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A hybrid financial analysis model for business failure prediction

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Abstract

Accounting frauds have continuously happened all over the world. This leads to the need of predicting business failures. Statistical methods and machine learning techniques have been widely used to deal with this issue. In general, financial ratios are one of the main inputs to develop the prediction models. This paper presents a hybrid financial analysis model including static and trend analysis models to construct and train a back-propagation neural network (BPN) model. Further, the experiments employ four datasets of Taiwan enterprises which support that the proposed model not only provides a high predication rate but also outperforms other models including discriminant analysis, decision trees, and the back-propagation neural network alone.
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1. Introduction

The prediction of business failures is one of the major activities to audit enterprise risks and/or uncertainties. Business failure can be defined as a situation that a firm cannot pay lenders, preferred stock shareholders, and suppliers, a bill is overdraw, or the law makes the firm go bankruptcy (Dimitras, Zanakis, & Zopounidis, 1996).

The development of financial analysis models to predict business failures can be thought of as 'early warning systems', which proves to be very helpful for managers, and relevant authorities who can prevent the occurrence of failures. In addition, these models are able to assist the decision-makers of financial institutions to evaluate, assess. and select the firms to collaborate with or invest in (Ahn, Cho, & Kim, 2000; Balcaen & Ooghe, 2006).

Earlier studies related to financial forecasting mainly utilized various statistical methods such as multiple discriminant analysis, regression analysis, and linear discriminant analysis (Altman, 1968; Collins & Green, 1972). It was not until recently that much related work focuses on the development and application of artificial intelligence and machine learning techniques (Ahn et al., 2000; Min & Lee, 2005; Shin, Lee, & Kim, 2005; West, Dellana, & Qian, 2005). In addition, these studies have shown that machine learning models outperform traditional statistical models. Kumar and Ravi (2007) provide a detailed review of these models in the domain of bankruptcy prediction.

Financial ratios are important tools to predict business failures and it is commonly used to develop the models or classifiers. Financial analysis includes fiscal indicators and statistical forecasting which allow people to measure the current fiscal condition of the operating units and consequently predict trends for their future fiscal condition. Fiscal indicators can be used to provide quantitative information to evaluate the fiscal conditions and compare current financial statements with that of previous years and also that of other similar units. Fiscal indicators focus on proportional distributions within the reports, which is usually called as 'static analysis' and on factors and trends over a relatively long period of time, which is referred as 'dynamic analysis' or 'time serials analysis'. The process of developing fiscal indicators provides a framework for assembling and analyzing information about enterprises

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on a regular basis (Damodaran, 2002; Mulford & Comiskey, 2002; Penman, 2003).

In general, there are two types of financial analysis models, which are static and trend analysis models (Damodaran, 2002; Mulford & Comiskey, 2002; Penman, 2003). For the static financial analysis model, its main characteristic is aimed at some significant financial ratios and compares the relationship between these significant financial ratios and the outcomes they expected. On the other hand, the main characteristic of the trend financial analysis model is focused on tracking to the one or the few characteristic marks, maybe the value or the ratios or any others. Each of these two analysis models has its own distinctive capabilities and certainly some inherited limitations. It is believed that if the strengths and weaknesses of these two aforementioned models could be combined, more flawless analyses are likely to be acquired (Anandarajana & Anandarajanb, 1999; Andr, Landajo, & Lorca, 2005; Calderon & Cheh, 2002).

There are a number of arguments which promote the consideration of the hybrid analysis model for business failure prediction using some machine learning technique. First, the underlying problem to use of a large number of parameters as the inputs is that each parameter has its mutual influence. One specific parameter may not be significant in statistics, but it would present the significant result when several pieces of parameters 'interact' at the same time, which is called covariation (Gujarati, 2002).

Second, if we only consider the minority important financial ratios which lead people to place focus on these pieces of values, enterprises would be able to play tricks most frequently and cover up these conspicuous ratios. On the other hand, if we could put a lot of effort into the analysis with carefulness, enterprises which cover up the financial ratios would show their slip in some places (Mulford & Comiskey, 2002).

Third, from the view point of pathology, let us personify an enterprise and auditor to be a person and a doctor, respectively. An effective and accurate method to diagnose a person is to make a detailed inspection to the whole body and then, track it regularly for a long time. In addition, if the symptoms could match the condition database with abundant case information, it will bring out the best outcome in each other. It is, thus, believed that such the diagnosis concept that most people can accept.

Using the same scenario, the following issues can be thought of as our diagnose model. ‘‘Check in detail all over to find out the condition’’ as ‘‘Use various relevant financial rates as input parameters to find out the enterprise's risk’’. ‘‘Follow the trail of the condition regularly’’ as ‘‘Use the time serials method to analyze enterprise's risks’’, and ‘‘Abundant pathology database’’ as ‘‘Perfect disciplined risk database’’.

This paper is organized as follows. Section 2 briefly describes artificial neural networks as the learning model or classifier used in this paper. Section 3 presents the research methodology including the proposed hybrid financial analysis model. Section 4 reports the experimental results as system evaluation. Finally, the conclusion is given in Section 5.

2. Artificial neural networks

Neural networks (or artificial neural networks) learn by experience, generalise from previous experiences to new ones, and can make decisions, and they are motivated by information-processing units as neurons in the human brain that a neural network is made up of artificial neurons (Haykin, 1999). A neural network can be thought of as a *black box* non-parametric classifier (Bishop, 1995). That is, different from naïve Bayes, we do not need to make assumptions about the distribution densities. Neural networks are therefore more flexible.

A multilayer perceptron (MLP) network consists of an input layer including a set of sensory nodes as input nodes, one or more hidden layers of computation nodes, and an output layer of computation nodes. The input nodes/neurons are the feature values of an instance, and the output nodes/neurons (usually lying in the range $[0,1]$) represents a discriminator between its class and all of the other classes. That is, each output value is a measure of the network's confidence that the class corresponding to the highest output value is returned as the prediction for an instance. Each interconnection has associated with it a scalar weight which is adjusted during the training phase. Fig. 1 shows an example of a three-layer feed-forward network having input, output, and one hidden layers.

The neurons receive inputs from the initial inputs or the interconnections and produce outputs by using an adequate non-linear transfer function. The common transfer function is shown below.

$$Y_j = f\left(\sum W_{ij}X_i - \theta_j\right) = f(\mathrm{net}_j) \quad (1)$$

where Y_j means the output signal of the neuron, f for the transfer function of the neuron, i.e. transferring the input

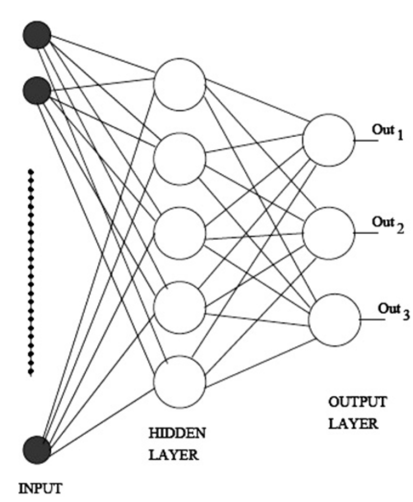

Fig. 1. The three-layer neural network.

Table 1
Financial ratios and weights

Categories	Financial ratios	Weights
Financial structure	Shareholder's Equity/Total Assets Ratio	0.333
	Debt Ratio (Total Liability/Total Assets)	0.333
	Long-term Capital/Fixed Assets Ratio	0.333
Credit standing	Current Ratio	0.333
	Quick Ratio	0.333
	Interest Coverage Index	0.333
Operating standing	Accounts Receivable Turnover Ratio	0.166
	Average days for cash receipts	0.166
	Inventory Turnover Ratio	0.166
	Average days for sale of goods	0.166
	Fixed Assets Turnover Ratio	0.166
	Total Assets Turnover Ratio	0.166
Profitability	Return on Total Assets	0.166
	Return on Shareholder's Equity	0.166
	Operating income/Real Capital Ratio	0.166
	Earning Before Income Tax/Real Capital Ratio	0.166
	Net income/Revenue Ratio	0.166
	Earning Per Share	0.166
Short-term credit standing	Cash flow Ratio	0.333
	Cash flow Adequacy Ratio	0.333
	Cash reinvest Ratio	0.333

value of the neuron into the output value of the neuron, W_{ij} for the interconnected weight of the neuron to express the incentive intensity that input signals toward neurons, X_i for the input signal of the neuron, and θ_j for the outlier value of the neuron.

A multilayer network is typically trained by a backpropagation learning algorithm. It performs weights tuning to define whatever or not hidden unit representation is most effective at minimising the error of misclassification. That is, for each training example its inputs are fed into the input layer of the network and the predicted outputs are calculated. The differences between each predicted output and the corresponding target output are calculated. This error is then propagated back though the network and the weights between two layers are adjusted so that if the training example is presented to the network again, then the error would be less. As a result, the algorithm captures properties of the input instances which are most relevant to learning the target function (Haykin, 1999).

3. Research methodology

3.1. Dataset

As indicated earlier, this paper focuses on business failure prediction in Taiwan. The risk enterprises defined in this research, are derived from Taiwan Economic Journal (TEJ) that Taiwan Stock Exchange/Over the Counter (TSE/OTC) listed company and recorded as delisted companies. Then, the annual financial statement of each TSE/OTC listed company is collected from the database in TEJ. Care was taken, however, to insure that enterprises on the brink of failure were not included in the category of fine enterprises. In addition, we selected firms in the same period to neutralize the influence of operating in different climates.

Table 2
Category variable-rates (an example)

Categories	Financial ratios	Base period	Previous period	Weights	Variable-rate
Financial structure	Shareholder's Equity/Total Assets Ratio	9.64	19.17	0.333	−0.3287
	Debt Ratio (Total Liability/Total Assets)	90.36	80.83	0.333	
	Long-term Capital/ Fixed Assets Ratio	34.17	87.13	0.333	
Credit standing	Current Ratio	88.23	140.65	0.333	−0.3317
	Quick Ratio	33.55	73.88	0.333	
	Interest Coverage Index	−4.81	−5.21	0.333	
Operating standing	Accounts Receivable Turnover Ratio	4.59	8.98	0.166	−0.0503
	Average days for cash receipts	79.59	40.65	0.166	
	Inventory Turnover Ratio	0.38	0.44	0.166	
	Average days for sale of goods	956.54	833.61	0.166	
	Fixed Assets Turnover Ratio	0.25	0.43	0.166	
	Total Assets Turnover Ratio	0.07	0.11	0.166	
Profitability	Return on Total Assets	−9.36	−11.15	0.166	0.4912
	Return on Shareholder's Equity	−73.59	−51.51	0.166	
	Operating income/Real Capital Ratio	−4.73	−1.26	0.166	
	Earning Before Income Tax/Real Capital Ratio	−54.73	−67.29	0.166	
	Net income/Revenue Ratio	−159.02	−112.75	0.166	
	Earning Per Share	−5	−7	0.166	
Short-term credit standing	Cash flow Ratio	0.5	1.86	0.333	−0.5218
	Cash flow Adequacy Ratio	−14.4	−18.05	0.333	
	Cash reinvest Ratio	0.49	1.34	0.333	

Table 3
Examples of the input and output information

Com No	Date	Ratio_1a	Ratio_1b	Ratio_1c	Ratio_2a	Ratio_2b	Ratio_2c	Ratio_3a	Ratio_3b	Ratio_3c	Ratio_4a	Ratio_4b	Ratio_4c	Ratio_5a	Ratio_5b	Ratio_5c	State
C	C	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
U	U	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	O
1106	200312	0.100165	0.148965	−1	−0.18725	0.000728	−1	0	0	−1	−0.08572	0.093102	−1	0.200901	−0.16675	1	−1
1206	200112	−0.32869	−0.1915	−1	−0.33145	0.034332	−1	−0.05014	−0.04346	−1	0.491375	0.301286	1	−0.52205	−0.79208	1	−1
1208	200012	−0.01696	0.236716	−1	−0.45794	−0.3693	−1	0.000136	0.030594	−1	0.526805	0.066496	1	0.420019	−1.08554	1	−1

Row 1: Field name.
Row 2: Data type, C is category, R is real.
Row 3: Practice parameter, U is uselessness, I is input, O is output.
Row 4–end: Data value.
Ratio_1*x*–Ratio_5*x*: The numbers of the categories.
ComNo: Company number.
Ratio_na: Variable-rate between Base Period and Previous Period.
Ratio_nb: Variable-rate between Previous Period and the Period before Previous Period.
Ratio_nc: Trends between Ratio_na and Ratio_nb, if Ratio_na > Ratio_nb then 1, if Ratio_na ≦Ratio_nb then −1.
State: Risk state of the enterprise, risk is −1, fine is 1.

3.2. The hybrid financial analysis model

According to Taiwan Securities & Futures Information Center (SFI), 21 ratio items with influence power and the practice to set each ratio its own weight are used. These 21 ratios can be classified into five categories, which are "financial structure", "credit standing", "operating standing", "profitability", and "short-term credit standing" as shown in Table 1. Next, the difference between the base previous period and base period are analyzed and the variable-rate of each of the aforementioned 5 categories is calculated.

The financial ratios come from three financial reports which are "balance sheet", "income statement", and "cash-flow report". The variable-rate is obtained by

$$\text{Variable} - \text{rate} = \frac{\text{Date at Previous Period} - \text{Data Base Period}}{\text{Data at Base Period}} \tag{2}$$

After calculating each ratio's variable-rate, and then we can refer to Table 1 for more detail. Each category's variable-rate is converted based on the weights, these variable-rates can be represented as the variation of the categories. Table 2 shows one sample example of the categories variable-rates.

3.3. Back-propagation neural network

The business software iDA is used to construct and train the back-propagation neural network (BPN). There are 15 variables as the input, in which 5 category ratios between the base period and previous period, 5 category ratios between the previous period and the period before the previous period, and the last 5 are dummy variables used to analyze each category's trend between different periods. The output number '1' represents a 'fine enterprise' and '−1' for a 'risk enterprise'. Note that there are two hidden layers of the neural network model. Table 3 provides some examples of the input and output information.

4. Experiments

4.1. Evaluation methods

The system evaluation is based on a confusion matrix shown in Table 4. In addition, five measures are used for further analyses described below.

- Total prediction accuracy (Total_Compare):
  This measures the rate of prediction accuracy of the model for fine and risk enterprises.
- Risk identification 1 (RealF(SysF)):
  This result is used to examine the model in terms of the degree of identifying risk enterprises as real risk enterprises.

Table 4
The confusion matrix

	Predicted		Total
	Fine enterprise	Risk enterprise	
Actual			
Fine enterprise	S_{11}	S_{12}	N_{1y}
Risk enterprise	S_{21}	S_{22}	N_{2y}
Total	N_{x1}	N_{x2}	N_{Total}

- Risk identification 2 (RealR(SysR)):
  This result means that the model can identify risk enterprises in the dataset of real risk enterprises.
- Prediction error 1 (SysF(RealF)):
  This shows the prediction error rate of the model to incorrectly classify fine enterprises into risk enterprises.
- Prediction error 2 (SysR(RealR)):
  Opposed to Prediction error 1, this presents the prediction error rate of the model to incorrectly classify risk enterprises into fine enterprises.

4.2. Results

To train the neural network model (BPN), the input parameters are 15 and the hidden layers are 2. As different numbers of neurons in the hidden layer can result in different prediction rates, the authors test the model by using different numbers of neurons in the two hidden layers. Tables 5 and 6 show the testing results by considering 10,000 and 50,000 training epochs, respectively.

As a result, the authors choose the 'best' model for the following case studies, which is the 15-30-15-1 neural network model.

4.2.1. Dataset 1

The first dataset contains 131 fine and 133 risk enterprises, respectively, of three-season reports of 2004. Table 7 shows the prediction result.

4.2.2. Dataset 2

The second dataset contains 66 fine and risk enterprises, respectively, of three-season reports of 2004. The prediction result is shown in Table 8.

Table 7
The prediction result

	Predicted		Total
	Fine enterprise	Risk enterprise	
Actual			
Fine enterprise	129	2	131
Risk enterprise	3	130	133
Total	132	132	264

Total_Compare: $(129 + 130)/264 = 98.11\%$.
RealF(SysF): $130/132 = 98.48\%$.
RealR(SysR): $130/133 = 97.74\%$.
SysF(RealF): $2/131 = 1.53\%$.
SysR(RealR): $3/133 = 2.26\%$.

Table 5
The predication accuracy (represented by %)

BPN framework	Epochs = 10,000, convergence = 0.01, learning rate = 0.1				
	Toal_Compare	RealF(SysF)	RealR(SysR)	SysF(RealF)	SysR(RealR)
15-30-30-1	62	96	28	57	88
15-30-15-1	58	98	18	54	90
15-15-15-1	60	86	34	57	71
15-15-9-1	59	92	26	55	76
15-9-9-1	65	90	40	60	80
15-9-6-1	62	84	42	59	72
15-9-3-1	62	92	32	58	80
15-5-3-1	61	90	32	57	76
15-5-2-1	61	84	38	58	70

Table 6
The predication accuracy (represented by %)

BPN framework	Epochs = 50,000, convergence = 0.01, learning rate = 0.1				
	Toal_Compare	RealF(SysF)	RealR(SysR)	SysF(RealF)	SysR(RealR)
15-30-30-1	68	80	56	65	74
15-30-15-1	71	90	52	65	84
15-15-15-1	69	88	50	64	81
15-15-9-1	65	90	40	60	80
15-9-9-1	64	84	44	60	73
15-9-6-1	68	92	44	62	85
15-9-3-1	69	88	50	64	81
15-5-3-1	68	92	44	62	85
15-5-2-1	63	86	40	59	74

Table 8
The prediction result

	Predicted		Total
	Fine enterprise	Risk enterprise	
Actual			
Fine enterprise	56	10	66
Risk enterprise	21	45	66
Total	77	55	132

Total_Compare: $(56 + 45)/132 = 76.52\%$.
RealF(SysF): $45/55 = 81.82\%$.
RealR(SysR): $45/66 = 68.18\%$.
SysF(RealF): $10/66 = 15.15\%$.
SysR(RealR): $21/66 = 31.28\%$.

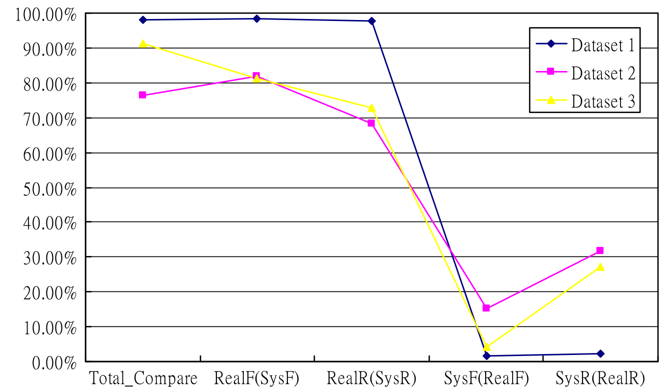

Fig. 2. Summary of using the first three datasets.

4.2.3. Dataset 3

The third dataset is different from the previous two datasets that the training data is based on 32 risk enterprises and 128 fine enterprises of 2001–2003 annual reports. The test data contains 132 risk enterprises and 528 fine enterprises of 2002–2004 annual reports. The prediction result is shown in Table 9.

4.2.4. Dataset 4

This study aims to compare the proposed hybrid analysis model with other models including discriminant analysis, decision trees, C5.0 decision trees, and the general back-propagation network (BPN) models. The training dataset contains 102 risk and fine enterprises, respectively, of 2004 first three-season reports. The testing data is based on 30 risk and fine enterprises, respectively, of the third season reports of 2004. The comparative result is shown in Table 10 in terms of prediction accuracy.

Table 9
The prediction result

	Predicted		Total
	Fine enterprise	Risk enterprise	
Actual			
Fine enterprise	506	22	528
Risk enterprise	36	96	132
Total	542	118	660

Total_Compare: $(506 + 96)/660 = 91.21\%$.
RealF(SysF): $96/118 = 81.36\%$.
RealR(SysR): $96/132 = 72.73\%$.
SysF(RealF): $22/528 = 4.17\%$.
SysR(RealR): $36/132 = 27.27\%$.

4.3. Discussion

Regarding to the experimental results, the proposed hybrid financial analysis model combining with BPN is capable of providing a very high prediction accuracy rate. Fig. 2 summarizes the performance of using the first three datasets for prediction.

The result shows that our system can produce a high rate of risk identification (i.e. Total_Compare, RealF(SysF), and RealR(SysR)) and a low rate of prediction error (i.e. SysF(RealF) and SysR(RealR)) by using three different datasets.

Moreover, when the proposed system compares with other models (see Table 10), on average the prediction rate is higher than the other four models. This shows the reliability and applicability of the proposed system in the domain of business failure prediction.

5. Conclusion

Business failure prediction can be approached differently by using machine learning techniques, whose prediction accuracy has shown more superiors to other traditional statistical methods. In this paper, the authors propose a hybrid financial analysis model composed of static and trend analysis models (i.e. financial structure, credit standing, operating standing, profitability, and short-term credit standing). The experimental results report that the proposed model using a back-propagation neural network produces good performance of prediction accuracy and outperforms other models including discriminant analysis,

Table 10
The comparison of different models

	Discriminant analysis (%)	Decision trees (%)	Decision trees C5.0 (%)	BPN (%)	The hybrid analysis model (%)
Total_Compare	71.57	66.67	70	78.33	*86.67*
RealF(SysF)	88.24	59.57	74.47	72.34	*97.87*
RealR(SysR)	54.90	92.31	53.85	*100*	46.15
SysF(RealF)	*66.18*	96.55	85.37	100	86.79
SysR(RealR)	82.35	38.71	*36.84*	50	85.71

decision trees, and the back-propagation neural network alone.

However, one restriction of this model is that it requires much time for training and constructing the prediction model, which is the limitation of neural networks technique. That is, the network model needs to be trained repeatedly to ensure minimum error. On the other hand, the strongest advantage of this proposed model is that it can predict the risk by comparing with the other enterprises, and thus it can adapt the changes such as time, economic, environment, and other factors.

Although the proposed hybrid financial analysis model in this research is likely to provide a good performance of prediction accuracy, there are several issues that can be considered in the future to further improve the proposed system. For example, the weight of every ratio, the choice of the ratios, instance selection by using genetic algorithms for example (Kim, 2006), the periods of the hybrid model, and the relations for each other, and the design of dummy variables are all possible areas deserving further investigation and/or exploration.

References

Ahn, B. S., Cho, S. S., & Kim, C. Y. (2000). The integrated methodology of rough set theory and artificial neural network for business failure prediction. *Expert Systems with Applications, 18*, 65–74.

Anandarajana, M., & Anandarajanb, A. (1999). A comparison of machine learning techniques with a qualitative response model for auditor's going concern reporting. *Expert Systems with Applications, 16*, 385–392.

Andr, J. D., Landajo, M., & Lorca, P. (2005). Forecasting business profitability by using classification techniques: A comparative analysis based on a Spanish case. *European Journal of Operational Research, 167*, 518–554.

Altman, E. I. (1968). Financial ratios, discriminant analysis and prediction of corporate bankruptcy. *The Journal of Finance, 23*, 589–609.

Balcaen, S., & Ooghe, H. (2006). 35 years of studies on business failure: An overview of the classic statistical methodologies and their related problems. *The British Accounting Review, 38*(1), 63–93.

Bishop, C. M. (1995). *Neural networks for pattern recognition*. Oxford University Press.

Calderon, T. G., & Cheh, J. J. (2002). A roadmap for future neural networks research in auditing and risk assessment. *International Journal of Accounting Information Systems, 3*, 203–236.

Collins, R. A., & Green, R. D. (1972). Statistical methods for bankruptcy forecasting. *Journal of Economics and Business, 32*, 349–354.

Damodaran, A. (2002). *Investment valuation: Tools and techniques for determining the value of any asset* (2nd ed.). Addison Wiley.

Dimitras, A. I., Zanakis, S. H., & Zopounidis, C. (1996). A survey of business failures with an emphasis on prediction methods and industrial applications. *European Journal of Operational Research, 90*, 487–513.

Gujarati, D. N. (2002). *Basic econometrics w/data disk* (4th ed.). McGraw-Hill.

Haykin, S. (1999). *Neural networks: A comprehensive foundation* (2nd ed.). Prentice Hall.

Kim, K.-J. (2006). Artificial neural networks with evolutionary instance selection for financial forecasting. *Expert Systems with Applications, 30*(3), 519–526.

Kumar, P. R., & Ravi, V. (2007). Bankruptcy prediction in banks and firms via statistical and intelligent techniques – A review. *European Journal of Operational Research, 180*(1), 1–28.

Min, J. H., & Lee, Y.-C. (2005). Bankruptcy prediction using support vector machine with optimal choice of kernel function parameters. *Expert Systems with Applications, 28*, 603–614.

Mulford, C. W., & Comiskey, E. E. (2002). *The financial numbers game: Detecting creative accounting practices*. Addison Wiley.

Penman, S. (2003). *Financial statement analysis and security valuation* (2nd ed.). McGraw-Hill.

Shin, K.-S., Lee, T. S., & Kim, H.-J. (2005). An application of support vector machines in bankruptcy prediction model. *Expert Systems with Applications, 28*(1), 127–135.

West, D., Dellana, S., & Qian, J. (2005). Neural network ensemble strategies for financial decision applications. *Computers & Operations Research, 32*, 2543–2559.