A Comparative Analysis of Corporate Failure Prediction: A Case from Iran

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Balance sheet and income statement provide potentially vast volumes of information. Despite the large number of predictive variables, in most cases, the user cannot make a judgment easily about the survival of a company. In this paper, we indicate a set of useful variables for failure prediction by Step-wise Discriminant Analysis (SDA). Furthermore, this study applied a data mining technique to explore and compare the performance of Particle Swarm Optimization (PSO), Classification and Regression Tree (CART) and Support Vector Data Description (SVDD). The results showed that PSO does not significantly differ from CART, but due to lower average error rate, PSO is more efficient than CART and PSO and CART significantly perform SVDD.

Introduction

Over the four decades, Corporate Failure Prediction (CFP) has become an important research topic in the finance area. In general, the objective of CFP is to develop models that can extract novel knowledge from previous observations and appraise corporate status. Two factors that are effective in CFP area are: significant predictor variables and the classifiers used in developing the prediction model (Lin *et al.*, 2011).

Since 1966, a lot of research has been carried out in the area of CFP. Methodological approaches employed in these studies have been classified into statistical and artificial intelligence methods (Min and Jeong, 2009). Statistical methods include multiple discriminant analysis used in Beaver (1966) and Altman (1968) and logit or probit applied in Ohlson (1980), Zmijewski (1984), Koh (1991) and Hopwood *et al.* (1994). There are lots of methods that can be used in the category of artificial intelligence, new algorithms such as support vector machines (Tsai and Cheng, 2012), neural networks (Ashoori and Mohammadi, 2011; and Olson *et al.*, 2012), fuzzy support vector machine (Chaudhuri and De, 2011), decision tree classification (Chen, 2011) and genetic algorithm (Sun *et al.*, 2011; and Mokhatab *et al.*, 2011).

The purpose of this paper is summarized in three parts. First, finding the effective financial future by prior studies and using Step-wise Discriminant Analysis (SDA) and secondly, to apply tenfold cross-validation to find out the optimal models. Thirdly, it tries to demonstrate the applicability of the proposed models and comparison of these models (see Figure 1).

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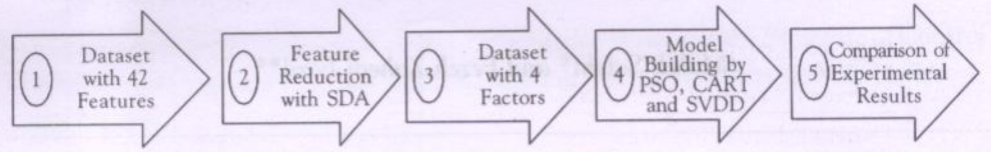
Figure 1: Steps of Corporate Failure Prediction



Methodology

Data Collection

The financial data used for this study is obtained from the Tehran Stock Exchange (TSE). The dataset used for this study consists of 146 Iranian manufacturing companies in total (73 from bankrupt[1] and 73 from non-bankrupt companies) and covering the duration 2001-2011. It should be noted that due to the low number of listed companies in TSE as well as the lack of non-bankrupt companies in some industries such as textile companies, two groups (bankrupt and non-bankrupt companies) could not match completely in terms of industries.

Variable Selection

Selection of appropriate parameters to achieve the optimal allocation of a classification model is a very important job and in most cases is not an easy task. The process of finding a subset of variables that play a role in optimal form of classification is called feature selection or variable selection. According to researchers, faster and more cost-effective predictors reduce the running time of an algorithm, better understanding of the final classification model and more efficiency and effectiveness are some of the advantages of feature selection (Guyon and Elisseeff, 2003; and Ashoori and Mohammadi, 2011).

Table 1: Variables Used in the Study

No.	Predictor Variable Name	Financial Ratios	Means of Group 1	Means of Group 2	Sig. Level
X1	Earnings before interest and taxes/ Total assets	EBIT/TA	0.18	0.05	0.00
X2	Long-term debt/Shareholders' equity	LTD/SE	0.20	0.56	0.06
X3	Retained earnings/Stock capital	RE/SC	0.65	0.02	0.00
X4	Marked value of equity /Total liabilities	MVE/TL	1.40	0.66	0.00
X5	Marked value of equity /Shareholders' equity	MVE/SE	2.42	2.57	0.22
X6	Marked value of equity /Total assets	MVE/TA	0.77	0.48	0.00
X7	Cash /Total assets	Ca/TA	0.05	0.03	0.00
X8	Log (total assets)	Size	5.25	5.23	0.83

[1] Under paragraph 141 of Iran Trade Law, a firm is bankrupt when the total value of its retained earnings is equal to or more than 50% of its listed capital.

Table 1 (Cont.)

No.	Predictor Variable Name	Financial Ratios	Means of Group 1	Means of Group 2	Sig. Level
X9	Total liabilities/Total assets	TL/TA*	0.67	0.80	0.00
X10	Current liabilities/Shareholders' equity	CL/SE	2.27	4.76	0.00
X11	Current liabilities/Total liabilities	CL/TL	0.86	0.85	0.94
X12	(Cash+Short-term investments)/ Current liabilities	(Ca+STI) /CL	0.11	0.05	0.00
X13	(Receivables+Inventory)/Total assets	(R+Inv)/TA	0.57	0.57	0.88
X14	Receivables/Sales	R/S	0.53.	0.40	0.10
X15	Receivables/Inventory	R/Inv	1.18	1.00	0.93
X16	Shareholders' equity/Total liabilities	SE/TL	0.63	0.32	0.00
X17	Shareholders' equity/Total assets	SE/TA	0.35	0.22	0.00
X18	Current assets/Current liabilities	CA/CL	1.31	1.07	0.00
X19	Quick assets/Current liabilities	QA/CL	0.70	0.57	0.00
X20	Quick assets/Current assets	QA/TA	0.37	0.36	0.73
X21	Fixed assets/(Shareholders' equity+ Long-term debt)	FA/ (SE+LTD)	0.60	0.91	0.01
X22	Fixed assets/Total assets	FA/TA	0.22	0.24	0.63
X23	Current assets/Total assets	CA/TA	0.70	0.68	0.66
X24	Cash/ Current liabilities	Ca/CL	0.09	0.04	0.00
X25	Interest expenses/Gross profit	IE/GP	–0.02	–1.21	0.48
X26	Sales/Cash	S/Ca	35.30	44.80	0.11
X27	Sales/Total assets	S/TA	0.93	0.70	0.00
X28	Working capital/Total assets	WC/TA	0.13	0.00	0.00
X29	Paid in capital/Shareholders' equity	PIC/SE	0.53	0.86	0.00
X30	Sales/Working capital	S/WC	2.87	1.73	0.96
X31	Retained earnings/Total assets	RE/TA*	0.08	–0.03	0.00
X32	Net income/Shareholders' equity	NI/SE	0.42	–0.03	0.00
X33	Net income/Sales	NI/S	0.16	–0.02	0.00
X34	Net income/Total assets	NI/TA*	0.13	0.00	0.00
X35	Sales/Current assets	S/CA	1.34	1.07	0.00
X36	Operational income/Sales	OI/S*	0.20	0.06	0.00
X37	Operational income/Total assets	OI/TA	0.17	0.03	0.00
X38	Earnings before interest and taxes/ Interest expenses	EBIT/IE	–5.21	–0.45	0.05
X39	Earnings before interest and taxes/Sales	EBIT/S	0.52	0.10	0.00

Table 1 (Cont.)

No.	Predictor Variable Name	Financial Ratios	Means of Group 1	Means of Group 2	Sig. Level
X40	Gross profit /Sales	GP/S	0.27	0.15	0.00
X41	Sales/Shareholders' equity	S/SE	3.32	4.68	0.05
X42	Sales/Fixed assets	S/FA	6.29	6.44	0.33

Note: *Final variables selected by SDA. Group 1: non-bankrupt company and Group 2: bankrupt company.

Table 2: Variables Selected with a Review of Studies Since 2000

No.	Mentioned by
X1	Grice and Dugan (2001), Brabazon and Keenan (2004), Sun and Shenoy (2007), Chaudhuri and De (2011), Lin *et al.* (2011) and Sun and Li (2011).
X2	Etemadi *et al.* (2009) and Min and Jeong (2009).
X3	Gestel *et al.* (2010), Andrés *et al.* (2011) and Xiao *et al.* (2012).
X4	Sun and Shenoy (2007), Chaudhuri and De (2011) and Chen *et al.* (2011).
X5	Tseng and Hu (2010), Chaudhuri and De (2011) and Chen (2012).
X6	Ding *et al.* (2008), Martens *et al.* (2008) and Etemadi *et al.* (2009).
X7	Etemadi *et al.* (2009).
X8	Etemadi *et al.* (2009).
X9	Min and Lee (2005), Shin *et al.* (2005), Bhimani *et al.* (2009) and Mokhatab *et al.* (2011).
X10	Wu *et al.* (2007), Chaudhuri and De (2011), Sun and Li (2011) and Xiao *et al.* (2012).
X11	Min and Lee (2005) and Etemadi *et al.* (2009).
X12	Sun and Shenoy (2007), Chen *et al.* (2011), Lin *et al.* (2011) and Sun and Li (2011).
X13	Etemadi *et al.* (2009).
X14	Grice and Dugan (2001), Min and Lee (2005), Wu *et al.* (2007) and Min and Jeong (2009), Chaudhuri and De (2011), Chen *et al.* (2011) and Lin *et al.* (2011).
X15	Sun and Shenoy (2007) and Etemadi *et al.* (2009).
X16	Grice and Dugan (2001), Ding *et al.* (2008), Martens *et al.* (2008), Tseng and Hu (2010), Andrés *et al.* (2011) and Lin *et al.* (2011).
X17	Brabazon and Keenan (2004), Min and Lee (2005), Sun and Shenoy (2007), Chen *et al.* (2011), Lin *et al.* (2011) and Mokhatab *et al.* (2011).
X18	Wu *et al.* (2007), Etemadi *et al.* (2009) and Xiao *et al.* (2012).
X19	Brabazon and Keenan (2004), Koh and KeeLow (2004) and Etemadi *et al.* (2009).
X20	Brabazon and Keenan (2004), Wu *et al.* (2007), Chen *et al.* (2011), Mokhatab *et al.* (2011) and Sun and Li (2011).
X21	Min and Lee (2005), Shin *et al.* (2005), Ding *et al.*(2008), Mokhatab *et al.* (2011) and Sun and Li (2011).

Table 2 (Cont.)

No.	Mentioned by
X22	Ding *et al.* (2008), Etemadi *et al.* (2009), Chen *et al.* (2011) and Andrés *et al.* (2012).
X23	Grice and Dugan (2001), Martens *et al.* (2008), Lin *et al.* (2011) and Sun and Li (2011).
X24	Koh and KeeLow (2004), Etemadi *et al.* (2009) and Mokhatab *et al.* (2011).
X25	Etemadi *et al.* (2009) and Chen *et al.* (2011).
X26	Etemadi *et al.* (2009) and Andrés *et al.* (2012).
X27	Ding *et al.* (2008), Chen *et al.* (2011), Sun and Li (2011) and Wu *et al.* (2007).
X28	Andrés *et al.* (2012), Chen (2011) and Etemadi *et al.* (2009).
X29	Wu *et al.* (2007), Ding *et al.* (2008), Martens *et al.* (2008), Lin *et al.* (2011), Sun and Li (2011), Chen (2012) and Xiao *et al.* (2012).
X30	Brabazon and Keenan (2004), Etemadi *et al.* (2009) and Lin *et al.* (2011).
X31	Brabazon and Keenan (2004), Min and Lee (2005), Etemadi *et al.* (2009) and Chen (2011).
X32	Etemadi *et al.* (2009), Chaudhuri and De (2011), Chen *et al.* (2011) and Andrés *et al.* (2012).
X33	Brabazon and Keenan (2004), Tseng and Hu (2010), Chen (2011) and Xiao *et al.* (2012).
X34	Grice and Dugan (2001), Wu *et al.* (2007), Ding *et al.* (2008), Tseng and Hu (2010) and Lin *et al.* (2011).
X35	Martens *et al.* (2008), Etemadi *et al.* (2009), Min and Jeong (2009), Lin *et al.* (2011) and Sun and Li (2011).
X36	Min and Lee (2005), Wu *et al.* (2007), Ding *et al.* (2008), Chen (2011), Mokhatab *et al.* (2011) and Sun and Lee (2011).
X37	Min and Lee (2005), Wu *et al.* (2007), Chen (2011), Mokhatab *et al.* (2011), Sun and Li (2011) and Tseng and Hu (2010).
X38	Shin *et al.* (2005), Sun and Shenoy (2007), Min and Jeong (2009), Lin *et al.* (2011) and Chen (2012).
X39	Brabazon and Keenan (2004), Etemadi *et al.* (2009), Min and Jeong (2009), Chaudhuri and De (2011) and Chen (2011).
X40	Ding *et al.* (2008), Etemadi *et al.* (2009) and Chen (2011).
X41	Sun and Shenoy (2007), Etemadi *et al.* (2009) and Chen *et al.* (2011).
X42	Sun and Shenoy (2007), Ding *et al.* (2008), Martens *et al.* (2008), Chaudhuri and De (2011) and Lin *et al.* (2011)

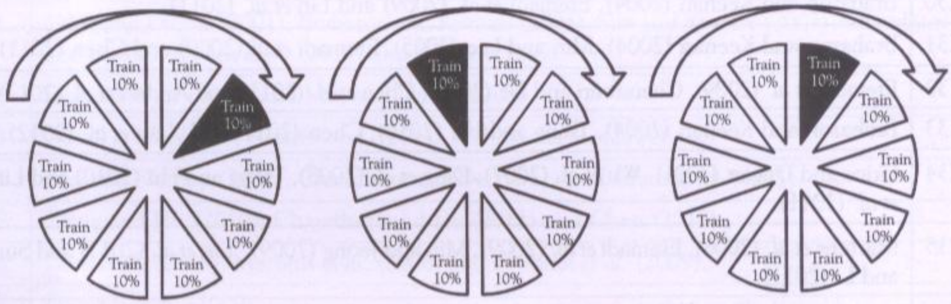
Variables selection process in this study has been based on both—future selection techniques and also done experimentally. In this process, three stages have been employed. At first, 42 variables, as shown in Tables 1 and 2, were chosen after reviewing the literature dealing with corporate failure. Then variables that potentially had the ability of predicting corporate failure in the model were selected by *T*-test (see Table 2). Eventually, final variables were defined by SDA (total liabilities to total assets (x_9), retained earnings to total assets (x_{31}), operational income to sales (x_{36}) and net income to total assets (x_{34}) are selected as financial ratios).

Model Development

Cross-Validation

The cross-validation is the standard methodology of data mining that is implemented to evaluate and compare learning algorithms. It splits data into two main subdivisions: test and training set. In *K*-fold cross-validation, firstly, the dataset is spilt into subsets of approximately, or exactly the equal size and then iterations of training and test are performed. In every iteration, a variant fold of the data is heldout for validation while the rest are applied for learning (see Figure 2). Using fold cross-validation, all observations are utilized for both training and test sets (Alpaydin, 2010) is often 10 or 30 (in this research $K = 10$)

Figure 2: Three Steps of Tenfold Cross-Validation



Particle Swarm Optimization (PSO)

PSO method was first presented by Kennedy and Eberhart in 1995. It is one of the techniques of meta-heuristic algorithms. This technique is inspired by social relationships and interactions of a mass movement of birds or fishes in the sea. Swarm in PSO includes a collection of members that each member is called a particle in the population. In this, the technique used is *gbest* neighborhood topology concept. In PSO, each member of the population has one velocity (shift), the corresponding moves in the search space. Each particle recalled its previous best position and the best position for each particle in the population. In other words, each particle moves in the direction of its best previous position and towards the best particle. Suppose that search space of issue is D-dimensional space, i^{th} member of swarm is indicated with D-dimensional vector and is shown below:

$$X_i = (x_{i1}, x_{i2}, ..., x_{id})$$

The velocity each particle is represented as follows:

$$V_i = (v_{i1}, v_{i2}, ..., v_{iD})$$

The best solution that is achieved by each particle is called personal best or *pbest* and the best solution obtained by any particle in the neighborhood is called general best or *gbest*, and *n* shows the number of iterations and finally population move in accordance with the following equation:

$$v_{i,d}^{n+1} = w.v_{i,d}^{n} + c_1 r_1^n (pbest_{i,d}^n - x_{i,d}^n) + c_2 r_2^n (gbest_d^n - x_{i,d}^n)$$

$$x_{id}^{n+1} = x_{id}^{n} + v_{id}^{n+1}$$

where $v_{i.d}^{n}$: Current velocity, $v_{i.d}^{n+1}$: Modified velocity

$d = 1, 2, ..., i = 1, 2, ..., N$ (N is the total number of companies)

Also W is called inertia weight that is an indicator of the convergence behavior of this proposed algorithm. c_1 and c_2 are two positive and constants coefficients that are called cognitive and social parameters, respectively. c_1 and c_2 are random numbers in the range of (1,0) with the uniform distribution and $n = 1, 2, ...$ specifies the number of iterations. Inertia weight achieved by the following equation:

$$W = w_{max} - \frac{(w_{max} - w_{min}) \times n}{iTer_{max}}$$

where

w_{max} : Initial rate of inertia weight;

w_{min} : Final amount of inertia weight;

$iter_{max}$: Maximum number of iterations; and

n : The current iteration number.

The pseudocode of the PSO algorithm is given in Figure 3.

Figure 3: The Pseudocode of the PSO Algorithm

```
For each particle
    Initialize particle
End For
Do
    For each particle
        Calculate fitness value of the particle
      /*updating particle's best fitness value so far)*/
          If is better than
              set current value as the new
    End For
   /*updating population's best fitness value so far)*/
   Set to the best fitness value of all particles
    For each particle
```

Figure 3 (Cont.)

Calculate particle velocity according Equation (1)

Update particle position according Equation (2)

End For

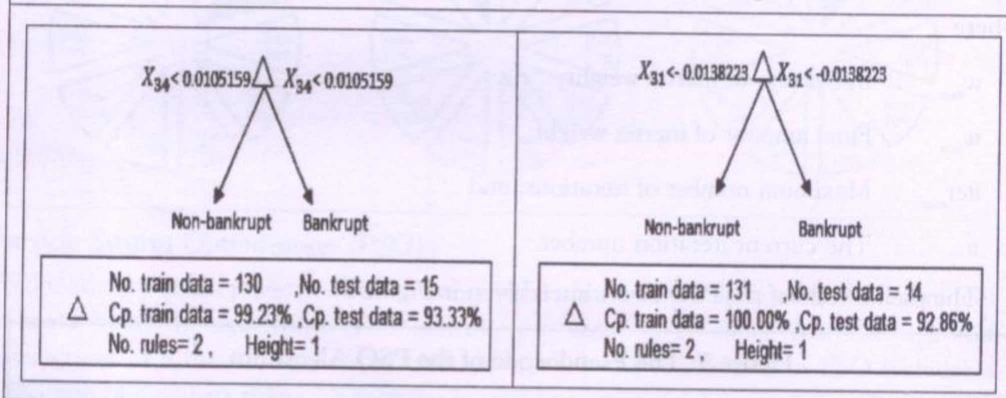
While maximum iterations OR

minimum error criteria is not attained

Classification and Regression Tree (CART)

Classification and Regression Tree (CART) is a classification method which applies historical data to build decision trees. Then decision trees are used to classify new data by a set of questions which splits the training sample into smaller and smaller parts. This algorithm searches for all possible variables and all possible values. The question is that divide the data into two parts with maximum homogeneity, as can be seen from Figure 4. Then the process is repeated for each of the resulting data fragments (Timofeev, 2004).

Figure 4: Estimates – Smallest Trees by CART Algorithm



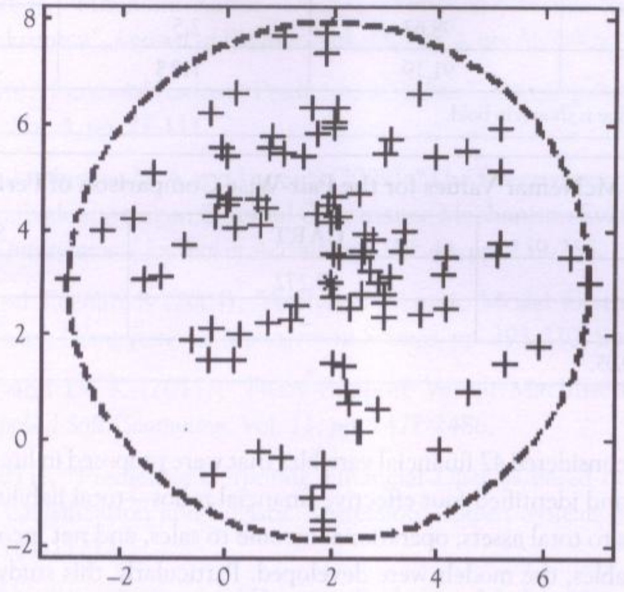
Support Vector Data Description (SVDD)

The SVDD is a one class classification technique that evaluates the distributional support of a dataset. A flexible closed boundary function is applied to separate trustworthy data on the inside from outliers on the outside. The main aim of SVDD is to find a minimum sphere with all the objective samples and none of the nonobjective samples (Tax and Duin, 2004; and Gorgani *et al.*, 2010). The sphere is characterized by its center *a* and its radius *R*, as shown in Figure 5.

Results and Discussion

Tables 3 and 4 show the result of CFP by PSO, CART and SVDD for holdout data. Since the error rate of the algorithm PSO and CART are not normally distributed, we used a nonparametric test for comparison. To evaluate the significant differences between the algorithms of this study, we used the McNemar test at 5% statistical significance level. Table 5 shows the results of the McNemar test. As shown in Table 5, PSO outperforms CART

Figure 5: Sphere is Specified by Center and Its Radius R



and SVDD at 5% statistical significance level. PSO does not significantly differ from CART, but due to lower average error rate, PSO is more efficient than CART; in addition, PSO and CART significantly perform SVDD. These results were also confirmed by performing a Wilcoxon test. The results are presented in Tables 3, 4 and 5.

Table 3: The Detailed Results Obtained by PSO via Tenfold Cross-Validation

Fold	Accuracy (%)		Type I Error (%)		Type II Error (%)	
1	100	100	0	0	0	0
2	100	100	0	0	0	0
3	100	99.23	0	1.54	0	0
4	100	100	0	0	0	0
5	100	100	0	0	0	0
6	100	100	0	0	0	0
7	92.86	100	20	0	0	0
8	100	100	0	0	0	0
9	100	100	0	0	0	0
10	100	100	0	0	0	0
Average	**99.29**	**99.92**	**2**	**0.15**	**0**	**0**

Table 4: Results Obtained by Different Classifiers

Classifier	Accuracy (%)	Type I Error(%)	Type II Error(%)
PSO	**99.29**	2	0
CART	98.62	2.5	0
SVDD	91.19	**1.25**	16.31

Note: The best value is shown in bold.

Table 5: McNemar Values for the Pair-Wise Comparison of Performance

	CART	SVDD
PSO	–0.272	–2.279
CART	–	–2.153

Note: *P*-value < 0.05.

Conclusion

In this paper, we considered 42 financial variables that were proposed in literature. We applied SDA technique and identified four effective financial ratios—total liabilities to total assets, retained earnings to total assets, operational income to sales, and net income to total assets. Using these variables, the models were developed. Particularly, this study utilized a tenfold cross-validation. The average accuracy of PSO models for holdout sample was 99.29%. In addition, accuracy of PSO model was higher than the other two methods and for this specific set of data, the best fit was obtained with the PSO. The second best fit was presented by the CART model. The SVDD model had lower correct classification fit for bankruptcy prediction. Also, the results from McNemar and Wilcoxon tests at 5% statistical significance level demonstrate that PSO and CART are significantly different from SVDD and they can present a better prediction model than SVDD.

For further research, we propose a combined model. In this model, we can apply more than one algorithm and create a stronger and more robust model. It is also recommended that for identifying variables, data mining techniques like decision tree can be used. In addition, researchers can also focus on both of potential nonfinancial and financial indicators. ✪

References

1. Alpaydin E (2010), *Introduction to Machine Learning*, 2nd Edition, MIT Press, London.
2. Andrés J, Landajo M and Lorca P (2012), "Bankruptcy Prediction Models Based on Multinorm Analysis: An Alternative to Accounting Ratios", *Knowledge Based Systems*, doi: 10.1016/j.knosys. 2011.11.005.
3. Andrés J D, Lorca P, Juez F J and Sánchez-Lasheras F (2011), "Bankruptcy Forecasting: A Hybrid Approach Using Fuzzy c-means Clustering and Multivariate Adaptive Regression Splines (MARS)", *Expert Systems with Applications*, Vol. 38, pp. 1866-1875.

4. Ashoori S and Mohammadi S (2011), "Compare Failure Prediction Models Based on Feature Selection Technique: Empirical Case from Iran", *Procedia Computer Science*, Vol. 3, pp. 568-573.
5. Altman E (1968), "Financial Ratios. Discriminant Analysis and the Prediction of Corporate Bankruptcy", *Journal of Finance*, Vol. 23, No. 4, pp. 589-609.
6. Beaver W (1966), "Financial Ratios as Predictors of Failure", *Journal of Accounting Research* (Supplement), Vol. 4, pp. 71-111.
7. Bhimani A, Gulamhussen M A and Lopes S (2009), "The Effectiveness of the Auditor's Going-concern Evaluation as an External Governance Mechanism: Evidence from Loan Defaults", *The International Journal of Accounting*, Vol. 44, pp. 239-255.
8. Brabazon A and Keenan B (2004), "A Hybrid Genetic Model for the Prediction of Corporate Failure", *Computational Management Science*, pp. 293-310, Springer-Verlag.
9. Chaudhuri A and De K (2011), "Fuzzy Support Vector Machine for Bankruptcy Prediction", *Applied Soft Computing*, Vol. 11, pp. 2472-2486.
10. Chen M Y (2011), "Predicting Corporate Financial Distress based on Integration of Decision Tree Classification and Logistic Regression", *Expert Systems with Applications*, Vol. 38, pp. 11261-11272.
11. Chen M Y (2012), "Visualization and Dynamic Evaluation Model of Corporate Financial Structure with Self-Organizing Map and Support Vector Regression", *Applied Soft Computing*, Vol. 12, No. 8, pp. 2274-2288.
12. Chen H L, Yang B, Wang G *et al.* (2011), "A Novel Bankruptcy Prediction Model Based on an Adaptive Fuzzy k –nearest Neighbor Method", *Knowledge-Based Systems*, Vol. 24, pp. 1348-1359.
13. Ding Y, Song X and Zen Y (2008), "Forecasting Financial Condition of Chinese Listed Companies Based on Support Vector Machine", *Expert Systems with Applications*, Vol. 34, pp. 3081-3089.
14. Etemadi H, Anvary Rostamy A A and Farajzadeh Dehkordi H (2009), "A Genetic Programming Model for Bankruptcy Prediction: Empirical Evidence from Iran", *Expert Systems with Applications*, Vol. 36, pp. 3199-3207.
15. Gestel T V, Baesens B and Martens D (2010), "From Linear to Non-linear Kernel Based Classifiers for Bankruptcy Prediction", *Neurocomputing*, Vol. 73, pp. 2955-2970.
16. Gorgani M E, Moradi M and Sadoghi Yazdi H (2010), "An Empirical Modeling of Companies Using Support Vector Data Description", *International Journal of Trade, Economics and Finance*, Vol. 1, No. 2, pp. 221-224.
17. Grice G S and Dugan M T (2001), "The Limitations of Bankruptcy Prediction Models: Some Cautions for Researcher", *Review of Quantitative Finance and Accounting*, Vol. 17, pp. 151-166.

18. Guyon I and Elisseeff A (2003), "An Introduction to Variable and Feature Selection", *Journal of Machine Learning Research*, Vol. 3, pp. 1157-1182.

19. Hopwood W S, McKeown J C and Mutchler J F (1994), "A Re-Examination of Auditor Versus Model Accuracy within the Context of the Going-Concern Opinion Decision", *Contemporary Accounting Research*, Vol. 10, No. 2, pp. 409-431.

20. Koh H C (1991), "Model Predictions and Auditor Assessments of Going Concern Status", *Accounting and Business Research*, Vol. 21, No. 84, pp. 331-338.

21. Koh H C and Kee Low C (2004), "Going Concern Prediction Using Data Mining Techniques", *Managerial Auditing Journal*, Vol. 19, No. 3, pp. 462-476.

22. Lin F, Liang D and Chen E (2011), "Financial Ratio Selection for Business Crisis Prediction", *Expert Systems with Applications*, Vol. 38, pp. 15094-15102.

23. Martens D, Bruynseels L, Willekens B M and Vanthienen J (2008), "Predicting Going Concern Opinion with Data Mining", *Decision Support Systems*, Vol. 45, pp. 765-777.

24. Min J H and Jeong C (2009), "A Binary Classification Method for Bankruptcy Prediction", *Expert Systems with Applications*, Vol. 36, pp. 5256-5263.

25. Min J H and Lee Y C (2005), "Bankruptcy Prediction Using Support Vector Machine with Optimal Choice of Kernel Function Parameters", *Expert Systems with Applications*, Vol. 28, pp. 603-614.

26. Mokhatab Rafiei F and Manzari S M and Bostanian S (2011), "Financial Health Prediction Models Using Artificial Neural Networks, Genetic Algorithm and Multivariate Discriminant Analysis: Iranian Evidence", *Expert Systems with Applications*, Vol. 38, pp. 10210-10217.

27. Ohlson J S (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", *Journal of Accounting Research*, Vol. 18, No. 1, pp. 109-131.

28. Olson D L, Delen D and Meng Y (2012), "Comparative Analysis of Data Mining Methods for Bankruptcy Prediction", *Decision Support Systems*, Vol. 52, pp. 464-473.

29. Shin K S, Lee T S and Kim H J (2005), "An Application of Support Vector Machines in Bankruptcy Prediction Model", *Expert Systems with Applications*, Vol. 28, pp. 127-135.

30. Sun J, He K Y and Li H (2011), "SFFS-PC-NN Optimized by Genetic Algorithm for Dynamic Prediction of Financial Distress with Longitudinal Data Streams", *Knowledge-Based Systems*, Vol. 24, pp. 1013-1023.

31. Sun J and Li H (2011), "Dynamic Financial Distress Prediction Using Instance Selection for the Disposal of Concept Drift", *Expert Systems with Applications*, Vol. 38, pp. 2566-2576.

32. Sun L and Shenoy P P (2007), "Using Bayesian Networks for Bankruptcy Prediction: Some Methodological Issues", *European Journal of Operational Research*, Vol. 180, pp. 738-753.

33. Tax D and Duin R (2004), "Support Vector Data Description", *Machine Learning*, Vol. 54, pp. 45-66.

34. Timofeev R (2004), "Classification and Regression Tree, Theory and Application (A Master Thesis, Berlin Applied Statistics and Economics Humboldt University)", *Dissertation Abstracts International*, Vol. 39, pp. 1-40.

35. Tsai C F and Cheng K C (2012), "Simple Instance Selection for Bankruptcy Prediction", *Knowledge-Based Systems*, Vol. 27, pp. 333-342.

36. Tseng F M and Hu Y C (2010), "Comparing Four Bankruptcy Prediction Models: Logit, Quadratic Interval Logit, Neural and Fuzzy Neural Networks", *Expert Systems with Applications*, Vol. 37, pp. 1846-1853.

37. Wu C H, Tzeng G H, Goo Y J and Fang W C (2007), "A Real-Valued Genetic Algorithm to Optimize the Parameters of Support Vector Machine for Predicting Bankruptcy", *Expert Systems with Applications*, Vol. 32, pp. 397-408.

38. Xiao Z, Yang X, Pang Y and Dang X (2012), "The Prediction for Listed Companies' Financial Distress by Using Multiple Prediction Methods with Rough Set and Dempster – Shafer Evidence Theory", *Knowledge-Based Systems*, Vol. 26, pp. 196-206.

39. Zmijewski M E (1984), "Methodological Issues Related to the Estimation of Financial Distress Prediction Models", *Journal of Accounting Research* (Supplement), Vol. 22, pp. 59-86.

Reference # 33J-2013-09-02-01