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Comparing the abilities of artificial neural networks and genetic algorithm in bankruptcy prediction (Case study: Companies listed on Tehran Stock Exchange)

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ABSTRACT

The bankruptcy prediction has long been considered as one of the most important issues in the field of financial management and recognizing the optimal investment opportunities from undesirable ones and avoiding wasted important resources. Therefore, this research seeks to compare the results of financial bankruptcy prediction in companies listed on Tehran stock exchange by utilizing the neural networks and genetic algorithm as well as investigating the ways for overcoming the common ways of bankruptcy prediction by utilizing the genetic algorithm in the development of bankruptcy theory. The studied sample in this research consists of 70 pairs of bankrupt and non-bankrupt companies during 2001-2011. According to the studies on the information extracted from the financial statements in target companies, ultimately 5 financial variables are identified as the independent variables for utilization of both models. The results of this study indicate that the use of genetic algorithm is more effective than the neural network model in financial bankruptcy prediction, so that this model has been able to obtain the accuracy equal to 96.44, 97.94 and 95.53 in true financial bankruptcy prediction of companies in two years before the base year, a year before the base year, and the base year, respectively.

KEYWORDS: Bankruptcy, bankruptcy prediction, artificial neural networks, genetic algorithm

1.INTRODUCTION

The prediction is important in many aspects of our lives, so that the weak predictions can lead to the inefficient decisions. The managers' planning, decision making and other key tasks will fail without proper prediction. In general, the aim of prediction is to reduce the risk in decision-making and since the prediction cannot completely eliminate the risk, the decision-making process should clearly consider the results of remained uncertainty [1].From the perspective of macroeconomic theories, the economic development of society is in line with the amount of investment in that relationship. However, if these investments are not on the appropriate opportunities or they are used in a way that they are inefficient, this will cause damage to the national economy [2].

Providing the models for predicting the financial situation of companies is one of the ways to help the investors. The more the predictions are close to the reality, they will become the bases for more accurate decisions. The bankruptcy prediction model is one of the tools for estimating the future status of companies. The investors and creditors have high tendencies to bankruptcy prediction of firms because they will enforce to spend more costs in the case of bankruptcy. The applied models in prediction have their own strengths and weaknesses [3]. It is very complicated to choose a model proportional to the users' needs from their financial information and environmental conditions. In fact, if the possibility of bankruptcy in companies and enterprises is predicted through a model, and then the affairs of companies are modified by reason seeking and the use of problem solving methods, the waste of national wealth can be prevented in the form of physical and human capital and its side effects. Furthermore, such this model can be a good guide for financial decision-makers such as the investment companies, banks and government [4].

2.Problemstatement of research

The increasing competition of enterprises limits their access to the profit and enhances the possibility of their bankruptcy, thus the financial decisions have been more strategic than the past. Decision making in financial issues have always been associated with the risk and uncertainty. Providing the prediction models for general prospect of company is one of the ways to help the investors. The more the predictions are close to the reality, the more the basis of decisions will be accurate. Beaver believes that "The prediction is possible without making decision, but the minor decision cannot be made without a prediction" [5]. The bankruptcy prediction model is one of the techniques and tools of predicting the future situation of companies and estimates the probability of bankruptcy by combining a group of financial ratios. The ability of commercial and financial prediction is important from both private investor and social perspective since it is a clear sign of inappropriate allocation of resources. An early warning of possibility of bankruptcy enables the management and investors to take the preventive actions and recognize the favorable investment opportunities from the undesirable ones[6].

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The Article 141 of reform commercial code is the criterion for bankruptcy and exit from the stock exchange in Iran and Tehran Stock Exchange: If at least a half of firm capital is lost, the board should immediately invite the extraordinary general meeting of shareholders in order to vote and consult about the dissolution or maintenance of company. If this meeting does not vote for dissolution of company, it should reduce the firm capital by available capital in the same session and in compliance with the provisions in Article 6 of this law. In the case that the board does not invite the extraordinary general meeting in contrary to this Article or the invited meeting is concluded in accordance with the law, any stakeholder can ask the competent court about the dissolution of company [7].

3. RESEARCH LITERATURE

The neural network method is one of the methods for investigating the bankruptcy prediction models. The Odom and Sharda[8] initially utilized the neural networks in designing the bankruptcy prediction models. The research results indicate that the neural networks have higher precision and potential of prediction than the statistical models. Shah and Murtaza[9] provided a model using the neural network model. They utilized the data of 60 bankrupt companies and 54 non-bankrupt companies during 1992 to 1994. They utilized eight financial ratios. These ratios were selected based on the previous studies and consultation with financial experts. The model precision was obtained equal to 73 percent for this model [9].Wallace [10] designed a model by neural network method. This model utilized the values of key financial ratios which were reported as the best ratios in the previous bankruptcy studies. Wallace's model reviewed an overall precision of 94% and 65 different financial ratios in previous studies [10]. It should be noted that the other studies are conducted on the comparison of different neural networks such as the research by Adnan Khashman[11]who compared different neural networks to predict the credit risk. In this study, he compares different structures of neural network [11].

The use of genetic algorithm is one of the tools and techniques applied in the financial crisis analysis. Varetto[12] seriously utilized the genetic algorithm to predict the bankruptcy. His sample consists of 500 companies including 236 bankrupt companies and 264 non-bankruptones. The results of this research indicate that the prediction precision is equal to 93% a year before bankruptcy and 91.6% two years before bankruptcy [12].Min et al simultaneously utilized the genetic algorithm and support vector machine (SVM) and called it GA-SVM model. Their results indicate the prediction precision of 86.53% in the training set and 80.30% in experimental sample for a year before the bankruptcy [13]. Lensberg [14]has utilized the genetic programming in a research on 28 potential bankruptcy variables which were considered as the important variables in earlier studies, and thus 6 variables are considered as the important ones[14].

4.RESEARCH METHODOLOGY

In this study, we are seeking to provide a using a solution to overcome the limitations of current methods in predicting and developing the theory of bankruptcy by genetic algorithm model, thus this research is an analytical-mathematical research in terms of investigation method, and developmental according to the type of case study and objective.

The basic steps in conducting this research are as follows:

1- Identifying the financial ratios to predict the bankruptcy;
2- Measuring the financial ratios and other required parameters as the independent variables applied in experimental model;
3- Separating two samples of bankrupt and non-bankrupt companies by Article 141 of Commercial Code;
4- Investigating and comparing the accuracy of predicting the neural networks and genetic algorithm for predicting the bankruptcy

4.1.Statistical population and sample

The statistical population of this research consists of all companies listed on Tehran Stock Exchange during 2001 to 2011. The quality of information and ease of access to financial information are among the reasons for selecting the statistical population. The statistical sample in this study is classified into two groups. First, the companies which are gone bankrupt; the Article 141 of Commercial Code for bankruptcy is the criterion which is considered in this research for bankruptcy. Second, the non- bankrupt companies in this regard. In research data collection, we have tried to choose the partially similar non- bankrupt and bankrupt companies in terms of type of industry and size, unless it is impossible due to the small size of industry and this can be considered as one of the limitations of research. The information of companies from 1999 to 2009 is utilized since the financial information of two years before the bankruptcy is applied for each company. The base year (t) for bankrupt companies refers to the year when the company has suffered from a financial crisis or bankruptcy. In the case of non-bankrupt companies, the base year refers to the information of two years before the bankruptcy. According to the studies in this research, 82 companies are covered by this law during this period, but some companies have had ratios with large differences from other research samples that this reduces the performance and accuracy of prediction models. Therefore, we remove a number of bankrupt companies and selected pairs from research data, and thus the number of remaining and applied pairs (70 bankrupt and 70 non-bankrupt companies) is equal to 70.

4.2. Data collection and analysis method

From the systematic perspective, the existence of valid and appropriate input is very important to have the appropriate output. Since we need correct and accurate data in this research more than anything, the data associated with the tested financial ratios are is collected from the public archives of financial statements on Stock Exchange and CDs provided by that organization such as Rahavard Novin software and database of Tehran Stock Exchange. First, the Excel software is utilized to separate the collected data of financial statements from sample companies, and then the SPSS software is applied for statistical analysis of separated data. Furthermore, MATLAB software is utilized due to the non-linear relationship between the financial data as well as predicting the bankruptcy of companied listed on Tehran Stock Exchange.

4.3. Financial ratios of bankruptcy prediction

Since the financial ratios have been widely used in previous studies, we have selected 15 base ratios based on our judgment, and there were strong bankruptcy signs in several previous models of bankruptcy prediction, and thus we have included the ratios of each main analytical perspective namely the liquidity, profitability, dissolution and so no. The analysis of our primary variable is done by doing7computer-running. We have reported the results of variable for each computer running after 4000 periods and it resulted in50 reports. We examined each 15 variables at the time of any report in order to determine whether they have any impact on the ability to classify the best program at that moment of running or not. If a variable has a non-zero impact on the ability of classifying the best program, it receives the score 1, otherwise the score 0.

Finally, six financial ratios are utilized as independent variables in this study and they are as follows:

1- Quick ratio which refers to the quick assets divided by the current debt;
2- Debt ratio which refers to the total debt divided by the total assets;
3- Return on assets ratio which refers to the net income divided by the total assets;
4- Interest to income ratio which refers to the interest divided by the total income;
5- Gross margin to income ratio which refers to the gross margin divided by the total income;
6- Ratio of return on equity which refers to the net income divided by the equity

5. Neural network model

The neural networks are among a class of dynamical systems with transfer the rule behind the data to network structure by processing the experimental data. Therefore, these systems are called the intelligent because they learn the general rules according to the calculations on numerical data or samples.

In designing the neural network model, we should determine the number of hidden layer of network, the number of neurons in each layer, learning algorithms, conversion function, return function, learning rate, number of iterations, data normalization, the size of learning and experimental set. There are no systematic methods in determining these methods, thus the best network design is achieved by experience, trial and error. In other words, designing the neural networks combines the science and art.

Two main aspects should be considered in neural network operation. First, the neural network training should be based on the levels of decisions associated with a set of models for training, and these models should be classified accurately. The other aspect is the ability to generalize. After training, the neural network should be able to recognize and classify the models which are offered [11].

This research uses the Perceptron multi-layer structure as the applied neural network structure and also the Back propagation algorithm as the algorithm to train the neural network. This algorithm belongs to the supervising learning algorithms which are investigated as follows.

5.1.Multilayer perceptron structure

The Perceptron multi-layer neural network has the feed forward type in this research. In other words, all neurons are structured in a forward ordering and there is no connection between the neurons which are backward or forward. The Perceptron multi-layer neural network has an input layer, one or more hidden layers (selected by researcher or due to the problem which we are seeking to solve), and an output layer. It is noteworthy that the applied structure in this study is obtained by trial and error, so that various structures are analyzed, and among the studied structures, the following model has better result than other structures. The structure of neural network, applied in this study, has 5 layers. An input layer, three hidden layers and an output layer constitute the structure of this network. It is noteworthy that the input layer of this network has 6 neurons (equal to the number of financial ratios used in this study). 15, 10 and 1 neurons are utilized in hidden layers of this network, respectively. The output layer of this network also has a neuron.

To create a better understanding of multilayer perceptron neural network model in this study, we have provided the overall schema of this network in Figure 1. It should be noted that all neurons are connected to the neurons of the next layer in hidden layers of presented neural network in Figure 1, but they are not shown for simplicity.

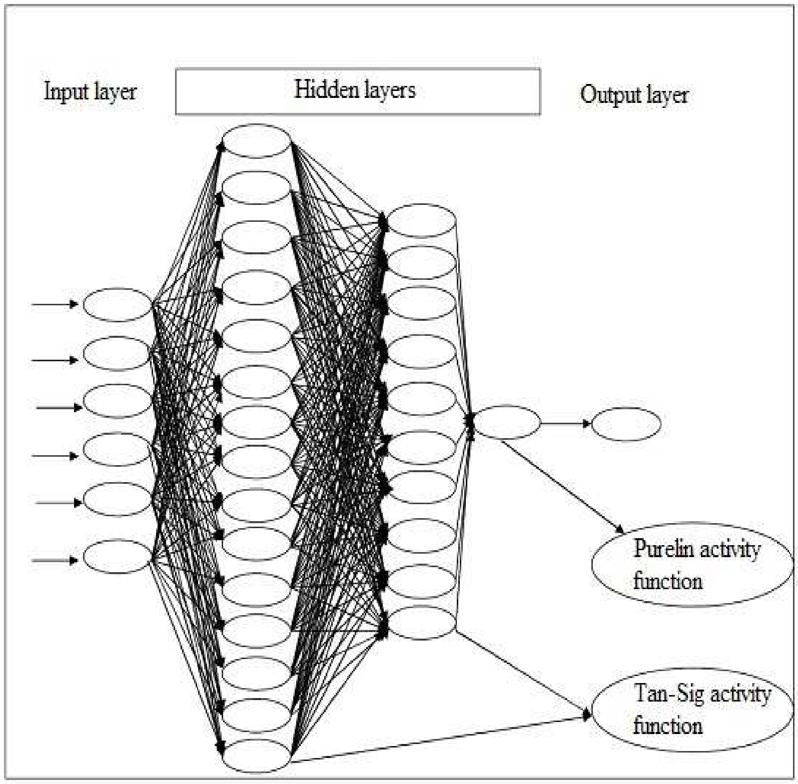

Fig.1. Scheme of MLP network

5.2. Analysis of neural network model

In this section of research, we predict the bankruptcy of companies listed on Tehran Stock Exchange by neural networks according to the independent variables. In this regard, the multilayer perceptron network is utilized along with the back-propagation learning algorithm. It should be noted that this algorithm belongs to a group of supervising learning algorithms, and the MATLAB software is used to create the neural network model in this research.

Here, the details of test are investigated. Therefore, three stages are conducted as follows:

1) First stage: Data preparation.
2) Second stage: Multilayer perceptron neural network learning by back-propagation learning algorithm.
3) Third stage: Testing the trained networks.

5.2.1. First stage: Data Preparation

The spectroscopy of most of the applied ratios in this study show us large numbers, thus we are seeking to reduce the impact of this case on the performance of neural network by normalization. The ratio of accumulated loss and profit to capital is used for network learning. Therefore, the companies with the accumulated loss and profit to capital ratios larger than -0.5, are introduced as the non-bankrupt companies, and those with accumulated loss and profit to capital ratios less than -0.5 are introduced as the bankrupt companies. In this regard, the bankrupt and non-bankrupt companies are ranked and their ranks are based on the accumulated loss and profit to capital ratio which is considered as the criterion of bankruptcy in the Commercial Code of Iran.

5.2.2.Second stage: Multilayer perceptron neural network training with propagation algorithm

At this stage, we do the multilayer perceptron neural network training using the financial ratios derived from the sample companies of research. Therefore, the data is classified into two parts: Data used for teaching and data used for testing, thus we apply 50 pairs of research data for network training and 20 pairs of data for testing the network.

To compare the performance of neural network with genetic algorithm, we have sought to teach this network to a certain precision, and then test the results. The selected precision is equal to $1e^{-4}$ for this purpose. After doing the early stages, 50 pairs of bankrupt and non-bankrupt companies are randomly selected, so that we can use this data for network learning. Other data, including 20 pairs of bankrupt and non-bankrupt companies, is considered for network testing.

The process of reducing the errors in multilayer perceptron neural network training by back propagation learning algorithm is shown in Figure 2. As shown, the applied neural network has received our target precision, $1e^{-4}$, at554 epochs and it is an acceptable level. It should be noted that the neural network software tool kit in MATLAB software is used to create the proposed neural network model.

The regression diagram, which shows the network training process, can be applied to analyze the reaction of network. This diagram is shown in Figure 3. The line, which is the bisector of horizontal and vertical vector, is the target vector, and the more the data density is close to the line, the more the process of training is done properly.

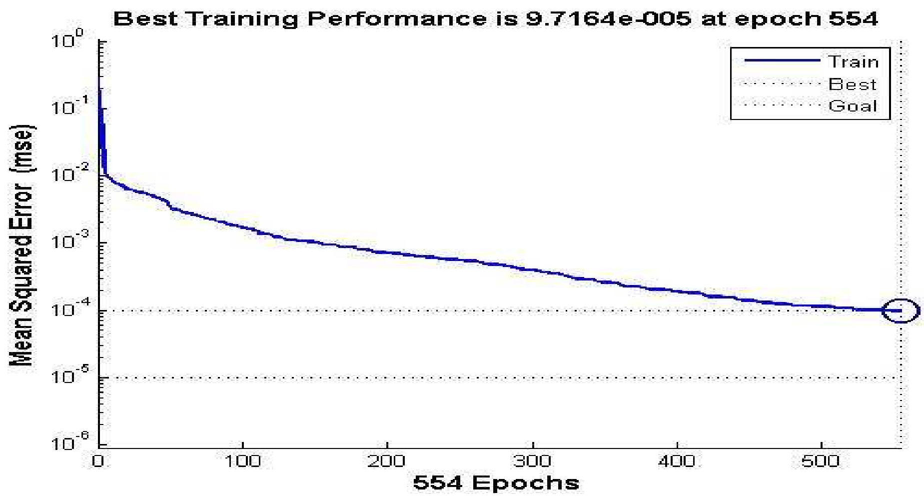

Fig. 2. The schema of error reduction in BP Network training

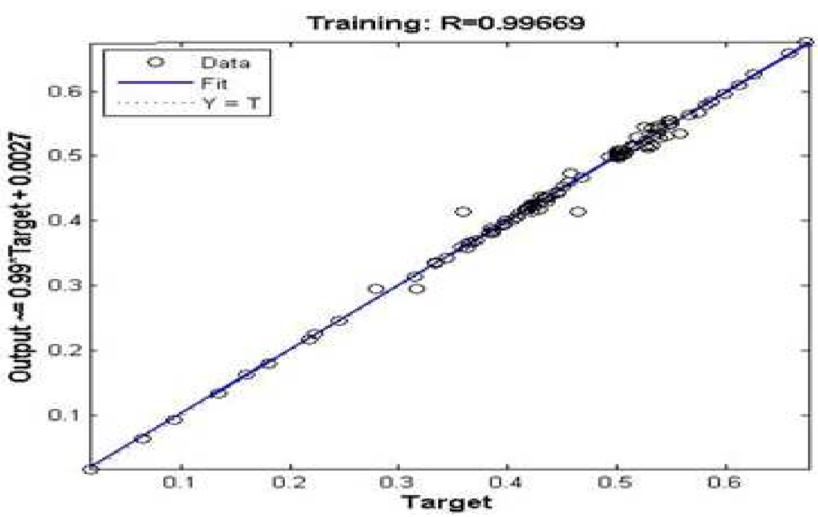

Fig.3. Regression diagram of network training

5.2.3.Thirdstage: Training network test

We perform the network testing after training the target neural network with arbitrary precision. In data preparation, we consider a part of data to test the network. This data have not been provided for network yet. Therefore, the prediction by network is done in the conditions under which the network has no knowledge of this data. Therefore, the conducted prediction can be a criterion for evaluating the network efficiency. To test the network as stated in the data preparation, 2o pairs of data, which are considered for testing, enter the designed multilayer perceptron. The results of implementing each model are discussed in data analysis section.

5.3.Results of implementing the neural network model

We perform the network testing after training the desired neural network with arbitrary precision. In data preparation, we consider a part of data for testing the network. These types of data have not been provided for network yet. Therefore, was prediction carried out by the network is done in conditions under which the network has no information about these types of data. Therefore, the conducted prediction can be a criterion for evaluating the network efficiency. As mentioned in data preparation section, we enter 20 pairs of data, which are considered for testing, to MLP network and the obtained results are presented in Table 1.

Table 1. The results of testing the multilayer perceptron neural network for data ofyear'st-2

Status	No.	Number of true predictions	Number of wrong predictions	Percentage of true predictions	Percentage of wrong predictions	Prediction error
Bankrupt companies	20	19	1	95%	5%	1.103289
Non-bankrupt companies	20	18	2	90%	10%	2.206578
Total	40	37	3	92.5%	7.5%	3.309867

The test results indicate the high efficiency of MLP neural network. Given the results shown in Table (1), it is found that the proposed model with 19 true predictions in bankrupt companies and 18 true predictions in non-bankrupt companies has the performance of 92.5% in true prediction of future situation in companies in the next two years. According to the presented table, it is found that the MLP network performance in predicting the status of bankrupt companies is better than then on-bankrupt companies (The percentage of true prediction in these two sectors is equal to 95% and 90%, respectively). We have shown the prediction error of network in test in the last column. It should be noted that the presented error in this section in the error of network in the whole prediction of target section. The total prediction error is equal to 1.1032 for the bankrupt companies and 2.206 for non-bankrupt ones. These numbers indicate that the network has high efficiency in predicting the companies of Tehran Stock Exchange. Finally, the entire network error is obtained equal to 3.309 in predictions by that number.

The financial information for the year prior to the base year (t-1) and the base year (t) is extracted from the financial statements of studied companies and tested by MLP neural network and the obtained results are presented in Tables 2 and 3respectively.

According to the results shown in Table 2, it is found that the presented model with 19 true predictions in both bankrupt and non-bankrupt companies has been able to be successful in true prediction of future status of companied in two next years with precision of 95 percent.

Table 2. The results of testing the multilayer perceptron neural network for data of year t-1

Status	No.	Number of true predictions	Number of wrong predictions	Percentage of true predictions	Percentage of wrong predictions	Prediction error
Bankrupt companies	20	19	1	95%	5%	1.103289
Non-bankrupt companies	20	19	1	95%	5%	1.103289
Total	40	38	2	95%	5%	2.206578

Table 3. The results of testing the multilayer perceptron neural network for data of year t

Status	No.	Number of true predictions	Number of wrong predictions	Percentage of true predictions	Percentage of wrong predictions	Prediction error
Bankrupt companies	20	19	1	95%	5%	1.103289
Non-bankrupt companies	20	17	3	85%	15%	3. 309867
Total	40	35	4	90%	10%	4. 413156

The results presented in Table 3 also confirm the efficiency of MLP neural network. With respect to the results of table in the base year (t), it is concluded that the presented model in this study with 19 true predictions in bankrupt companies and 17 true predictions in non-bankrupt companies has been able to have the performance of 90% in true prediction of future status in companies in the base year. The performance of presented MLP neural network for predicting the bankruptcy of companies through financial year t (base),like the financial information of t-1and t-2, is better status in predicting the non-bankrupt companies than the bankrupt ones(the percentage of true prediction in these two parts is equal to 95% and 85%, respectively 95).

Like the previous tables, the final column of this table belongs to the display of total prediction error of network in performed test. The presented error in this table is the error of network in the whole prediction according to the information of base year. The total prediction error is equal to 1.103289 for bankrupt companies, while this error is equal to 3.309867 for predictions in non-bankrupt companies. These numbers indicate that the MLP network has better performance in predicting the non-bankrupt companies than the bankrupt ones; in other words, this network performs the predictions for non-bankrupt companies with high precision than the bankrupt ones. The total prediction error for this network is equal to 4.413156 in the base year.

6. Genetic Algorithm Model

The genetic programming algorithm is a technique which allows the researcher to find a solution to problem without the need to pre-specify the type of model. In other words, the solution can be any model which can be described by mathematics. The aim is to allow the data displaying the facts, so that the rate of previous structure, which presents the functional forms and statistical selection methods, is minimized [11].

Essentially, the genetic programming algorithm should have the structure and function in order to make decision about the movement or non-movement towards the bankruptcy when the data of company is given to it. In short, the genetic programming should be able to solve the problem of classifying the samples into two categories. A category consists of the companies, which will go bankrupt, and the other consists of the companies which are profitable. Therefore, we should initially classify the data into the training and experimental data.

6.1. Training and experimental sets

To apply the genetic programming algorithm for prediction problems, the data set is classified into two groups: The training and experimental sets which are randomly selected. In the case of unbalanced data base (the low ratio of bankrupt companies compared to the non-bankrupt ones), it is necessary to consider this ratio in selecting the training set. To allocate the data for the training and experimental sets, 50 pairs of bankrupt and non-bankrupt companies are randomly selected, so that this data is applied for model training. We allocate other data, which contain 20 pairs of bankrupt and non-bankrupt companies, for network testing.

6.2.Classification

The classification is done as follows. We consider $\mathrm{X} = \{\mathrm{x}_0, \dots, \mathrm{x}_\mathrm{N}\}$as a vector which consists of the information of classified company. Furthermore, we consider $f(X)$as a function which is defined by a single tree structure in genetic programming.

The value of y is obtained from f(X) depending on the input vector X

$$y = f(x_0, x_1, \dots, x_N) \qquad (1)$$

We can enter X as the input of genetic programming tree and calculate the output y. When the numerical value of y is measured, the result of classification is as follows:

$$y > 0,\ \ X \in B \qquad (2)$$

$$y \leq 0,\ \ X \in \bar{B} \qquad (3)$$

Where,B refers to the category which the bankrupt companies belong to and $\bar{B}$ refers to thecategory to which the profitable companies belong.

If the assessment of genetic programming tree results in the numerical value greater than zero, that company is put in the class of companies progressing towards he bankruptcy, while if it is smaller than and equal to zero, the company is classified as a profitable company.

6.3.Fitness assessment

The applied database may be very unbalanced, so that only 5 to 6 percent of companies in database are bankrupt. This issue should be considered for designing the fitness function. Otherwise, the assessment may be converted into the convergent structure which classifies all companies into the profitable ones (i.e. they are not in fact classified), and thus the success rate is obtained very favorable. There are three ways to cope with this problem:

- Sampling from a larger category;
- Over sampling from the smaller category;
- Value change (weight) related to the misclassification of positive and negative category to compensate the imbalanced ratio of two categories. For instance, if the imbalanced ratio of 1 to 10 is in favor of negative category, the fine form is classification of positive sample should be 10 times higher [15].

Therefore, the fitness function is as follows:

$$Fitness = \sum_{i=1}^{n} u_i \qquad (4)$$

Where,

$$u = \begin{cases} 0\text{: Misclassification} \\ 1\text{:The bankrupt companies are correctly classified.} \\ \frac{n_{b=0}}{n_{b=1}}\text{: The profitable companies are correctly classified.} \end{cases}$$

$n_{b=0}$Refers to the number of bankrupt companies in training set and $n_{b=1}$refers to the number of profitable companies in training set.

6-4- Main parameters

Table (4) shows the main parameters in assessment.

Table 4.GP parameters

Initial method	Ramped half and half
Replacement operator	Generation with elitism (0.2%)
Selection operator	Tournament selection
Size of tournament group	10
Cloning rate	0.05
Integration function	Non-identical tree integration
Rate of internal node selection	0.9
Integration rate	0.5
Integration rate for "volume" control	0.45
Maximum initial depth of tree	7
Maximum depth of tree	18
Population size	500
Total run	20
Stop and finish criterion	Generation

6.5.Results of implementing the GA model

The results obtained for each of years are presented in Table 5. The first row of table shows the results obtained in two years before the base year, the second row of table shows the results in a year before the base year and the finally the third and last row of table shows the results obtained in the base year. Each table shows the results obtained in training, testing and total. The first column shows the gained success percentage (i.e. the number of true predictions); the second column shows the percentage of True Positive (TP) (the number of companies which are properly classified as the bankrupt companies); and the third column indicates the percentage of true negative (TN) (the number of non-bankrupt companies which are correctly classified).

Table 5. Results of Genetic Programming Test for data of year's t-2, t-1 and t

Status	Training			Experimental			Total		
	Success (%)	TP (%)	TN (%)	Success (%)	TP (%)	TN (%)	Success (%)	TP (%)	TN (%)
Year t-2	98.12	99.00	88.00	94.92	96.47	84.83	96.44	97.48	84.32
Year t-1	99.69	100.00	89.10	96.94	98.59	83.31	97.94	98.04	85.28
Year t	97.50	98.50	86.40	93.04	96.00	82.57	95.53	96.67	83.72

According to this table, the results obtained by GP are satisfactory in training mode. The best structure of GP achieves the success percentage of about 99.7% in training set. Furthermore, the best structure of GP achieves the success percentage of about 97% in experimental set. The model designed by the genetic programming algorithm obtained the success percentage of about 98% in its best structure and these results indicate the high ability of genetic algorithm to predict the bankruptcy in companies listed on Tehran Stock Exchange.

For empirical completion, we compare the mean error of prediction obtained from the genetic algorithm model with the neural network model according to the statistical t test at the significance level of 95 percent. This statistical test is selected due to the independent performance of each model. Therefore, the $H_0$and $H_1$are measured and studied as follows:

- **H_0**: There is no significant difference between the performance of genetic algorithm model and performance of neural network model in terms of predicting the bankruptcy in companies listed on Tehran Stock Exchange.
- **H_1**: There is a significant difference between the performance of genetic algorithm model and performance of neural network model in terms of predicting the bankruptcy in companies listed on Tehran Stock Exchange.

Table 6. Information about the test

Group Statistics					
	Code	N	Mean	Std. Deviation	Std. Error Mean
Error	ANN	140	0.08081667	0.126180736	0.027950743
	GA	140	0.03082799	0.094513487	0.014943894

Table 7. Results of t test

		t-test for equality of means						
							95% confidence interval of difference	
		t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Error	Equal variances assumed	2.005	78	0.048	0.04998868	0.024927082	0.000362676	0.099614693
	Equal variances not assumed	2.005	72.285	0.049	0.04998868	0.024927082	0.000300797	0.099676572

As shown in Table (6), the mean error of prediction made by the GA model (0.03082799) is much lower than the mean error of multiple-discriminant analysis model (0.08081667). The results of Table 7 also indicate that the value of signum function(Sig) is lower than 0.05 at the significance level of 95%, thus the results of this analysis indicate that the $H_0$is rejected and H_1accepted. Therefore, it can be concluded that there is a significant difference between the performance of genetic algorithm model and neural network model in terms of predicting the bankruptcy in companies listed on Tehran Stock Exchange.

7. Conclusion

The bankruptcy is a global and very important issue which affects the economy of all countries. The high social costs, incurred by different stakeholders for bankrupt companies, lead to search for the ability to predict and understand this theory.

Using the popular models, this research predicts the financial bankruptcy in companies listed on Tehran Stock Exchange in the period of 2001-2011. We select the applied financial ratios in this research from the financial statements of 70 pairs of bankrupt and non-bankrupt companies which were under the Article 141 of Commercial Act of Iran during the research period (82 companies were involved this Act in initial survey, but some of them were excluded from the statistical population after some considerations).

The research data is tested by neural network models and genetic algorithm in order to identify the efficient and appropriate model of bankruptcy. First, the values of model variables are extracted from the financial statements of companies, and then the bankruptcy of companies listed on Tehran Stock Exchange is predicted by neural networks. In this regard, we have utilized the multilayer perceptron feed forward neural network with error back- propagation learning algorithm and this algorithm belongs to the supervising learning algorithms. A 5-layer structure, including an input layer (6 neurons), three hidden layers (15, 10 and 1 neurons), and an output layer (1 neuron), is obtained after MLP network training in precision of $1e^{-4}$. The obtained results indicate the high efficiency of neural network model in this study. The true predictions of neural network in this study are obtained equal to 92.5%, 95% and 90%for two years before the base year, a year before the base year and the base year, respectively. The results of this study are presented in the Tables 1, 2 and 3, respectively.

Using a genetic algorithm, we predict the bankruptcy of companies listed on Tehran Stock Exchange by described independent and dependent variables. According to the results of Table (5), the genetic algorithm model is able to predict the bankruptcy of companies properly through the financial data of two years before the base year, a year before the base year, and the base year with the precision of 96.44, 97.94 and 95.53, respectively. These results indicate the high ability of genetic algorithm in predicting the bankruptcy of companies listed on Tehran Stock Exchange compared to the neural network model.

Finally, with respect to the conclusion section, it can be argued that the genetic algorithm, applied in this study, is very efficient because it has been able to predict the bankruptcy or non-bankruptcy of companies by low error percentage and through financial data of two prior years. Therefore, it can claim that the applied genetic algorithm model in this research has the appropriate precision and is the appropriate model for predicting the bankruptcy of companies.

Another issue is the imbalance between the number of companies progressing towards the bankruptcy and the number of profitable companies as well as the amount of not-available information in database for analyzing in some similar studies. This problem can be solved by normalizing the data and application of a fitness function that solves the imbalance problem. The obtained results in this study are very satisfactory. As mentioned, the best GP structure received the success percentage of about 99.7% in training set and97% in experimental set.

REFERENCES

[1] Aghaei, M. and Gh. Kordestani, The ability of profit to predict the cash flow and future profits,1996 and 1997.Quarterly journal of Accounting and Auditing Reviews, 18 and 19: 42-55.

[2] Reese, W, Financial Analysis(second ed.) 1995. London: Prentice Hall.

[3] Altman, E, Predicting Financial Distress of Companies, 2000. Retrieved on September 4th, working paper.

[4] Lee, K.C. and I. Han and Y. Kwon, Hybrid neural network models for bankruptcy predictions, Decision Support Systems 1996. (18), 63-72.

[5] Beaver, W, Financial Ratios as Predictors of Failure 1196.Journal of Accounting Research,71-111.

[6] Mehrani, S and N. Bahramfar. And F.Ghayour, Investigating the correlation between the traditional liquidity ratios and the ratios of cash flow statements for evaluating thesurvivalofcompanies2005.Quarterly Journal of Accounting and Auditing Reviews, 40. 3-17.

[7] Jahangir, M, Commercial Code along with the Cheque Code: The reform regulation of registering the non-commercial organizations and institutes2000.Tehran: Didar Publication.

[8] Odom, M.D. and R. Sharda, A Neural Network Model for Bankruptcy Prediction 1990.IJCNN International Joint Conference on Neural Networks. San Diego: CA, Vol. 2, pp. 163-168.

[9] Shah, J. and M. Murtaza A neural network based clustering procedure for bankruptcy prediction 2000. American Business Review 18(2): 80–86

[10] Wallace Wanda, A, Risk assessment by internal auditors using past research on bankruptcy applying bankruptcy models 2004.

[11] Khashman, A, Neural networks for credit risk evaluation: Investigation of different neural models and learning schemes 2010. Expert Systems with Applications (37). 6233–6239.

[12] Varetto, F, Genetic Algorithms application in the analysis of insolvency risk1998.

[13] Min, S.H. and J. Lee and I. Han, Hybrid genetic algorithms and support vector machines for bankruptcy prediction 2006.Expert systems with applications. 31: 652-660.

[14] Lensberg, T. and A. Eilifsen and T.E. McKee, Bankruptcy theory development and classification via genetic program 2006.European Journal of operational research. 169، 677-697.

[15] Alfaro, E. and K.A. Sharman, Genetic Programming Approach for Bankruptcy Prediction Using a Highly Unbalanced Database2007. European Journal of Evolutionary Computing. 93, pp 132-143.