

# **Empirical analysis of bankrupt companies using linear and nonlinear techniques in Japanese Stock Markets**

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## **Abstract**

This study predicted the bankruptcy companies listed in Japanese Stock Markets for the entire industry and individual industries using Multiple Discriminant Analysis (MDA), artificial neural networks (ANN) and support vector machines (SVMs), and compared the method which is the best method to predict the bankruptcy companies more precisely. The financial statements of the listed companies in the Tokyo Stock Exchange, the Osaka Securities Exchange, and other stock exchanges in Japanese stock markets were used as data. The data of 244 bankrupt companies that went bankrupt between 1991 and 2014 are used. On the other hand, data of 64708 non-bankrupt companies that did not go bankrupt between 1991 and 2014 for 24 years are used. The data is acquired from Nikkei NEEDS database. In MDA and ANN analysis, only for some industries bankruptcy prediction could be made accurately. On the other hand, SVM could predict bankruptcy in companies almost perfectly for each industry.

## **Keywords**

Bankruptcy, artificial neural networks (ANN), support vector machines (SVMs), Multiple Discriminant Analysis (MDA), empirical analysis

## **1. Introduction**

In recent years, Japanese companies are improving their corporate performance and financial structure because of the yen depreciation and gradual recovery of the economy. Though the number of bankruptcies has decreased, even today it is a highly important management subject to determine whether a company will become bankrupt. The causes of bankruptcy are diverse, and they can be qualitative and quantitative factors. In this research, we use financial indicators as the quantitative factors to explain the reason for bankruptcy in the industry. This research deals with 224 bankrupt companies that went bankrupt from 1992 to 2015. To be specific, the financial statements of the listed companies in the Tokyo Stock Exchange, the Osaka Securities Exchange, and other stock exchanges in Japanese stock markets were used as data in this study. The data of 244 bankrupt companies that went bankrupt between 1992 and 2015 are used. On the other hand, data of 64708 non-bankrupt companies that did not go bankrupt

between 1992 and 2015 for 24 years are used. Although the bankruptcy after the collapse of the bubble economy in 1989 is slight, the zero interest rate policy of the Bank of Japan was lifted in 2000 and the number of bankruptcies soared to 23 in 2001. However, the global financial crisis occurred as a result of the subprime mortgage loan that occurred in 2007, the number of bankruptcies in 2008 was 39, the highest number of bankruptcies in history. In addition, the default crisis in the United States occurred in October 2013, but Japanese companies have not been affected significantly.

A bankruptcy discrimination research was first conducted by Beaver. Altman classified companies into groups by using Multiple Discriminant Analysis (MDA) to distinguish between bankrupt and non-bankrupt companies, and further developed the research by Beaver. Logistic regression was first employed by Ohlson. Subsequently, studies of bankruptcy discrimination have been using statistical analysis such as MDA, multiple regression equation, logistic model, and probit model. In recent years, techniques for overcoming such limits have been developed, and studies incorporating artificial intelligence, such as k-nearest neighbors, decision trees, artificial neural networks (ANN), genetic algorithm, and support vector machines (SVMs), are increasing. MDA, ANN and SVMs are used in this study as the methods of linear and nonlinear techniques for predicting bankruptcy. This research predicted the bankruptcy of all the industries by using three methods without separating the entire industry into individual industries at first. However, it was impossible to predict bankruptcy accurately in MDA and ANN. Therefore, we decided to classify the entire industry into eleven industries.

The significance of this research is that clients, investors, and financiers can prevent loss before finalizing a deal based on the information of financial indicators from bankruptcy prediction. On the other hand, managers can improve their business by paying attention to these financial indicators.

## **2. Theoretical framework**

### **2.1 Multiple Discriminant Analysis (MDA)**

MDA can be used for selecting bankrupt companies using a statistical theory. The model is built by a bankruptcy prediction model using statistical analysis method. We call this model as MDA Model. The formula of MDA Model is shown as below.

$$y = a_1x_1 + a_2x_2 + \dots + a_nx_n \quad (n=1,2,\dots, n) \quad (2.1)$$

### **2.2 Artificial neural networks (ANN)**

#### **2.2.1 Outline of Neural Network**

The neural network is a problem optimization method modeling the neural circuit of the human brain. The neural network is classified without teacher signal with teacher signal optimized by inputting teacher signal and teacher signal without using teacher signal. Teacher signal present is used when the solution is already known. No teacher signal is used to classify given data without reference. Also, it is classified into a hierarchical type and a mutually coupled type network by the neuron connection method. With supervised signals, the hierarchical network approach is perceptron, back propagation and so on. There are methods such as association, hopfield network, Boltzmann machine, etc. as a mutually coupled network with teacher signal. Basically, by extending the perceptron, giving the correct answer to the output layer as a teacher signal, we obtain the error between the teacher signal and the output and change the weight.

#### **2.2.2 Bankruptcy discrimination model using ANN**

The bankruptcy discrimination model using ANN is bankruptcy if the value of the output layer of bankruptcy is "1". In this research, the number of times of learning is 100,000 times, and a bankruptcy discrimination model is constructed from three layers of the input layer, the intermediate layer, and the output layer by using the backpropagation method. Neurons in the input layer changed financial indicators, and the number of neurons in the middle layer changed for each index number. The number of neurons in the output layer is 2 layers of bankruptcy / non-bankruptcy. Also, the ANN model uses variables. The number of neurons in the input layer is determined from among the 1 to 23 indices of the number of financial indicators, based on the in-sample data and out-samples results, the one with the highest discrimination power and reliability is determined and the bankruptcy discrimination model is determined as ANN model. A sigmoid function was used as an output function, and the open source statistical software R was used in numerical experiments.

### **2.3 Support vector machines (SVMs)**

An SVM, presented as machine learning by Vapnik, is a data analysis method that mainly deals with classification and regression problems. An SVM is a high dimensional hypothesis space that can be linearly separated, and it can be understood as follows as it is a method that follows a linear approach. We define the training data sets as  $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$ , where  $\mathbf{x} = (x_1, x_2, \dots, x_p)^T$  is the feature vector of the individual and  $y$  is the objective variable that is a numerical value in the regression problem and it is the label of the class in the classification problem. The data consists of a pair of feature vectors  $x_i \in \mathbf{R}^n, i=1, 2, \dots, l$  and class  $y_i \in \{-1, 1\}$ .  $x_i$  is the financial indicator of company  $i$ , such that  $y_i=-1$  represents bankruptcy and  $y_i=1$  indicates non-bankruptcy. For linear regression and linear discrimination problems, the following linear model is used:

$$y = \mathbf{w}^T \mathbf{x} + b \quad (2.2)$$

Positive and negative samples are separated by hyperplane  $H_0: \mathbf{w}^T \mathbf{x} + b = 0$ .

SVM determines the coefficient that maximizes the margin, and performs the discrimination as follows:

$$y = \begin{cases} 1, & \text{if } \mathbf{w}^T \mathbf{x} + b \geq 1 \\ -1, & \text{if } \mathbf{w}^T \mathbf{x} + b \leq -1 \end{cases} \quad (2.3)$$

The interval between the straight lines  $\mathbf{w}^T \mathbf{x} + b = 1$  and  $\mathbf{w}^T \mathbf{x} + b = -1$  is the margin; maximizing margin  $M$  is a problem of maximizing  $M = \min \left( \frac{|y_i(\mathbf{w}^T x_i + b)|}{\|\mathbf{w}\|} \right) = \frac{2}{\|\mathbf{w}\|}$ .

The maximization of the margin is equal to the minimization of  $\|\mathbf{w}\|$ ; therefore, the SVM problem for obtaining hyperplane  $H_0$  that maximizes the margin is formulated as the following quadratic programming problem:

$$\text{Minimize } \frac{1}{2} \mathbf{w}^T \mathbf{w} \quad (2.4)$$

Subject to  $y_i(\mathbf{w}^T x_i + b) \geq 1; i = 1, 2, \dots, n$

## 2.4 Fitness function

The fitness function used herein is expressed in Eq. (2.5). The fitness function is defined as the number of successes in the correct classification of bankrupt and non-bankrupt companies. This function utilizes the financial indicators of both correct and incorrect predictions.

$$f = \frac{T_p + F_n}{T_p + T_n + F_p + F_n} \quad (2.5)$$

Where, true positive ( $T_p$ ) is the number of bankrupt companies that the rule states are bankrupt, false positive ( $F_p$ ) is the number of non-bankrupt companies that the rule predicts to be bankrupt, true negative ( $T_n$ ) is number of bankrupt companies that the rule predicts to be non-bankrupt, and false negative ( $F_n$ ) is number of non-bankrupt companies that the rule predicts to be non-bankrupt.

## 3. Simulation design

### 3.1 Sample size and industries

We generated a bankruptcy prediction model using MDA, ANN and SVMs. The data of the company to be used are the financial statements of the listed companies in the Tokyo Stock Exchange, the Osaka Securities Exchange, and other stock exchanges. Bankruptcy was defined as a company that applied the civil rehabilitation law, bankruptcy suspension, bankruptcy, business activity stoppage, and the data of 244 bankrupt companies that went bankrupt between 1991 and 2014 are used. On the other hand, data of 3260 non-bankrupt companies that did not become bankrupt between 1991 and 2014 for 24 years are used. In total, 64708 non-bankruptcy company's data has been used. The data is acquired from Nikkei NEEDS database. It is possible to consider bankruptcy prediction for all the industries, but considering special circumstances according to the industry, it is believed that the bankruptcy prediction can be achieved with a high accuracy. The data of 244 bankrupt companies are classified into 11 industries: construction industry (43 companies), real-estate industry (34 companies), services industry (20 companies), retail industry (19 companies), electrical equipment industry (17 companies), machinery industry (16 companies), wholesale industry (15 companies), other financial services industry (13 companies), textiles and apparels industry (9 companies), information and telecommunications industry (8 companies), and other industries (31 companies).

### 3.2 Financial indicators and software

We selected some financial indicators with high discrimination power from the 23 financial indicators presented in the Appendix. We first investigated the 23 financial indicators and categorized the companies based on profitability, safety, efficiency, ability to pay, fund recovery capacity, funding capacity, and cash flow. The software used to perform the simulation, predict, and conduct the overall study is the open source statistical software R.

Table 1 Financial indicator

Ratio	Number	Ratio	Number
Deb capacity ratio	$x_1$	Short-term debt rotation period	$x_2$
Net sales margin ratio	$x_3$	Debt ratio for total assets	$x_4$
Loan To Value	$x_5$	Ratio of profit before tax to sales	$x_6$
Capital share	$x_7$	Total capital net income margin	$x_8$
Quick ratio	$x_9$	Current liability turnover	$x_{10}$
Total capital ordinary income ratio	$x_{11}$	Interest-bearing debt monthly sales ratio	$x_{12}$
Debt monthly sales magnification	$x_{13}$	Debt turnover period	$x_{14}$
Ordinary income ratio	$x_{15}$	Interest coverage ratio	$x_{16}$
Operating profit per employee	$x_{17}$	Operating profit per employee	$x_{18}$
Sales financial balance ratio	$x_{19}$	Long-term debt repayment years	$x_{20}$
Finance cost ratio	$x_{21}$	Ratio of operating profit to operating capital	$x_{22}$
Return on asset	$x_{23}$		

## 4. Empirical analysis result

### 4.1 Result and discussion

#### 4.1.1 Entire industries classification

The result of entire industries classification is shown from Table 2 to Table 4.

Table 2 All industries utilizing MDA

		bankruptcy status		Total	Total precision(%)
		0	1		
Number	0	43	181	224	99.38%
	1	219	64489	64708	
%	0	19.20%	80.80%	100.00%	
	1	0.34%	99.66%	100.00%	

In Table 2, the value of 99.38% in the precision column is the value of fitness function  $f$ . On the other hand, positive ( $T_p$ ) is 19.20%. In the table, 0 represents bankruptcy and 1 represents non-bankruptcy. In addition, the figure is the number of companies.

Table 3 All industries utilizing ANN

		bankruptcy status		Total	Total precision(%)
		0	1		
Number	0	0	224	224	99.66%
	1	0	64708	64708	
%	0	0.00%	100.00%	100.00%	
	1	0.00%	100.00%	100.00%	

In Table 3, the value of 99.66% in the precision column is the value of fitness function  $f$ . On the other hand, positive ( $T_p$ ) is 0.00%.

Table 4 All industries utilizing SVM

		bankruptcy status		Total	Total precision(%)
		0	1		
Number	0	218	6	224	99.99%
	1	0	64708	64708	
%	0	97.32%	2.68%	100.00%	
	1	0.00%	100.00%	100.00%	

In Table 4, the value of 99.99% in the precision column is the value of fitness function  $f$ . On the other hand, positive ( $T_p$ ) is 97.32%.

SVM is more precisely classify the bankruptcy companies than MDA and ANN. As the discrimination rate in case of MDA and ANN analysis is bad, and so we decided to classify the entire industry into eleven industries.

#### 4.1.2 Each industry classification

The results were shown in Table 5-Table 22.

Table 5 Construction industry using MDA and ANN

		bankruptcy status		Total	Total precision(%)
		0	1		
Number	0	11	32	43	99.17%
	1	1	3931	3932	
%	0	25.58%	74.42%	100%	100%
	1	2.33%	99.70%	100%	

Table 6 Construction industry using SVM

		bankruptcy status		Total	Total precision(%)
		0	1		
Number	0	43	0	43	100.00%
	1	0	3932	3932	
%	0	100.00%	0.00%	100.00%	100.00%
	1	0.00%	100.00%	100.00%	

Table 7 Real estate industry using MDA and ANN

		bankruptcy status		Total	Total precision(%)
		0	1		
Number	0	27	7	34	98.60%
	1	3	677	680	
%	0	79.41%	20.59%	100.00%	100.00%
	1	0.44%	99.56%	100.00%	

Table 8 Real estate industry using SVM

		bankruptcy status		Total	Total precision(%)
		0	1		
Number	0	34	0	34	100.00%
	1	0	680	680	
%	0	100.00%	0.00%	100.00%	100.00%
	1	0.00%	100.00%	100.00%	

Table 9 Service industry using MDA and ANN

		bankruptcy status		Total	Total precision(%)
		0	1		
Number	0	10	10	20	99.72%
	1	2	4247	4249	
%	0	50.00%	50.00%	100.00%	100.00%
	1	0.05%	99.95%	100.00%	

Table 10 Service industry using SVM

		bankruptcy status		Total	Total precision(%)
		0	1		
Number	0	20	0	20	100.00%
	1	0	4249	4249	
%	0	100.00%	0.00%	100.00%	100.00%
	1	0.00%	100.00%	100.00%	

Table 11 Retail industry using MDA and ANN

		bankruptcy status		Total	Total precision(%)
		0	1		
Number	0	9	10	19	99.70%
	1	5	5022	5027	
%	0	47.37%	52.63%	100.00%	100.00%
	1	0.10%	99.90%	100.00%	

Table 12 Retail industry using SVM

		bankruptcy status		Total	Total precision(%)
		0	1		
Number	0	18	0	18	99.98%
	1	1	5027	5028	
%	0	100.00%	0.00%	100.00%	
	1	0.02%	99.98%	100.00%	

Table 13 Electric appliances industry using MDA and ANN

		bankruptcy status		Total	Total precision(%)
		0	1		
Number	0	7	10	17	99.79%
	1	3	6286	6289	
%	0	41.18%	58.82%	100.00%	
	1	0.05%	99.95%	100.00%	

Table 14 Electric appliances industry using SVM

		bankruptcy status		Total	Total precision(%)
		0	1		
Number	0	17	0	17	100.00%
	1	0	6289	6289	
%	0	100.00%	0.00%	100.00%	
	1	0.00%	100.00%	100.00%	

Table 15 other financial industry using MDA and ANN

		bankruptcy status		Total	Total precision(%)
		0	1		
Number	0	12	1	13	99.81%
	1	0	511	511	
%	0	92.31%	7.69%	100.00%	
	1	0.00%	100.00%	100.00%	

Table 16 Other financial industry using SVM

		bankruptcy status		Total	Total precision(%)
		0	1		
Number	0	13	0	13	100.00%
	1	0	511	511	
%	0	100.00%	0.00%	100.00%	
	1	0.00%	100.00%	100.00%	

Table 17 Textile and apparels industry using MDA and ANN

		bankruptcy status		Total	Total precision(%)
		0	1		
Number	0	5	4	9	99.74%
	1	2	2331	2333	
%	0	55.56%	44.44%	100.00%	
	1	0.09%	99.91%	100.00%	

Table 18 Textile and apparels industry using SVM

		bankruptcy status		Total	Total precision(%)
		0	1		
Number	0	9	0	9	100.00%
	1	0	2333	2333	
%	0	100.00%	0.00%	100.00%	
	1	0.00%	100.00%	100.00%	

Table 19 Information and telecommunication industry using MDA and ANN

		bankruptcy status		Total	Total
		0	1		precision(%)
Number	0	4	4	8	99.75%
	1	7	4429	4436	
%	0	50.00%	50.00%	100.00%	
	1	0.16%	99.84%	100.00%	

Table 20 Information and telecommunication industry using SVM

		bankruptcy status		Total	Total
		0	1		precision(%)
Number	0	8	0	8	100.00%
	1	0	4436	4436	
%	0	100.00%	0.00%	100.00%	
	1	0.00%	100.00%	100.00%	

Table 21 other industry using MDA and ANN

		bankruptcy status		Total	Total
		0	1		precision(%)
Number	0	7	24	31	99.90%
	1	1	26036	26037	
%	0	22.58%	77.42%	100.00%	
	1	0.004%	99.996%	100.00%	

Table 22 Other industry using SVM

		bankruptcy status		Total	Total
		0	1		precision(%)
Number	0	31	0	31	100.00%
	1	0	26036	26036	
%	0	100.00%	0.00%	100.00%	
	1	0.000%	100.000%	100.000%	

## 4.2 Discussion

This research predicted the bankruptcy of all the industries by using MDA, ANN and SVM method without separating the entire industry into individual industries at first. However, it was impossible to predict bankruptcy accurately. Therefore, we decided to classify the entire industry into eleven industries.

In the entire industry classification, SVM is more precisely classify the bankruptcy companies than MDA and ANN. To be specific, in MDA analysis, the value of 99.38% in the precision column is the value of fitness function  $f$ . On the other hand, positive ( $T_p$ ) is 19.20%. In ANN analysis, the value of 99.66% in the precision column is the value of fitness function  $f$ . On the other hand, positive ( $T_p$ ) is 0.00%. In SVM analysis, the value of 99.99% in the precision column is the value of fitness function  $f$ . On the other hand, positive ( $T_p$ ) is 97.32%. We can find that SVM can predict bankrupt companies precisely. SVM is more accurate than MDA and ANN models in predicting the entire industries classification. The analysis each industry classification is better classification then the entire industry from the Table 5 to Table 22.

As we know in the viewpoint of the result of Table 5 to Table 22, the classification of MDA and ANN is the same result. The ability of classification in the bankruptcy companies the same in these data. When we check the results of MDA and ANN, true positive ( $T_p$ ) is 79.41% in real industry (Table 7) and true positive ( $T_p$ ) is 92.31% in other industry (Table 15). The number of samples in both industries is small compared to the number of samples in other industries. As a result, it can be said that true positive ( $T_p$ ) is high, so MDA and ANN can predict bankruptcy quite accurately in case of a small number of samples.

When bankruptcy prediction is performed using ANN, the search range of the number of neurons in the middle layer and the learning coefficient is set. Next, learning data (85%) and test data (15%) are randomly generated for all combinations of neuron number and learning coefficient, a neural network model is constructed, and the

discrimination ratio is calculated. In consideration of the difference in discrimination accuracy rate by data set, the above data creation and learning were performed ten times, and the average value of discrimination rate was calculated. For example, we would like to show the result of other financial industry. Table 25 shows the results of the learning data (85%), Table 26 shows the results of the test data (15%), and Table 27 shows the result of the sum of these. The empirical results of Table 22 to Table 5 show only the results of Table 27 which is total of the results of the learning data (85%) and the results of the test data (15%). Therefore, Table 15 is the same as Table 27, and the other industry is the same as this example.

Table 25 Other financial industry using ANN (85%)

		bankruptcy status		Total	Total
		0	1		precision(%)
Number	0	10	0	10	100.00%
	1	0	435	435	
%	0	100.00%	0.00%	100.00%	
	1	0.00%	100.00%	100.00%	

Table 26 Other financial industry using ANN (15%)

		bankruptcy status		Total	Total
		0	1		precision(%)
Number	0	3	0	3	100.00%
	1	0	76	76	
%	0	100.00%	0.00%	100.00%	
	1	0.00%	100.00%	100.00%	

Table 27 Other financial industry using ANN (total)

		bankruptcy status		Total	Total
		0	1		precision(%)
Number	0	13	0	13	100.00%
	1	0	511	511	
%	0	100.00%	0.00%	100.00%	
	1	0.00%	100.00%	100.00%	

On the other hand, SVM is also more accurate than MDA and ANN models in predicting each industry classification industries classification, as the same as the entire industry classification.

The SVM prediction of bankruptcy was perfectly conducted to discriminate the industries. As the default of kernel in the open source statistical software R, "kernel = rbf dot" and "kernel = polydot" are used other than "kernel = laplace dot". To be specific, kernel = "laplacedot" of kernel was able to predict bankruptcy and non-bankrupt companies almost perfectly, so "4. Empirical analysis result" shows only the result of kernel = "laplacedot". Here, the effectiveness of "kernel = laplacedot" is shown below for the construction industry as an example.

The following is an example of kernel = "rbfdot", cross = 5).

```
<ksvm(bunrui~a1+a2+a3+a4+a5+a6+a7+a8+a9+a10+a11+a12+a13+a14+a15+a16+a17+a18+a19+a20+a21+a22+a23,data=X,type="Csvc",kernel="rbfdot",cross=5))
```

Table 28 Kernel="rbfdot",cross=5

		bankruptcy status		Total	Total
		0	1		precision(%)
Number	0	75	149	224	99.77%
	1	0	64708	64708	
%	0	33.48%	66.52%	100.00%	
	1	0.00%	100.00%	100.00%	

The following is an example of kernel="rbfdot", C=10, cross=5.

```
<ksvm(bunrui~a1+a2+a3+a4+a5+a6+a7+a8+a9+a10+a11+a12+a13+a14+a15+a16+a17+a18+a19+a20+a21+a22+a23,data=X,type="Csvc",kernel="rbfdot",C=10,cross=5))
```

Table 29 Kernel="rbfdot",C=10,cross=5

		bankruptcy status		Total	Total
		0	1		precision(%)
Number	0	134	90	224	99.86%
	1	0	64708	64708	
%	0	59.82%	40.18%	100.00%	
	1	0.00%	100.00%	100.00%	

The following is an example of kernel="laplacedot", C=10,cross=5.

```
>ksvm(bunrui~x1+x2+x3+x4+x5+x6+x7+x8+x9+x10+x11+x12+x13+x14+x15+x16+x17+x18+x19+x20+x21+x22+x23,data=X,type="C-svc",kernel="laplacedot",C=10,cross=5))
```

Table 30 Kernel="laplacedot",C=10,cross=5

		bankruptcy status		Total	Total
		0	1		precision(%)
Number	0	218	6	224	99.99%
	1	0	64708	64708	
%	0	97.32%	2.68%	100.00%	
	1	0.00%	100.00%	100.00%	

As shown in empirical analysis results, "kernel =" laplacedot ", C = 10, cross = 5" was predictable almost perfectly even in industries other than the construction industry. The result of this research clarified the relationship between bankruptcy in the industry and financial indicators for forecasting bankruptcy in Japanese Stock Markets. This research proposed financial indicators that can predict bankruptcy precisely for each industry, so this prediction bankruptcy system will assist companies to improve their financial situation.

The computer used is a PC (OS: Windows 7 Home Premium 64 bit) equipped with Intel (R) Core (TM) i7-3770 CPU@3.4 GHz CPU and 16.0 GB memory in this research.

## 5. Conclusion

This study predicted the bankruptcy companies listed in Japanese Stock Markets for the entire industry and individual industries using Multiple Discriminant Analysis (MDA), artificial neural networks (ANN) and support vector machines (SVMs), and compared the method which is the best method to predict the bankruptcy companies more precisely. From empirical analysis result described above, we may conclude that SVM is more accurate than the other models in predicting bankrupt companies. In MDA and ANN analysis, only for some industries bankruptcy prediction could be made accurately. On the other hand, SVM could predict bankruptcy in companies almost perfectly for the entire industry and each industry. It can be derived the following conclusions from the results of this study. This bankruptcy predicting model helps for customers, investors and financiers to prevent losses by focusing on the information of these financial indicators before finalizing the transaction. In future research, I would like to use different methods like xgboost and logistic regression and compare with the method which is the best method to predict the bankruptcy companies more precisely..

## References

- Altman, E. I., Financial indicators, discriminant analysis and the prediction of corporate bankruptcy, *The Journal of Finance*, 23(4), pp. 589–609, 1968
- Barniv, R., Agarwal, A., and Leach, R., Predicting the outcome following bankruptcy filing-A three-state classification using neural networks, *Intelligent Systems in Accounting, Finance and Management*, 6, pp.177–194, 1997
- Beaver, W. H., Financial indicators as predictors of Failure, *Journal of Accounting Research*, Empirical Research in Accounting: Selected Studies: Supplement, 4, pp.71–111, 1966
- Chang,C.C., Lin,C.J., LIBSVM: A Library for Support Vector Machines, <http://www.csie.ntu.edu.tw/~cjlin/paper/libsvm.pdf>
- Cortes,C. and Vapnik, V., Support-vector network, *Machine Learning*, Vol.20, No.3, pp.273-297, 1995
- Crammer,K., and Y.Singer, On the algorithmic implementation of multiclass kernel-based vector machines, *Journal of Machine Learning Research*, Vol.2,pp.265-292, 2001
- Deakin, E., A discriminant analysis of predictors of business failure, *Journal of Accounting Research*, Spring 1972, pp. 167-179.

- Odom, M., and Sharda, R., A neural networks model for bankruptcy prediction, Proceedings of the IEEE international conference on neural network, Vol. 2, pp. 163–168, 1990
- Ohlson J.A., Financial indicators and the probabilistic prediction of bankruptcy, Journal of Accounting Research, 18:109-131, 1980
- Holland, J. H., Adaptation in natural and artificial systems, The University of Michigan Press, 1975
- Hsu, C.W., Lin, C.J., A Simple Decomposition Method for Support Vector Machines, Machine Learning, Vol.46, No.1-3, pp.291-314, 2002
- Karatzoglou A., Smola A., Hornik K., Zeileis, A., Journal of Statistical Software, vol.11, No.9, pp.1-20, 2004.
- Kin Meitetsu (editing), DONG Yanwen, Data Science of Management and Credit Risk, Kyoritsu Publishing, 2015
- Mohatab Rafiei F., Manzari S. M., Bostanian S., Financial health pre-diction models using artificial neural networks, genetic algorithm and multivariate discriminant analysis-Iranian evidence, Expert Systems with Applications 38, pp. 10210-20217, 2011
- Vanik V., Statistical Learning Theory, New York, Wiley, 1998
- Weston, J. Gammernan, A., Stitson, M., Vapnik, V., Vovk, V. and Watkins, C., Support Vector Density Estimation. In B. Scholkopf, C.J.C. Burges and, A. Smola, editors, Advances in Kernel Methods— Support Vector Learning, MIT Press, Cambridge, MA. p. 293-306, 1999
- Yanwen DONG, Xiyang HAO, Hideo SATO, Investigation of the Impact of Data Comparability on Performance of Support Vector Machine Models for Credit Scoring, Innovation and Supply Chain Management, Vol.9, No.1, 31-38, 2015
- Zhang, G., Hu, Y. M., Patuwo, E. B., and Indro, C. D., : Artificial neural networks in bankruptcy prediction, General framework and cross validation analysis, European Journal of Operational Research, 116, pp.16–32, 1999

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