so forth , selected from patients documents (patients document of Atieh and Ekbatan hospitals of hamedan) .

2.1 Feature analysis

After primary statistical analysis, the two tailed student t-test was used to determine the statistical significance of the difference between the two groups (patients with and without stomach cancer). 8 of 50 features which showed more significant difference between cancerous and noncancerous group were used as inputs for ANN analysis (statistical analysis was completed by SPSS-15 software)

These features are: age(19 to 107) , anorexia (0 for patients without anorexia and 1 for patients with anorexia), weight loss(0 for patients without weight loss and 1 for patients with weight loss) , M.C.H(0 when M.C.H was normal and 1 when M.C.H was abnormal) , M.C.H.C(0 when M.C.H.C was normal and 1 when M.C.H.C was abnormal), Na^+ (0 when Na^+ was normal and 1 when Na^+ was abnormal) Ca^{2+} (0 when Ca^{2+} was normal and 1 when Ca^{2+} was abnormal) and X-ray radiography (0 when radiogram was normal and 1 when radiogram was abnormal)

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 8 neurons corresponding to eight input features; the hidden layer contained eight neurons transforming the input features from input layer to hidden layer. Finally, the output layer had only one neuron, representing two possible diagnosis states cancerous or noncancerous. 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. When the performance function has the form of a sum of squares then the Hessian matrix can be approximated as

(1) $H = J^T J$

And the gradient can be computed as

(2) $G = J^T e$

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

(3) $W_{k+1} = W_k - [J^T J + \mu I]^{-1} J^T e$

3 Problem Solution

The training process of the created neural network was performed with LM algorithm, the training process finished at around 17 epochs as seen in fig. 1; assembling and training of artificial neural network was done by matlab software r2007b.

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. 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 who 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 0.833.

We plot the real target against output of trained network (for testing dataset) fig. 3. The regression coefficient was 0.927.

4 Conclusion

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.

Usually physicians analyze clinical and laboratory symptoms of gastric cancer qualitatively and finally use endoscopic biopsies as a better experiment for detection of cancerous or noncancerous patient. Then accurate and reliable detection of cancer need a distress of patient, more laboratory cost and much duration. In this research we apply simple and quick clinical and laboratory symptoms for quantitative detection of gastric cancer.

Therefore by using trained ANN we can prognosis cancer with least clinical and laboratory features and without requirement of much time. Accuracy of the detection of cancer 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 0.833. These results demonstrate high performance of ANN training. Regression coefficient between known results of testing date set and output of trained ANN was 0.927. This coefficient illustrates a good relation between trained ANN output and real target for test dataset, then high performance of training of ANN too. In summery area under the ROC curve, performance of training and regression coefficient value, all, demonstrate the good learning process of ANN and accurate prediction of cancer.

In order to improve the performance of training process we will use the bigger sample size (more patient). Finally we will use the weight and bias matrix value of trained network and assembled ANN structure to program software for quick and accurate detection of cancer qualitatively

Figures and legends:

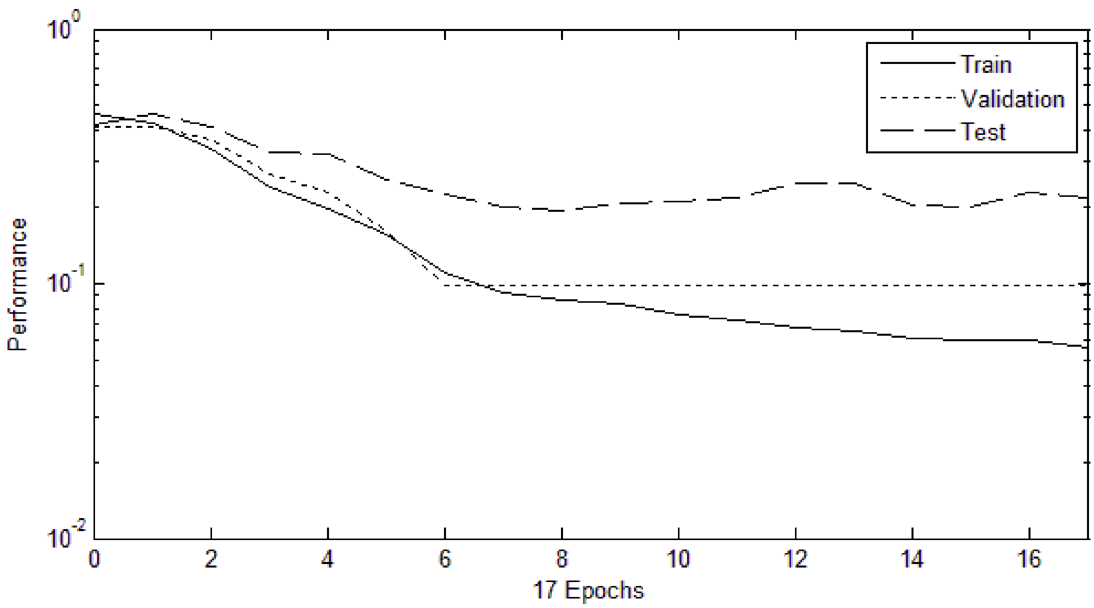

Figure1: training plots of the assembled ANN, the training error was minimized at around 17 epochs.

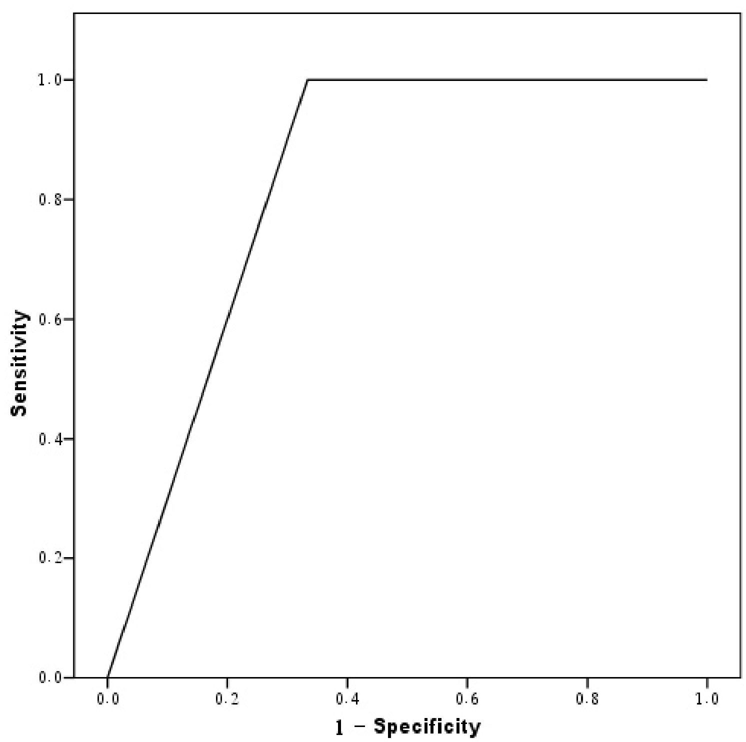

Figure2: plot of sensitivity against (1-specificity) .the area under ROC curve used to measure the accuracy of trained ANN results.

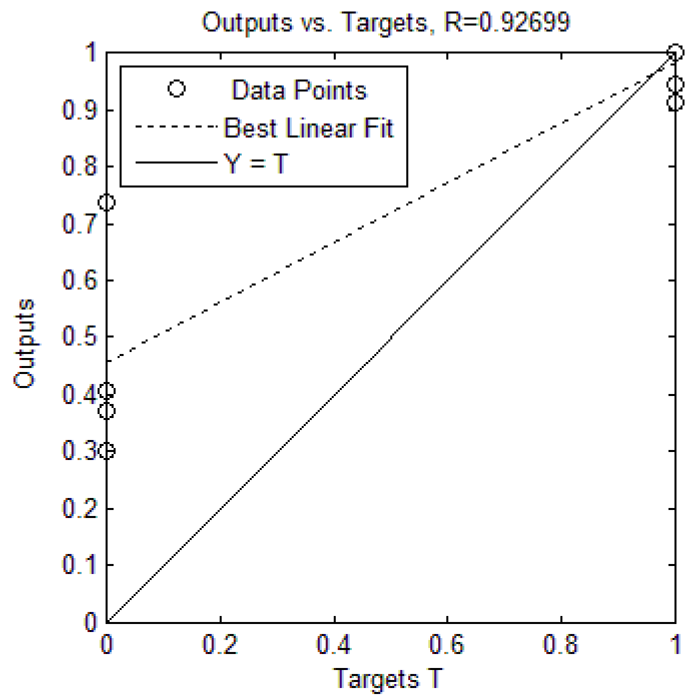

Figure3: regression plot between target value of test dataset and output of trained neural network for test dataset.

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