Hybrid Neural Network Bankruptcy Prediction: An Integration of Financial Ratios, Intellectual Capital Ratios, MDA, and Neural Network Learning

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Abstract

One purpose of this paper is to propose the hybrid neural network models for bankruptcy prediction. The proposed hybrid neural network models are, respectively, a MDA model integrated with financial ratios, a MDA model integrated with financial ratios and intellectual capital ratios, a MDA-assisted neural network model integrated with financial ratios, and a MDA-assisted neural network model integrated with financial ratios and intellectual capital ratios. The performance of the hybrid neural network model is compared with MDA model integrated with financial ratios as a benchmark. Empirical results using Taiwan bankruptcy data show that hybrid neural network models are very promising ones in terms of accuracy and adaptability.

Keywords: Bankruptcy prediction; Neural network; Hybrid neural network

1. Motivation and Literature review

The importance of computational intelligence to economics and finance is quite evidentiary [3,4]. Areas of business classification include bankruptcy prediction, accounting method choice, audit opinion decisions, credit rating, and bank loan classification. Classification refers to separating distinct sets of observations and allocating new observations into the previously defined groups. Bankruptcy prediction has been a major research issue in accounting and finance for years. Neural networks have been performed well in business classifications including bankruptcy prediction. There exist studies in bankruptcy prediction using statistical approaches [1,2,6,7,8] and computational intelligence approaches [5,9,11,12,14]. MDA has been the dominant method in failure prediction. Neural networks also have been applied to classification problems such as management forecasting, bond rating, stock price prediction, interest rate prediction, and extraction of accounting knowledge.

Researches proposed hybrid neural network models and proved with higher predictive performance [10,13]. This study proposes four kinds of hybrid bankruptcy prediction models: (1) a MDA model integrated with financial ratios, (2) a MDA model integrated with financial ratios and intellectual capital ratios, (3) a MDA-assisted neural network model integrated with financial ratios, and (4) a MDA-assisted neural network model integrated with financial ratios and intellectual capital ratios. Other purposes of this study are (1) to explore the accuracy of four forecasting models in predicting bankruptcy; (2) to compare the prediction capabilities between model 1 and model 2, as well as the prediction capabilities between model 3 and model 4, i.e. with or without intellectual capital ratios; (3) to evaluate the prediction capabilities between model 1、2 and model 3、4, i.e. with or without two stages hybrid bankruptcy prediction models.

A MDA-assisted neural network model is a neural network model operating with input variables selected by MDA method. The experimental samples in this study consist of bankruptcy cases reported in R.O.C. from 2002 through 2005. We employ 75 enterprises as experimental samples. The 80 financial ratios and 12 intellectual capital ratios are used as input variables.

2. Classification models for bankruptcy prediction

2.1 Multivariate discriminating analysis

Multivariate discriminating analysis (MDA) is a statistical method commonly used in classification. It estimates the linear function which can most effectively classify the objects as follows:

$$D=B_0+B_1X_1+B_2X_2+\ldots..+B_i X_i$$

Where D is a discriminate score, B_0 is an estimated constant, B_i are the estimated coefficients, and X_i are the variables.

2.2 MDA-assisted neural network

The intention underlying the MDA-assisted neural network model is that MDA method is used as preprocessing mechanism for selecting important input variables which will be used in the neural network model.

2.3 Neural network

Since our problem is constructed of continuous input variables and discrete output variables, we can use the multilayer feed-forward network. By using Functional approximation capability of neural network theorem and Kolmogorov's mapping neural network existence theorem, we define the hidden layers by determining how many layers are necessary and how many nodes are optimal in the hidden layer [7]. The functional approximation theorem means that the one hidden layer architecture could solve all kinds of problem, if the input variables are normalized from zero to one. Kolmogorov's theorem suggests that the maximum number of nodes in a hidden layer should be restricted to 2n+1, where n is the number of input nodes.

Multilayer feed-forward networks use the generalized delta rule for weight updating. The weight updating rule has two coefficients of learning rate and momentum. This model is known as slop learning. We vary learning rate from 0.04 to 0.07 and fix the momentum at 0.5. The weight updating rule used in our experiment is as follows:

$$\Delta W_{ji}(n+1) = \eta(\delta_{pj} \; o\,p_j) + \Delta W_{ji}(n)$$

$$\Delta \Theta_j(n+1) = \eta\,\delta_{pj} + \alpha\,\Delta \Theta_j(n)$$

Where $\Delta W_{ji}(n)$ is the derivative of weight from mode I to J at time n, $\Delta \Theta j(n)$ is the derivative of the bias of node j at time n, η is the learning rate, α is momentum, δ_{pj} is the delta of node j and pattern p, and $o\,p_j$ is the output node j and pattern p.

As to transfer function, since the output variable ranges from 0 to 1, and for the purpose of smooth the effect of input variables, we, therefore, employ the sigmoid function in back-propagation algorithms and apply a commercialized package called "Neural Solution 4" for this study.

3. Research data and modeling

3.1 Research data

The experimental samples in this study consist of bankruptcy cases reported in R.O.C. from 2002 through 2005. They are selected from the bankruptcy companies listed in the Taiwan Stock Exchange. We define the state of bankruptcy as follows:

- The firms are under the process of corporate clearance.
- The firms closed business.
- The firms have had losses for the consecutive three years and are under legal control.
- The firms terminated to be listed by the Taiwan Stock Exchange.

By using the above definition of bankruptcy, we collect 25 bankruptcy enterprises. A failed firm is matched with two non-failed firms. Therefore, 75 firms in total are selected as experimental samples. The initial 10 categories of financial ratios are selected for prediction model. Hence, there are 80 seasonal financial ratios, 10 (categories) times 4 (seasons) times 2 (years), which used as input variables. The list of financial ratios is shown in table 1. In addition to financial ratios, there are 12 intellectual capital ratios, 6 (categories) times 2 (years), which also used as input variables. The initial 6 categories of intellectual capital ratios are listed in Table 2.

Table 1
A list of 10 financial variables

Section	Financial ratio
Profitability	Operating income margin
	Gross profit margin
	Other income-net ratio
Financial Structure	Debt ratio
	Time interest earned
	Quit ratio
	Working capital ration
	Long term funds to fixed assets
Working effectiveness	Inventory turnover
	Accounts receivable turnover

Table 2
A list of 6 intellectual capital variables

Section	Intellectual capital ratio
Structure capital	Times of changing accountant
	Times of changing financial prediction
	Employees ratio
Creativity capital	Research and development
Process capital	Management expense
	Enterprise ages

3.2 Modeling

Model 1: MDA model integrated with financial ratios

A list of financial ratios, Table 3, is selected as important variables for Model 1.

Model 2: MDA model integrated with financial

ratios and intellectual capital ratios
A list of financial ratios and intellectual capital ratio, Table 4, is selected as important variables for Model 2.

Table 3
A list of financial variables

Quarters	Financial ratio
Ex 5th	Long term funds to fixed assets
Ex 3rd	Gross profit margin
Ex 4th	Gross profit margin
Ex 6th	Gross profit margin

Table 4
A list of financial variables and intellectual capital variable

Quarters / Year	Financial ratio/ Intellectual Capital ratio
Ex 5th Q	Long term funds to fixed assets
Ex 3rd Q	Gross profit margin
Ex 4th Q	Gross profit margin
Ex 1 year	Management expense
Ex 6th	Gross profit margin

Model 3: MDA-assisted neural network model integrated with financial ratios
A list of financial ratios, Table 5, is selected by MDA as important variables for Model 3. Therefore, the four financial variables are placed in the input layer for neural network model. A list of parameters, Table 6, is selected as hidden layers and learning rates for neural network architectures. With one output neuron is placed in the output layer. We employ the value of root mean square error, RMSE, as a comparing standard.

Table 5
A list of financial variables

Quarters	Financial ratio
Ex 5th	Long term funds to fixed assets
Ex 3rd	Gross profit margin
Ex 4th	Gross profit margin
Ex 6th	Gross profit margin

Table 6
A list of parameters for neural network architectures

Hidden neurons	Learning rates
8	0.04 0.05 0.06 0.07
9	0.04 0.05 0.06 0.07
10	0.04 0.05 0.06 0.07
11	0.04 0.05 0.06 0.07
12	0.04 0.05 0.06 0.07

Model 4: MDA-assisted neural network model integrated with financial ratios and intellectual capital ratios
A list of financial ratios and intellectual capital ratio, Table 7, is selected by MDA as important variables for Model 4. Therefore, the four financial variables and one intellectual capital variable are placed in the input layer for neural network model. A list of parameters, Table 8, is selected as hidden layers and learning rates for neural network architectures. Finally, one output neuron is placed in the output layer. We employ the value of root mean square error, RMSE, as a comparing standard.

Table7
A list of financial variables and intellectual capital variable

Quarters / Year	Financial ratio/ Intellectual Capital ratio
Ex 5th Q	Long term funds to fixed assets
Ex 3rd Q	Gross profit margin
Ex 4th Q	Gross profit margin
Ex 1 year	Management expense
Ex 6th	Gross profit margin

Table8
A list of parameters for neural network architectures

Hidden neurons	Learning rates
12	0.04 0.05 0.06 0.07
13	0.04 0.05 0.06 0.07
14	0.04 0.05 0.06 0.07
15	0.04 0.05 0.06 0.07
16	0.04 0.05 0.06 0.07

4. Empirical results

For Model 3, the neural network structure {4-9-1} , with the learning rate of 0.05, performs the best. For Model 4, the neural network structure {5-12-1} , with the learning rate of 0.05, performs the best.

The prediction accuracy by model 1, MDA model integrated with financial ratios, is 86%. The prediction accuracy by model 2, MDA model integrated with financial ratios and intellectual capital ratio, is 88%.

The prediction accuracy by model 3, MDA-assisted neural network model integrated with financial ratios, is 88%. The prediction accuracy by model 4, MDA-assisted neural network model integrated with financial rations and intellectual capital ratio, is 89%. Those are prediction capability differences between with and without intellectual capital ratios, and prediction capability differences between with and without two stages hybrid bankruptcy prediction models. A list of prediction accuracies for classification models is presented in Table 9.

Table 9
Prediction accuracies of classification models

Models	Descriptions	accuracies
I	MDA model integrated with financial ratios	86%
II	MDA model integrated with financial ratios and intellectual capital ratios	88%
III	MDA-assisted neural network model integrated with financial ratios	88%
IV	MDA-assisted neural network model integrated with financial rations and intellectual capital ratios	89%

5. Concluding remarks

This paper proposed four kinds of hybrid bankruptcy prediction models: (1) a MDA model integrated with financial ratios, (2) a MDA model integrated with financial ratios and intellectual capital ratios, (3) a MDA-assisted neural network model integrated with financial ratios, and (4) a MDA-assisted neural network model integrated with financial ratios and intellectual capital ratios. The suggested hybrid neural network models perform very well in the bankruptcy prediction.

This study experimented MDA and hybrid neural network models using Taiwan bankruptcy data. Experimental results showed that the MDA-assisted neural network model integrated with financial ratios and intellectual capital ratios, model 4, performs the best, which implies the potential of integrating financial ratios, intellectual capital ratios, MDA, and neural network learning.

6. References

[1] E.I. Altman, "Financial Ratios, Discriminant Analysis and Prediction of Corporate Bankruptcy," *The Journal of Finance*, 23, pp. 589-609, September 1968.

[2] E.I. Altman, R.G. Haldeman, and P. Narayana, "Zeta Analysis: A New Model to Identify Bankruptcy Risk of Corporations," *Journal of Banking and Finance* , pp. 29-54, June 1977.

[3] S.H. Chen and C.H. Yeh, "Toward a computable approach to the efficient market hypothesis: An application of genetic programming," *Journal of Economic Dynamic & Control*," 21, pp. 1043-1063, 1997.

[4] S.H. Chen and T.W. Kuo, "Modeling International Shot-Term Capital Flow with Genetic Programming," in K. Chen, el al (eds.), *Proceedings of 7th Information Sciences* (JCIS 2003), Cary, North Carolina, U.S.A., pp. 1140-1144, September 26-30, 2003.

[5] H. Chung and K. Tam, "A Comparative Analysis of Inductive-Learning Algorithm," *Intelligent Systems in Accounting, Finance and Management*, 2, pp. 3-18, 1992.

[6] E.B. Deakin, "A Discriminant Analysis of Predictors of Business Failure," *Journal of Accounting Research*, pp. 167-179, Spring 1976.

[7] H. Jo, I. Han and H. Lee, "Bankruptcy Prediction Using Case-Based Reasoning, Neural Network, and Discriminant Analysis," *Expert Systems with Applications*, Vol. 13 No. 2, pp. 97-108, 1997.

[8] G.V. Karels and A. Prakash, "Multivariate Normality and Forecasting of Bankruptcy," *Journal of Business Finance and Accounting*, pp. 573-593, Winter 1987.

[9] K.C. Lee, I. Han, and Y. Kwon, "Hybrid neural network models for bankruptcy predictions," *Decision Support Systems*, 18, pp. 63-72, 1996.

[10] T. Liang, J. Chandler, and I. Han, "Integrating Statistical and Inductive Learning Methods for Knowledge Acquisitions," *Expert Systems with Applications*, 1, pp. 391-401, 1990.

[11] J.H. Min and Y.C. Lee, "Bankruptcy prediction using support vector machine with optimal choice of kernel function parameters," *Expert Systems with Applications*, 28, pp. 603-614, 2005.

[12] K.S. Shin, T.S. Lee, and H.J. Kim, "An application of support vector machines in bankruptcy prediction model," *Expert Systems with Applications*, 28, pp. 127-135, 2005.

[13] D. West, S. Dellana, and J. Qian, "Neural network ensemble strategies for financial decision applications," *Compters & Operations Research*, 32, pp. 2543-2559, 2005.

[14] G. Zhang, M.Y. Hu, B.E. Patuwo, and D.C. Indro, "Artificial neural networks in bankruptcy prediction: General framework and cross-validation analysis," *European Journal of Operational Research*, 116, pp. 16-32, 1999.