Investigating Financial Crisis Prediction Power using Neural Network and Non-Linear Genetic Algorithm

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Abstract

Bankruptcy is an event with strong impacts on management, shareholders, employees, creditors, customers and other stakeholders, so as bankruptcy challenges the country both socially and economically. Therefore, correct prediction of bankruptcy is of high importance in the financial world. This research intends to investigate financial crisis prediction power using models based on Neural Networks and to compare it with Non-Linear Genetic Algorithm. Based on the available information and statistics of the listed companies on Tehran Stock Exchange (TSE) during 1997-2010, from among these companies subjected to article 141 of the Commercial Law, 72 firms, and from among other firms, 72 firms were selected.

Results of McNemar Test for Non-Linear Genetic Algorithm and Neural Network indicated that although prediction accuracy of Non-Linear Genetic Algorithm (90%) was greater than that of Neural Network (70%), yet this difference was not statistically significant

Keywords: bankruptcy prediction, Non-Linear Genetic Algorithm, Neural Network.

1- Introduction

There are numerous factors that affect the bankruptcy phenomenon. High interest rate and heavy debts are among the factors which negatively affect the firm's financial state. In addition, prior research suggests that newly founded private firms and smaller companies, respectively, are more vulnerable compared to established and large companies (Dun and Bradstreet, 1980).

Competition intensification at industry level has led to bankruptcy of many firms and their removal from the competition field. This has given rise to some concerns among shareholders, managers, creditors and in general the whole society. Investors by estimation of financial crises and bankruptcy of firms try to prevent loss of their capital. If management of business unit is timely informed of bankruptcy risk, it can take preventive actions. Creditors are very sensitive about loss of their principal amount and interest in the granted loans and credits to potential and current customers, and since it imposes heavy economic and social bankruptcy costs on the society, it is also interesting from macroeconomic point of view, because the lost resources in the distressed economic unit could have been used for other profitable opportunities. Given the importance of bankruptcy, all people and stakeholders are interested in bankruptcy prediction before its actual occurrence.

Financial crisis or bankruptcy prediction using historical financial data is well known. Although the first effort in this relation dates back to 1930, but from 1966 and following the research carried out by Beaver on this topic it took a more serious form (Dimitras et al, 1996). Beaver (1966) is one of the first researchers who investigated prediction of financial crisis or bankruptcy and is regarded as one of the leading academic researchers in this field. After him, Altman (1968) using advanced statistical techniques succeeded in achieving significant results. Today, numerous prediction models are introduced by researchers. These models, according to the model construction method, number of model's variables, definition of bankrupt firms and other firms, are classified into various groups, such as traditional model versus Artificial Intelligence models, or univariate models versus multivariate models.

This research, in addition to setting the prior research in financial crisis prediction as the departure point which is based on data of one or several years, intends to construct and design a financial crisis prediction model based on financial variables during the understudy years using the Artificial Intelligence and Genetic Algorithm corresponding to Iranian economic condition.

2.Literature of Review and research background

Large scale financial crisis following financial distress and bankruptcy of firms operating in an economy by extension to crises at regional level may have international impacts. Financial distress in Oxford Dictionary is defined as hardship, pain, grief and lack of monetary resources and destitute. In financial literature, a variety of definitions have been offered for financial distress.

In this research, bankrupt firm is defined based on article 141 of the Commercial Law according to which a bankrupt company has an accumulated loss equal to 50% of the firm's capital. However, article 141 of the Commercial Law does suggest an immediate dissolution or liquidation of the firm, and only upon request of stakeholders the firm's activities are suspended.

Identification of exact reason(s) of bankruptcy and financial problems in every particular case is not easy. In most cases, a multiplicity of reasons altogether leads to financial crisis or bankruptcy. But, in general, the main causes of bankruptcy are the mentioned "financial and economic problems".

In some cases, causes of financial crisis or bankruptcy are identified by examination of financial statements. The accountants who are experienced in analysis of the firms' financial state can easily detect causes of financial crisis or bankruptcy. However, at times, some indices indicate favorable financial flow in a business unit for a relatively short period, concealing financial crisis or bankruptcy from the eyes of accountants.

Newton (1998) has divided the stages of firm's financial state worsening into incubation period, cash shortage, insolvency for payment of financial and commercial liabilities, insolvency for payment of total debt, and eventually financial crisis and bankruptcy (figure 1.2). Although most bankruptcies go through these stages, but some companies may without undergoing all these stages reach financial crisis and complete bankruptcy.

The state of business unit does not abruptly enter financial crisis or bankruptcy stage. In incubation period, there may be one or more unfavorable situation for the business unit, without immediately being detectable. For example, change in production demand, steady increase in overhead costs, abolishment of production methods, etc are among such factors. Often, economic losses occur during incubation period which reduce return on assets (ROA). If the problem is discovered at this stage, it would be ideal for the company, particularly since at this stage easier solutions are effective, while at later stages they may be of no use. The third point is that if the problem is discovered and resolved at this stage, public confidence in the firm will be undermined. Resolving the problem at later stages weakens public trust in the firm and as a consequence of which access to funds will be more difficult and the firm may be forced to refuse profitable investment projects.

The stage of cash deficit starts when the business unit for the first time does not have enough cash available to meet its current liabilities or future needs, although it may have much more physical asset relative to its current needs and profitability records. The point is that the assets cannot sufficiently be liquidated and the capital is in fact locked up.

At the stage of financial and commercial insolvency, the firm is still able to obtain sufficient funds from consumption channels, management is in a position to takes suitable measures such as use of financial and commercial specialists, credit granting committee, and financing methods restructuring. Taking these actions, the firm is still able to identify and resolve the financial problem.

At "bankruptcy" stage, the firm moves towards extinction. At this stage, total debt exceeds total asset value, and the firm can no longer avoid suspension of its operation, followed by rush of creditors and other stakeholders to collect their claims. At any rate, it should be noticed that bankruptcy is defined according to the law and should be considered from this perspective.

The extracted ratios and indices from financial statements have been always considered as signals of firms' current and future financial state (Galvao, 2004). Use of financial ratios is the most common technique in bankruptcy prediction. Application of financial ratios to bankruptcy prediction dates back to 1966 and Beaver's studies which for a long time has been regarded as the only possible method (Haber, 2006). In recent years, many critics have been made on prediction power of financial ratios. However, Beaver (2005) demonstrated that financial ratios are still the powerful tools for bankruptcy prediction.

2.1. Techniques employed in bankruptcy prediction

Due to the significant economic, social and political consequences imposed by bankruptcy phenomenon on various groups in the society, it has been always of special interest with researchers. Researches on bankruptcy prediction have taken a serious form since 1960, so as today we are witness of numerous and diverse methodologies applied to to bankruptcy prediction. This section addresses these techniques and describes their characteristics features and limitations.

In most studies on bankruptcy prediction, firms are basically classified into two groups: 1. financially healthy firms and 2. financially distressed firms. Based on this classification, firms can be classified by the dummy variable Y:

$$Y_i = \begin{cases} 1 & \textit{if the firm is healthy} \\ 0 & \textit{if the firm is bankrupt} \end{cases}$$

Some researchers suggest definition of more than two groups based on risk level, but due to general acceptance of the 2-category classification, it has become the dominant approach (Dimitras et al, 1996).

Bankruptcy prediction techniques according to their nature are classified into three groups of (classical) statistical approaches, Artificial Intelligence techniques, and Theoretical models.

Data mining models and Artificial Intelligence Techniques (AIT): AIT performs tasks similar to human's knowledge, intelligence and logic. In fact, the AI is a system which learns and improves performance of its problem solving given the past experiences. AI application in finance and particularly in bankruptcy prediction does not have a long record, yet due to its high efficiency and being free from the existing restrictive assumptions in statistical methods, it has been widely accepted by the researchers. These models are mainly focused on signals of commercial failure, are generally multivariate and the used variables in them are derived from the information available in the firm's accounts. Intelligent techniques are composed of neural networks, genetic algorithms, hard sets, Support Vector Machine, reasoning based on Fuzzy and logic and issues. Many studies have been carried out on application of these techniques for prediction of businesses failure among which it can be referred to Etemadi, Rostami and Farajzadeh Dehkordi (2009), Huang, Tsai, Yen and Cheng (2008), Hung and Chen (2009), Lin et al (2009), Min an Jeong (2009), Min and Lee (2008), Ravi and Pramodh (2008), Sun and Li (2008), and Wu (2010).

For structuralization of Computer systems neural networks, human learning process and inference pattern are followed. Architecture of neural networks in general is consisted of three input layers including input information, throughput (hidden) layer, and output layer. Identification of the best architecture for problem solving is a complex and difficult task, and the best architecture is obtained by trial and error.

Neural Networks which are also known as Artificial Neural Networks (ANN) are a data mining technique used to solve many problems. Among advantages of Neural Networks relative to other methods, according to the rules observed in data mining and artificial intelligence systems, it can be referred to the following ones:

- Since Neural Networks do not need a knowledge base for being structuralized, their use in problems about which there is little knowledge is useful.
- Processing in NN can be performed at high speed and accuracy relative to traditional methods, because these networks simultaneously examine all the information existing in one problem and the processing units or the neurons function along each other (Back et al, 1996).
- In these networks, the type of data distribution or communication structure of the existing variables does not require to be considered as the basic assumption (Wu et al, 2006). If the input data are incomplete and disturbed or have a high correlation with each other, or have not been already observed, traditional systems are hardly able to extract rules and patterns, but in the same conditions, neural networks provide reasonable answer, and after learning and adaptation, they will be able to generalize the results to similar instances.
- Low energy consumption, error tolerance, and high learning and adaptation capability are other advantages of this method.

However, NNs have some disadvantages as well. Their main limitation is lack of a definitive method for specification of optimal architecture. To design an NN model in solving a problem of classification type, there is no systematic principle and method, as a result, the best network topology is specified by trial and error. Many factors such as hidden layers, number of neurons in hidden layers, data normalization and learning algorithm can affect the network's performance. In defining network's architecture, one has to take this fact into account that a greater number of layers leads to more complexity of the network and to a problem called 'over-fitting' and non-usability of new data. In general, with increase in number of the middle neurons, the network's power in identification of existing complexities increases, but this may reduce the network's generalizability. In other words, if number of neurons in the middle layer is too large, the network memorizes in place of learning. Another shortcoming of these networks concerns their performance as a black box. Comprehension and verification of the mode these networks classify data and quality of relationships in layers' structure is not possible for the user. NN method does not specify significance of each variable in the final classification, and the assigned weights in this regard are not interpretable (Fallahpour, 1383). From among the researchers who employed NNs for prediction of bankruptcy and financial crisis in different countries it can be referred to Coates and Fant (1992), Serrano and Cinca (1996), and Shah and Murtaza (2000).

By contemplation on bankruptcy prediction models, it can be found that all of them are somehow the heritage of statistical techniques. For instance, AI models generally use both univariate and multivariate techniques so as they can be considered as the children of mechanized statistical techniques. Similarly, theoretical models often are derived from application of an appropriate statistical technique and are not directly derived from theoretical principles.

Artificial Neural Networks (ANN) is flexible and non-parametric modeling tools. They are able to execute every complex function with a satisfactory accuracy. The first effort for use of ANNs for bankruptcy prediction was made by Adam and Sharda (1999).

Franco Varreto (1998) used Genetic Algorithm for bankruptcy prediction. His sample included 500 companies, comprising 236 bankrupt firms and 264 non-bankrupt firms. Results of this research indicated a prediction accuracy of 93% one year ahead of the bankruptcy event and a prediction accuracy of 91.6% three years prior to bankruptcy. In addition, in this research, by comparing Genetic Algorithm with traditional prediction models, it was voted for superiority of genetic process, because these models in addition to being free from the restrictive assumptions, relative to traditional methods have a higher accuracy. In traditional models, with increase of time horizon from bankruptcy event, the model's accuracy significantly decreases, while this accuracy reduction is far less with GA models. Among other studies on this subject, it can be referred to Shin and Lee (2002) and McKee and Lensberg (2002).

Despite the large number of researches on the issue of bankruptcy prediction, few desirable results have been found (Plat & Plat, 1990). The created models did not come successfully out of the Test of Robustness. This may be due to several factors. One reason can be that the statistical models tend to use Matched Pairs of bankrupt and non-bankrupt firms. Next, data of the variables specifying cutoff points (thresholds) have been used for distinction of bankrupt from non-bankrupt firms. The used data for extraction of thresholds were year specific, and were tried for correct identification of firms in the hold-out sample (similar time periods). These cutoffs have less efficiency when used in different time periods (including their use in next studies).

Another cause of the accuracy drop in researches on bankruptcy prediction can be sought in the selected variables for model construction. Most studies select the used variables in the model based on their prevalence and desirability in the literature. They often have root in the notion of liquidity signal suggesting liquidity as a synonym to financial solvency. Therefore, these variables have been used in next studies with the least manipulation and modification.

Farajzadeh Dehkordi (2005), in his master thesis, investigated bankruptcy prediction modeling of the listed companies on the stock exchange using two models of Multiple Discriminant Analysis (MDA) and Genetic Planning. To construct the above models, first, he prepared a full list of financial ratios (93 ratios) and after study of the ratios, eventually, he extracted 42 financial ratios for construction of the models, and using Independent Samples Test (IST) of the two societies he constructed the two intended models. In fine, the Genetic Planning and MDA models succeeded in correct classification of the firms present in the training set with an accuracy of 94% and 77%, and firms present in the hold-out set with an accuracy of 90% and 73%, respectively.

Kiarasi (2009) investigated two models of Logistic Regression and Multivariate Discriminant Analysis for prediction of the firms' success or failure. He used 14 financial ratios and the results favored the regression model over the Multivariate Discriminant Analysis.

Saadatfar in his master thesis sought for the best neural network structure for prediction of firms' bankruptcy. He used three financial ratios of current ratio, gross profit margin and net profit to current debt to predict bankruptcy two years ahead of its actual occurrence. His results indicated superiority of the three-layer Neural Networks (Perceptron model with a structure made up of three neurons in the first layer, nine neurons in the middle layer, and one neuron in the output layer with learning algorithm Error-Back Propagation and cumulative learning method and Sigmoid Activity Function) to the four-layer Neural Networks.

Saee (2008) investigated application of Support Vector Machine in prediction of firms' financial insolvency using financial ratios. His research was mainly focused on the use of Support Vector Machine in prediction of firms' insolvency. The results obtained from this model were compared with those obtained from the Logistic Regression model and Support Vector Machine was found superior to Logistic Regression model.

Nouraddin (2010) constructed some models for prediction of financial crisis two years ahead of its occurrence. The obtained results indicated superiority of the Neural Networks model to other models.

3. Research Hypothesis

Given the purposes in this research, the main hypothesis is as follows:

Prediction power of Neural Networks (NN) models is greater than that of AIT models which are based on internal analysis (Non-linear Genetic Algorithm).

Since the financial crisis arises from financial distress and bankruptcy of the individual firms operating in the economy, in this research, for detection of financial crisis, it is made use of the firms' bankruptcy.

4. Statistical population and sample

The understudy statistical population in this research includes all the listed firms on TSE in the period 1997-2010. Based on the available information and statistics in the library of the Securities and Exchange Organization (SEC), during this period, 72 firms have been subjected to article 141 of the Commercial Law and hence, subjected to the random selection. To match them with the bankrupt firms in the same number, non-bankrupt firms using random sampling were selected. Due to the limited number of the listed firms on the stock exchange, it was not possible to compare the firms in terms of industry in which they operated. Since the firm size itself is considered as a potential variable for bankruptcy prediction, it is also dispensed with comparison of the firms based on the firm size. Therefore, in the sampling, the non-bankrupt firms were matched with the bankrupt firms only based on fiscal year.

5. Variable selection process

By accepting the assumption that various financial ratios represent firm's financial state, they can be used as the predicting variables of financial crisis or bankruptcy. To determine suitable ratios and indices for prediction of financial crisis or bankruptcy, the research literature has been thoroughly reviewed the result of which was a list of 23 financial ratios used in the prior research for prediction of financial crisis or bankruptcy. A full list of these ratios is provided in table 1.

Table 1: Independent variables used in the research

Variable	Financial ratio	Variable	Financial ratio
X1	Working capital to equity	X13	Total debt to accumulated profit or loss
X2	Working capital to sales	X14	Total debt to total asset
X3	Working capital to total debt	X15	Accumulated profit or loss to total asset
X4	Working capital to total asset	X16	Operational margin to sales
X5	EBIT to equity	X17	Financial cost to gross profit
X6	EBIT to sales	X18	Current asset to total asset
X7	EBIT to total debt	X19	Sales to current asset
X8	EBIT to total asset	X20	Current asset to current debt
X9	Equity to total debt	X21	Net profit to sales
X10	Equity to total asset	X22	Net profit to total asset
X11	Sales to total debt	X23	Current debt to total asset
X12	Sales to total asset		

In selection of these variables, first, the variables were refined according to the theory in which variables with quite similar effects were eliminated. For example, although the financial ratios “total asset to total debt” and “total debt to total asset” are numerically different, in fact, they represent an identical dimension of firm’s state and simultaneous presence of the two ratios only increases complexity of the required calculations for selection of the final variables. In the next stage, the ratios and indices the calculation of which was not possible based on the available information on the stock exchange were eliminated. Since use of all the 23 ratios for construction of the model is not possible and increases the model’s complexity and reduces its efficiency, a solution ought to be found in order to reduce the number of the financial ratios in a way that the model’s efficiency does not suffer.

To select the predictive variables, Stepwise Discriminant Analysis (SDA) is used. SDA is one of the exploratory elements of discriminant analysis which is often used for the purpose of variable selection. SDA technique, in the first step, searches through the 23 ratios to determine the financial ratio with the greatest power in distinction of bankrupt firms from the non-bankrupt ones. To do this, SDA uses the ratio of intra-group variance to intergroup variance. So the financial ratio with the least intra-group variance (within each group of bankrupt and non-bankrupt) and the greatest inter-group variance (between two groups of bankrupt and non-bankrupt) has the greatest power in distinction of the bankrupt from the non-bankrupt firms, because similarity in value of a financial ratio in the group of bankrupt firms, and on the other hand, the evident difference of these values from the figures of the non-bankrupt firms enhances distinction power of this ratio and reduces its errors.

After selection of the first variable, SDA process is resumed for selection of the second variable. At this stage, SDA selects the financial ratio that next to the first financial ratio has the greatest power in distinction of firms. In fact, at this stage, the joint effect of the two financial ratios in dividing the groups of companies is considered. This process is stopped when none of the not-selected ratios meet the specified condition of significance level (i.e. 0.1). In other words, the made improvement by these financial ratios (not-selected ones) in discriminating ability of the selected ratios is insignificant. It should be noted that in SDA process, because of continuous evaluation of the set's discriminating ability by F-Test, a financial ratio may several times enter and exit the set of the selected ratios. So a selected financial ratio may be removed and another financial ratio may come in its place. Table 2 presents the obtained results from the SDA process on 23 variables in the previous stage. In this table, the 23 financial ratios together with their significance degree in making distinction between the firms as well as the final variables are represented. Note that after selection of the first financial ratio with the highest significance level, the second selected financial ratio is X_{14} which in terms of significance is ranked 9 amidst 25 financial ratios. The reason for this selection is the high correlation of the significant financial ratios in second to eighth row with the financial ratio X_{14} and selection of these ratios does not increase discriminating power of the set of the selected variables. This also applies to other selected financial ratios.

In addition, it should be noted that since the specified significance level for inclusion or removal of the variables is set at 0.1, SDA process stops after selection of the fifth financial ratio since other ratios are not able to increase discriminating power of the set of the selected variables at least to the amount of 0.

Table 3 shows stages of SDA process. As is seen in this table, to select the final financial ratios, SDA process goes through five stages and at each stage one financial ratio is selected and added to the set of the financial ratios. Decrease of Wilks' Lambda at each stage means increase of discriminating power of the selected variables.

Table 2: Matrix of SDA process structure

Significance	Code	Significance	Code	Significance	Code
.243	X19	-.437	X14	.857	X16
.222	X23(a)	.359	X8(a)	.832	X1(a)
.221	X15(a)	.344	X11(a)	.750	X3(a)
-.157	X13(a)	.333	X9(a)	.745	X21(a)
-.102	X17	.318	X20(a)	.721	X2(a)
-.044	X4(a)	.305	X18	.636	X22(a)
.026	X5(a)	.270	X10(a)	.550	X6(a)
		.252	X12(a)	.477	X7(a)

Table 3: Summary of steps in variable selection process

Stages	Code	Change degree	F for exit	Wilks' Lambda
1	X16	1.000	71.858	
2	X16	.973	76.804	.986
	X14	.973	6.212	.697
3	X16	.804	35.601	.787
	X14	.925	8.740	.681
	X18	.766	6.281	.671
4	X16	.771	26.502	.731
	X14	.826	12.246	.675
	X18	.724	8.552	.661

Stages	Code	Change degree	F for exit	Wilks' Lambda
	X19	.851	4.726	.646
5	X16	.738	18.332	.711
	X14	.814	9.843	.654
	X18	.714	7.656	.641
	X19	.801	4.240	.635
	X17	.708	3.213	.617

Given the mentioned values, to construct the model, SDA process selects 5 variables from among the 23 candidate variables. These 5 variables are ranked below according to their discriminating power:

1) Ratio of operational margin to sales (profitability): X_{16}
2) Ratio of total debt to total asset (solvency): X_{14}
3) Ratio of current asset to total asset (liquidity): X_{18}
4) Ratio of sales to current asset (efficiency): X_{19}
5) Ratio of financial cost to gross profit (interest coverage)

As is observed, each selected ratio covers one important aspect of each the firm's financial state. Statistical significance of these ratios based on F-Test is 0.857, -0.437, 0.305, 0.243, and -0.102, respectively.

6. Construction of financial crisis or bankruptcy prediction model using Non-Linear Genetic Algorithm

The set of the understudy data which includes 72 bankrupt and 72 non-bankrupt firms has been randomly divided into two groups of training set and hold-out set. The training set which is used for construction and training of the model includes 51 bankrupt firms and 53 non-bankrupt firms. The hold-out set which includes 21 bankrupt firms and 19 non-bankrupt firms is used to examine generalizability of the obtained model and its external validity. To execute Genetic Algorithm process and to create financial crisis or bankruptcy prediction model, GeneXproTools software (version 4.0) is used. The cutoff and mutation operators have been determined at 0.6 and 0.06, respectively.

When the obtained result from Genetic Algorithm for a company is greater than or equal to 0.5 (threshold value), this company is placed in the group of bankrupt firms. On the contrary, when the obtained value from the Genetic Planning model is smaller than 0.5, the company is placed in the group of non-bankrupt firms. Comparison of the firms' real group with their predicted group, using Genetic Algorithm, measures the model's accuracy.

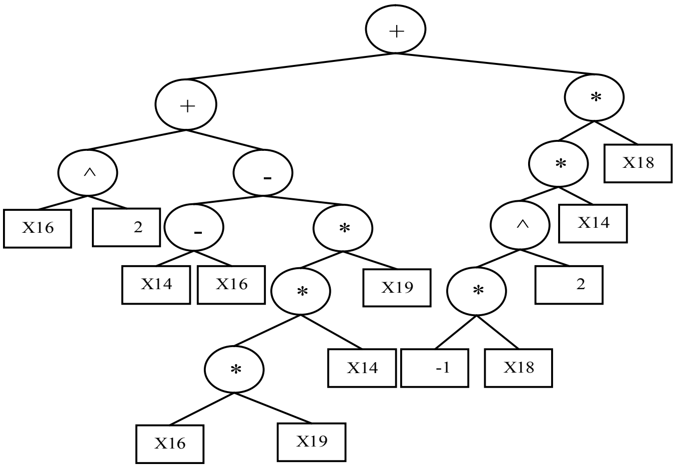
Diagram 1 presents the best model obtained from the Non-Linear Genetic Algorithm. This decision tree represents a chromosome. Result of this tree for a firm has to be compared with the threshold value 0.5 for specification of the firm's group.

Diagram 1: Best prediction model of financial crisis or bankruptcy obtained from Non-Linear Genetic Algorithm process

Given the above figure, the obtained model can be presented as follows:

$Y=(X16)^2 + (X14 - X16 - ((X16 \times X19) \times X14 \times X19)) + ((-X18)^2 \times X14 \times X18)$

In table 4, the number of the training sample and the hold-out sample as well as the number of errors in two samples are separately presented for the bankrupt and non-bankrupt firms in the Non-Linear Genetic Algorithm model.



The Non-Linear Genetic Algorithm succeeded in correct classification of firms present in the training sample into groups of bankrupt and non-bankrupt firms with an overall accuracy of 91%, so as from among 104 firms present in the training set, 85 firms have been correctly classified. Study of the results indicates that the Non-linear Genetic Algorithm had an accuracy of 86 percent in correct classification of firms in the training set (from among 51 bankrupt firms in this set, 44 firms have been correctly classified). In addition, this model had an accuracy of 96 percent in correct classification of non-bankrupt firms in the training set (from among 53 non-bankrupt firms present in this set, 51 firms have been correctly classified).

To examine generalizability and reliability of the Linear Genetic Algorithm, the model has been tested on the data of 40 firms present in the hold-our sample. The firms placed in the hold-out set had no interference in the model's construction process. Hence, they can be correctly used to test the model's external validity. The Non-Linear Genetic Algorithm succeeded in correct classification of firms present in the hold-our sample into groups of bankrupt and non-bankrupt firms with an overall accuracy of 90%, so as from among 40 firms present in the hold-out set, 36 firms have been correctly classified. The Non-linear Genetic Algorithm model had an accuracy of 81 percent in correct classification of firms in the hold-out set (from among 21 firms in this set, 17 bankrupt firms have been correctly classified). In addition, this model had an accuracy of 100% in correct classification of firms in the hold-out set (from among 19 non-bankrupt firms in this set, 19 firms have been correctly classified). These results indicate that the Non-linear Genetic Algorithm in addition to producing desirable results in prediction of firms' future state based on their financial information is not biased in classification of bankrupt or non-bankrupt firms and creates balanced and reliable results. Turbulence Matrix of the Non-linear Genetic Algorithm prediction result is shown in table 5.

Table 4: Number of sample and errors in Non-Linear Genetic Algorithm

	Training sample		Hold-out sample	
	Number of sample	**Number of error**	**Number of sample**	**Number of error**
Non-bankrupt	53	2	19	0
Bankrupt	51	2	21	4
Total	104	9	40	4

Table 5: Turbulence Matrix of Non-Linear Genetic Algorithm prediction result

		Real	
		Bankrupt	**Non-bankrupt**
Predicted	Bankrupt	TP = 17	FN = 0
	Non-bankrupt	FP = 4	TN = 19

Table 6: Results of Neural Network technique for the training sample

	Training sample		Hold-out sample	
	Number of sample	**Number of error**	**Number of sample**	**Number of error**
Non-bankrupt	53	15	19	6
Bankrupt	51	12	21	6
Total	104	27	40	12

Thus, the accuracy of Non-Linear Genetic Algorithm model which is 90% in the hold-out sample can be calculated as follows:

Accuracy of Non-Linear Genetic Algorithm $= \frac{TP+TN}{TP+FP+TN+FN} = \frac{19+17}{17+4+15+4} = 90\%$

7. Construction of Financial Crisis or Bankruptcy Prediction model using Neural Network

The used Neural Network is a fully interconnected network in which the learning algorithm Error-Back Propagation (EBP) is utilized for the purpose of training. The used Transformation Function in each neuron of this network is a sigmoid function as follows:

$$f(\mathrm{NET}) = (1 + e^{-\mathrm{NET}})^{-1}$$

In this relation, NET is the weighted sum of the neuron's input variables from the previous layer. Using this function, the numerical output value will be zero or one.

Number of the training sample, number of the hold-out sample, and number of errors in the two samples for bankrupt and non-bankrupt firms separately are presented in table 6.

Neural Network model succeeded in correct classification of the existing firms in the training sample into bankrupt and non-bankrupt groups with an overall accuracy of 74%, so as from among 104 companies present in the training set, 77 companies have been correctly classified.

Study of the results of this model indicates that the Neural Network model in correct classification of the bankrupt firms in the training set has an accuracy of 76% (from among 51 bankrupt firms in this set, 39 firms have been correctly classified). In addition, this model in correct classification of the non-bankrupt firms in the training set has an accuracy of 72% (from among 53 non-bankrupt firms in this set, 38 firms have been correctly classified).

To examine generalizability and reliability of the Neural Network model, this model has been tested on the data regarding the 40 firms present in the hold-out sample. The firms placed in the hold-out sample have had no part in the model construction process. Hence, they can be properly used to test the model's external validity.

The Neural Network model succeeded in correct classification of the existing firms in the hold-out sample into bankrupt and non-bankrupt groups with an accuracy of 70%, so as from among 40 firms present in the hold-out set, 28 firms have been correctly classified. The Neural Network model in correct classification of bankrupt firms in the hold-out set has an accuracy of 71% (from among 21 bankrupt firms in this set, 15 firms have been correctly classified). In addition, this model in correct classification of non-bankrupt firms in the hold-out set has an accuracy of 68% (from among the 19 non-bankrupt firms in this set, 13 firms have been correctly classified).

These results indicate that the Neural Network model in addition to generation of desirable results in prediction of firms' future state using their financial information, is not biased towards either bankrupt firms or non-bankrupt firms and produces balanced and reliable results.

As is observed, there are 40 firms in total in the hold-out sample consisted of 19 non-bankrupt firms and 21 bankrupt firms, and in the built model, from among 19 non-bankrupt firms 6 firms have been erroneously predicted (i.e. error of second type is equal to 6). In addition, in the constructed model, from among the 21 bankrupt firms 6 firms have been erroneously predicted (i.e. error of first type is equal to 6). In sum, total number of errors is equal to 12 firms whose bankruptcy or non-bankruptcy has been incorrectly predicted. The Turbulence Matrix of the Neural Network model prediction result is provided in table 7.

Table 7: Results of Neural Network Technique for the hold-out sample

		Real	
		Bankrupt	**Non-bankrupt**
Predicted	Bankrupt	TP = 15	FN = 6
	Non-bankrupt	FP = 6	TN = 13

Thus, the accuracy of Neural Network model which is 70% in the hold-out sample can be calculated as follows:

Accuracy of Non-Linear Genetic Algorithm = $\frac{TP+TN}{TP+FP+TN+FN} = \frac{15+13}{15+6+13+6} = 70\%$

8. Conclusion

To test the hypotheses of this research, prediction accuracy of the generated models in previous sections is compared using Linear and Non-Linear Genetic Algorithm and Neural Networks and MacNemar Test. As was observed, prediction accuracy of the models generated by Linear Genetic Algorithm, Non-Linear Genetic Algorithm, and Neural Network was 80, 90, and 70 percent, respectively. Now, the question arises as whether these differences between prediction accuracy of the constructed models using these techniques are significant or not? In this test, results of the generated models are compared with each other to decide about presence of any significant difference between them. Results of this test for presence of any significant difference between results of the models generated by Non-Linear Genetic Algorithm and Neural Network are provided in table 8. In general, results of this research indicate that prediction of financial crisis or bankruptcy is possible in the Iranian economic environment. In addition, since this prediction is made based on the financial information available in the firms' financial statements, it can be per se an evidence for presence of informative content of financial statement for more optimal functioning of the capital market. The findings of this study are consistent with research results of Huang, Tsai, Yen and Chang (2008), Hong and Cheng (2008), Lin et al (2009), Min and Jeong (2009), Min and Jeong (2008), Ravi and Pramod (2008), Sun and Li (2008), and Wu (2010).

Results of McNemar Test for Non-Linear Genetic Algorithm and Neural Network in table 4.12 indicate since the significance level is greater than 5% (0.059), there is no significant difference between results of Non-Linear Genetic Algorithm and Neural Network. Although prediction power of Non-Linear Genetic Algorithm (90%) is greater than that of Neural Network (70%), this difference is not statistically significant and accordingly the second sub-hypothesis suggesting a greater prediction power for the models based on Neural Networks relative to Non-Linear Genetic Algorithm is not confirmed.

Although prediction power of Non-Linear Genetic Algorithm is greater than that of Linear Genetic Algorithm and prediction power of the both is greater than that of Neural Networks, yet these differences are not statistically significant and in sum, the main hypothesis of this research suggesting a greater prediction power for the models based on Neural Networks compared to Artificial Intelligence techniques based on internal analysis (Genetic Algorithm) is rejected.

Table 8: Results of McNemar Test for Linear Genetic Algorithm and Neural Network techniques

NN & GANL		
NN	GANL	
	0	1
0	58	11
1	23	52

Test Statisticsb	
	NN & GANL
N	144
Chi-Squarea	3.559
Asymp. Sig.	.059
a. Continuity Corrected	
b. McNemar Test	

9. Research Suggestions

Based on the results of this research the following suggestions can be offered:

- The investors are recommended to use Non-linear Genetic Algorithm model as well as Neural Network model in evaluation of Iranian firm's financial state and in decision making regarding their investment. Investors should note that since in this research article 141 is used for definition of bankrupt firms, it does not lead to immediate dissolution of the firms and suspension of their activities.
- The Securities and Exchange Organization is recommended to use these models for admission of firms to the stock exchange and for evaluation

of firms operating on the stock exchange.
- Auditors are recommended to use these models in their comments on continuity of the audited firms' operation.

One of the main limitations of this research is unavailability of all the required information for calculation of financial ratios. If in the future this information is made available, researchers are recommended by applying the financial ratios, particularly financial ratios regarding cash flows, to redesign a model for prediction of financial crisis or bankruptcy.

Due to the high efficiency and effectiveness of Non-linear Genetic Algorithm and Neural Network in solving complex problems, researchers in the area of finance are recommended to utilize these models in other areas such as prediction of price, share return, the used indices, etc and compare their results with those obtained from the current techniques.

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