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Bankruptcy Prediction Using Artificial Neural Networks Evidences From IRAN Stock Exchange

[1] Mahmoud Samadi Largani, [2] Mohammadreza pourali lakelaye, [3] Meysam Kaviani, [4] Navid Samadi Largani
[1, 3, 4] Department of Accounting, Tonekabon Branch, Islamic Azad University, Tonekabon, Iran
[2] Department of Accounting, Chaloos Branch, Islamic Azad University, Chaloos, Iran
[1] m_samadi_largani@yahoo.com, [3] meysamkaviani@gmail.com, [4] MA_kimt@yahoo.com

ABSTRACT

The purpose of this study is to explore the applicability of a form of the artificial neural networks (ANNs) for predicting of financial bankruptcy of the companies in Tehran Stock Exchange. The model is tested against the recursive partitioning algorithm with a data set used in a previously published study. The model is then used with data obtained from the Compact Disclosures TM CD. Statistical methods of research are regression, Diagnostic analysis and artificial neural network. Neural network (NN) used in this type of multi-layer perception is trained using error back propagation algorithm. Sample included two groups of non- bankrupt and bankrupt companies.

The results show that the NN model able to predicted the bankruptcy of companies and model accurately in the detection in bankrupt companies is 82% and 93% of non- bankrupt companies. Generally, accuracy of model for training data is 90% and test data is 90.2 %.

Keywords: *Bankruptcy, Artificial Neural Networks, Financial ratios*

1. INTRODUCTION

For more than 30 years, researchers from throughout the world, work on the problem of business failure prediction. The problem of opportune and correctly predicting bankruptcy is of great significance for financial institutions. Modeling approaches perform either 'blindly' on a set of data, or with the aid, contribution and guidance of field experts, and vary from excellent cross-sectional statistical methods (Balcaen & Ooghe, 2004). The prediction of firm bankruptcy is of superior importance to a potential creditors and investors. One well studied quantitative technique for estimation the financial health of companies is linear discriminant analysis (Taffler, 1982). When the studies on bankruptcy predictions are tested, firstly, it is seen that statistical models have been used in this area. However, the supposition within the statistical models shows some objections about the subject of generalizing the success of these models.

Recent studies in ANNs show that ANNs are effective tools for pattern recognition and pattern sorting due to their nonlinear nonparametric adaptive-learning properties. ANN models have previously been used successfully for many financial problems including bankruptcy prediction (Zahedi, 1996). ANN has been used since 1990s and, in this way; high prediction successes have been supplied. But there is a significant disadvantage of ANN. The coefficients regarding the ANN model cannot be explained. So, it cannot be known how the independent variables are used in the model.

Thus, the focus of this article is on the empirical approach, especially the use of ANNs. In the next section we present some results of simulations that have performed, where we introduce new inputs that lead to substantial improvement in prediction accuracy. Section of final is the summary and conclusion of this paper.

2. ARTIFCAL NEURAL NETWORKS

In this study, the functional form is generated by using a multilayered feed forward artificial neural network. ANNs are made simpler models of the mutual connection between cells of the brain. Actually they are defined by Wasserman and Schwartz (1988) as "highly made simpler models of the human nervous system, showing abilities such as learning, generalization and unrealistic idea." Such models were developed in an attempt to examine the manner in which information is treating by the brain. These models have, in idea, been in existence for many years but the computer hardware requirements of even the most basic systems exceeded existing technology (Hawley, Johnson and Raina, 1990). Recent technological advances, however, have made ANN models a viable previous choice for many decision problems and they have the potential for improving the models of numerous financial activities such as prediction financial distress in firms. A general description of neural networks is found in Rumelhart, Hinton and Williams (1986)

The ANN has been shown to:

Approximate any Boral measurable functional mapping from input to output at any degree of desired accuracy if sufficient hidden layer nodes are used, Hornik, Stinchcombe and White (1989, 1990). The Borel

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measurable functional mapping is sufficiently general to include linear regression, logic and recurrent portioning algorithm (RPA) models as special cases.

Be free of distributional supposition.
Avoid problems of colinearity.
Be a general model form.

Therefore, a financial analyst familiar with the structure of the problem selects only the suitable inputs and outputs for an ANN model. The weights allocated to each input and the functional form of each of the relationships are determined by the neural network, as opposed to the expert's (e.g., statistician's) clear a priori supposition, Dorsey, Johnson and Powell (1994).

Regarding the specification of the functional form, the NN does not impose limitations such as linearity. This is because the neural net "learns" the underlying functional relationship from the data itself, thus, minimizing the necessary a priori non-sample information. Surely, a major justification for the use of a NN as a completely general estimation device is its function approximation abilities. That is to say, its ability to provide a generic functional mapping from inputs to outputs. This eliminates the need for exact previous specification. With a NN, the financial analyst has a tool which can aid in function approximation tasks, in the same light as a spreadsheet aids "what-if" analysis (Hawley, Johnson, and Raina, 1990). This is a major advantage of ANNs in bankruptcy applications.

3. LITERATURE REVIEW

ANNs have been studied widely as a practical tool in many business applications including bankruptcy prediction. In this part, we display a rather extensive review of the literature on the use of ANNs in bankruptcy prediction.

In number of studies further investigate the use of ANNs in bankruptcy or business distress prediction. For example, Rahimian et al (1993) assay the same data set used by Odom and Sharda (1990) using three NN model: back propagation network, Athena and Perception. A number of network training parameters are different to recognize the most efficient training paradigm. The focus of this study is principally on the improvement in efficiency of the back propagation algorithm Salchenberger et al (1992) present an A principally approach to predicting bankruptcy of savings and loan institutions. NN are establish to perform as well as or better than logic models across three deterrent lead times of 6, 12 and 18 months. To test the sensitivity of the network to different cutoff values in classification decision, they compare the results for the threshold of 0.5 and 0.2.

Wilson and Sharda (1994) and Sharda and Wilson (1996) suggest to use a rigorous experimental design methodology to test ANNs' effectiveness. Three mixture levels of bankrupt and no bankrupt firms for training set composition with three mixture levels for test set constitution yield nine different exploratory cells. Within each cell, resembling scheme is employed to generate 20 different pairs of training and test samples. The results more persuasively show the advantages of ANNs relative to discriminate analysis and other statistical methods.

Leshno and Spector (1996) appraise the prediction ability of various ANN models with different data span, NN architecture and the number of iterations. Their main conclusions are (1) the prediction ability of the model depends on the sample size used for training; (2) different learning techniques have important effects on both model fitting and test performance; and (3) over fitting problems are connected with large number of iterations.

Generally most researchers in bankruptcy prediction using neural networks focus on the relative performance of neural networks over other classical statistical techniques. While empirical studies show that ANNs produce better results for many classification or prediction problems, they are not always uniformly superior.

4. VARIABLES MEASURMENT

a. Dependent variable: is a virtual variable that have amount two of aero and one (bankrupt and no bankrupt).

b. Independent variable (Financial ratios): The independent variables examined in this study financial ratios of companies that include: equity to assets ratio (E/A), debt to net worth Ratio (D/ net worth), Debt to assets Ratio (D/A), Time interest earned, Return on assets (ROA), earnings per share (EPS), Return on Equity (ROE), Current Ratio, Quick Ratio, cash flow to debt ratio (CF/D), cash to sale ratio (C/S), inventory to assets ratio, inventory to sale ratio and Current assets total assets Ratio.

5. THE HYPOTHESES

Models base on artificial neural network is able financial Bankruptcy Prediction in the activity firms of Tehran stock exchange.

6. PURPOSES OF PAPER

This paper has the advantage of reviewing what is the virtual universe of published research on using ANNs to predicting bankruptcy in order to provide a 'meta analyses of the process. As a result, it uses these studies as data to draw inferences about:

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1. How can ANNs be accustomed to analyze bankruptcy decision data?
2. What ANN characteristics appeared the most effective for bankruptcy models?
3. Are there any interesting or irregular behaviors demonstrated by ANNs used to solve bankruptcy problems?

7. ANALYSIS OF DATA.

In order to analyze the data, descriptive statistics and inferential statistics were used. Average ratio of bankrupt companies and non bankrupt variables, were assessed using t test.

P-value indicates a significant amount of testing .If be the p-value of less than 0.05, is significantly and if the test is significantly higher than 0.05 is not a significantly. Standard deviation shown amount of variance around mean. Table 1 showing descriptive statistics about the Independent variables and Table 2 showing Variable values in the comparison between bankrupt and non bankrupt companies.

Table 1:

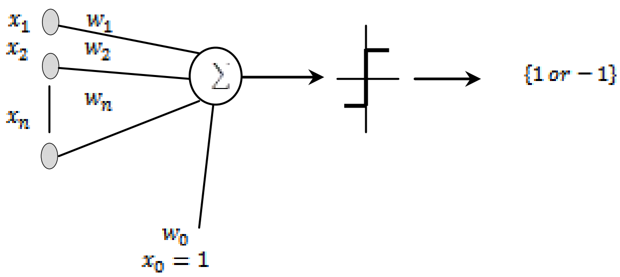
Financial ratios	mean	Standard division	min	max
E/A Ratio	0.06	1.02	-13.14	1.00
D/A Ratio	0.98	1.13	0.04	14.14
D/ net worth Ratio	1.30	42.07	-719.38	336.49
Time interest earned	52.07	359.11	-689.48	5062.56
ROA	0.05	0.32	-2.88	0.78
EPS	300.42	980.98	- 2817.00	1003.00
ROE	0.34	3.55	-50.46	21.11
Current Ratio	1509.41	36291.31	0.00	874766.81
Quick Ratio	82544.07	1968600.88	0.02	47449203.56
CA to assets Ratio	0.81	2.67	0.00	46.43
CF/D ratio	0.0001	0.0007	0.00	0.01
C/S ratio	52.42	144.40	0.00	3191.80
inventory to assets ratio	0.99	15.67	0.00	376.57
inventory to sale ratio	1.68	27.40	0.00	658.65

Table 2:

Financial ratios	Group of firm	mean	SD	t	P-Value
E/A Ratio	No bankrupt	0.367	0.171	7.970	0.000
	bankrupt	-0.395	1.466		
D/A Ratio	No bankrupt	0.663	0.239	-7.259	0.000
	bankrupt	1.443	1.643		
D/ net worth Ratio	No bankrupt	2.614	3.565	0.753	0.451
	bankrupt	-0.607	65.757		
Time interest earned	No bankrupt	85.08	426.106	2.819	0.05
	bankrupt	5.918	228.472		
ROA	No bankrupt	0.181	0.136	12.144	0.000
	bankrupt	-0.143	0.396		
EPS	No bankrupt	494	903.10	5.920	0.000
	bankrupt	15.80	1022.70		
ROE	No bankrupt	0.599	1.205	0.1.767	0.078
	bankrupt	-0.026	5.349		
Current Ratio	No bankrupt	1.669	6.552	-1.153	0.250
	bankrupt	6.90	69.51		
Quick Ratio	No bankrupt	2.424	30.424	0.081	0.938
	bankrupt	2.24	21.43		
CA to assets Ratio	No bankrupt	0.851	3.449	0.419	0.675

According to the Table.1, p-value of ratios mean E/A, D/A, Time interest earned, ROA, EPS, C/S in the comparison between companies is bankrupt and rarely no bankrupt of 0.05 is the result of this difference is statistically significant. But the other difference between the averages is not significant. Explanation the neural network is used by using techniques of clearing information and simulation. Neural function that used is Perception. A type of neural network based computational unit called the perception is built. Perception with inputs from the real values and a linear combination of these inputs is calculated.

If the perception is higher from threshold value, perception outputs an equal to 1 and otherwise would be equal to -1.



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Perception output was determined by the following relationship:

$$O(x_1, x_2, \ldots, x_n) = \begin{cases} 1 & if\ w_0 + w_1x_1 + w_2x_2 + \cdots + w_nx_n > 0 \\ -1 & otherwise \end{cases}$$

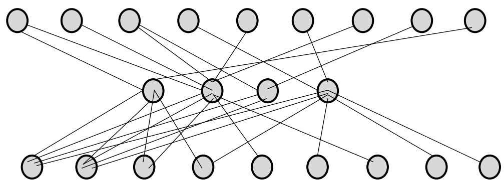
Multi-layer Perception (MLP)

A complex multi-layer perception networks that is for learn non-linear problems and problems with multiple decision-making.

Output Nodes

Internal Nodes

Input nodes



In the above graph, the accuracy of the neural networks has been identified. With repeated 5 times with the following results:
Table.3 shown accuracy amounts related to different neural networks.

Table 3:

Networks name	Training per.	Test per.
MLP 14-12-2	90.51724	86.29550
MLP 14-9-2	89.65517	88.43683
MLP 14-4-2	88.79310	87.36617
MLP 14-7-2	90.51724	91.00642
MLP 14-8-2	88.79310	86.72377

Table.4 shown that neural network models is MLP 14-7-2, which has a high percentage of the values is estimated (Training 91% and 91% test). After apply to the neural networks, the explaining bankrupt by per network is specified in the table 4.

Table 4:

Description		No bankrupt	bankrupt
MLP 14-12-2	Total observes	280	187
	Accurate estimate	270	133
	Incorrect estimate	10	54
	Percentage of Accurate estimate	96	71
	Percentage of Incorrect estimate	3	28
MLP 14-9-2	Total observes	280	187
	Accurate estimate	265	148
	Incorrect estimate	15	39
	Percentage of Accurate estimate	94	79
	Percentage of Incorrect estimate	5	20
MLP 14-4-2	Total observes	280	187
	Accurate estimate	258	150
	Incorrect estimate	22	37
	Percentage of Accurate estimate	92	80
	Percentage of Incorrect estimate	7	19
MLP 14-7-2	Total observes	280	187
	Accurate estimate	266	159
	Incorrect estimate	14	28
	Percentage of Accurate estimate	95	85
	Percentage of Incorrect estimate	5	14
MLP 14-8-2	Total observes	280	187
	Accurate estimate	271	134
	Incorrect estimate	9	53
	Percentage of Accurate estimate	96	71
	Percentage of Incorrect estimate	3	28

As mentioned above, base on Table 4 the best model based on neural network model is the MLP 14-7-2 and has the highest percentage of correct explanation. The total company is bankrupt and non bankrupt respectively is187 and 280. Accurate estimate of the number 266 and 159 non bankrupt and bankrupt estimate is correct. Non bankrupt correct estimate of 95% and 85% is bankrupt. Percent wrong in non bankrupt 5% and 14% of the bankrupt that shows better results than other models. The neural network method can explain about 90% of companies accept the null hypothesis (the model is neural networks to predict corporate bankruptcy) is rejected. So:

Neural networks model is able to predict corporate bankruptcy.

8. RESEARCH CONCLUSION

Research hypothesis can be accepted based on artificial neural network model is able to predict corporate bankruptcy. Model accuracy in the diagnosis of bankrupt companies is 82% and 93% of company's non bankrupt. Thus, the model is 90% for training data and test data, 2/90 percent. Given that the hypothesis was confirmed, claimed to be able to assess the accuracy of models used by companies in bankruptcy are the capital market of Iran. Thus, Iran could use these models in stock to pay for ranking companies. Same with this model safely in 93% and 82% in diagnostic companies recognize non bankrupt companies go bankrupt before the bankruptcy, it can be evaluated, it is recommended to users of financial information, before financial decisions using the above model, to assess the possibility of reducing the risk of bankruptcy and investment companies pay. Auditors also recommended the

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continuation of activities and comment on the bankruptcy probability of audit firms, the use of this model.

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