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Application of Liquidity Ratios in Predicting Corporate Financial Crisis; Comparison of Support Vector Machine Model and Neural Network in Cement Industry

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ABSTRACT

Investors and financial analysts increasingly rely on accurate tools to evaluate and interpret financial statements in order to make informed decisions and minimize risks. Among various methods, financial ratios remain one of the most widely used indicators for assessing corporate financial health and identifying early warning signs of potential crises. The main objective of this study is to predict the likelihood of corporate financial distress using liquidity ratios, with a comparative focus on two powerful machine learning techniques: support vector machines (SVM) and backpropagation neural networks (BPNN). The research employs a causal-comparative design and combines both quantitative and qualitative approaches, analyzing data from 2009 to 2013 (1389–1393 in the Iranian calendar). The findings reveal that the BPNN consistently outperforms the SVM, achieving higher predictive accuracy with statistically significant differences: 0.001 in year *t*, 0.005 in year *t-1*, and 0.030 in year *t-2*. These results demonstrate the neural network's superior ability to forecast corporate bankruptcy up to two years in advance, offering a valuable tool for investors and stakeholders. Furthermore, the analysis highlights that the capital-to-total-assets ratio exerts the strongest influence on bankruptcy prediction. The study underscores the importance of integrating advanced computational methods with traditional financial indicators to enhance decision-making in dynamic economic environments.

1. INTRODUCTION

Today, one of the most important risks that threatens many commercial units, regardless of the size and nature of their activities, is the failure to pay commitments. . For investors and many private companies affected by bankruptcy of companies, the use of quick and easy tools is of prime importance. Evidence suggests that over the past three decades, bankruptcy rates have grown dramatically in comparison with previous decades [1].

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Environmental changes and ever-increasing competition of firms have limited their profitability. . For investors and many private companies affected by bankruptcy of companies, the use of quick and easy tools is of prime importance. Because they often have to make quick decisions about their capital and they may not have an analytical understanding of corporate performance [2].

The cement industry is recognized as the industry's leading industry for direct contact with 123 upstream and downstream industries. For this reason, this industry is known in every country of the mother industry [3]. A glimpse of the financial situation of companies in the cement industry also reveals that among the companies admitted to the Tehran Stock Exchange there are companies that suffer from financial problems and operational problems. In terms of operations, liquidity and circulating capital are in crisis. One of the most important challenges facing the cement industry from the viewpoint of cement producers, which confirms the importance of the subject matter, is the shortage of liquidity and inadequate working capital due to rising costs for cement factories. [4]

1.1. Literature and subject matter

Considering that bankruptcy forms the main issue of the research, this section attempts to discuss the historical course of bankruptcy and its various dimensions to be described. But it's better to outline the concepts and reasons behind bankruptcy before describing the history of bankruptcy. Many different statistical and mathematical models have been used to predict financial distress since the first publications in the 1960s. Beaver1 presented a univariate model in 1966 and two years later Altman2 pioneered the use of discriminant analysis in the field. Altman's work has been the subject of much later research, including that of Deakin3 who increased the number of explanatory variables and Edminster4 who focused on small businesses. Agarwal and Taffler5 analyze an Altman – style model using UK data over a period of 25 years. From this extensive empirical test, they concluded that the discriminant analysis approach has useful real – world predictive ability [5].

1.2. Altman (1968)

First to use multiples Discriminant Analysis (MDA) methodology, to predict distress. Altman set out to integrated a number of ratios and developed an insolvency prediction model the Z–Score model. Model _A' z-score was developed for use with private manufacturing companies. In its initial test, the Altman Z-Score was discovered to be 72% precise in predicting bankruptcy two years prior to the event, the model was found to be approximately 80-90% accurate in predicting bankruptcy one year prior to the event [6].

In 1980, Ohlson's pioneering work used logistic regression as a way of overcoming restrictive assumptions of discriminant analysis, such as normality and equal covariance [7].

In 1993, Theodossiou7 introduced sequential cumulative sum (CUSUM) procedures to predict financial distress with excellent empirical results. The soft computing methods known as artificial neural networks have also been used for financial distress prediction – Tan provides a summary [8].

Zmijewski (1984) using the experience and analysis method, four patterns were developed. The variables of this model are current assets/current liabilities, total liabilities/total assets and net profit/total assets. This model was tested for 40 bankrupt companies and 80 non-bankrupt companies, which achieved a 78% confidence one year before bankruptcy [9].

Bloom used a review analysis to analyze the model and found that this model distinguishes bankrupt companies from top companies with an accuracy of approximately 90% in the first year before the failure, 34% in the second year and 84% in the third, fourth and fifth years before the bankruptcy. And redefined. The best Bloom prediction index has a higher ratio of total debt to liquidity among variables, although the relative importance could not be explained [10].

Nikbakht and Sharifi, in their research entitled "Financial Bankruptcy Prediction of Tehran Stock Exchange Companies by Using Artificial Neural Networks", mean values related to key financial ratios, total investment capital, total net assets, total liabilities, total assets, current assets Current and current assets and current assets have been selected along with their comparison with the analysis method as inputs of neural networks. An equal set of data was analyzed using neural networks and multiple differentiation analyzes. A comparison of the capabilities of

neural network predictions and multiple differentiation analysis is presented. The prediction of neural networks is also provided. The results showed that there is a significant difference between the audit analysis and the neural network. Also, according to the results, the first type error is low on the second type prediction error [11].

Hosseini Nasab et al. In their research entitled "Comparison of the accuracy of backup machine and artificial neural networks approaches in predicting the earnings per share of the company accepted in the stock exchange". In this study, using financial data of sample companies in the yield period of 1391-1384 and Using a backup machine and a neural network, they used models to predict the earnings per share. In the end, the backup machine could predict the earnings of each share of the year with an expected 5% error rate. Also, the results showed that the two models had the same accuracy in predicting the earnings of each share [12].

2. METHOD

The main objective of this study is to evaluate which of the models to predict the financial crisis is more accurate than other models. For the measurement was used of three independent variables such as Liquidity ratios, and one dependent variable. Background the research has been penetrated independent variables used in this study.The dependent variable in this research is qualitative nature is the firm's financial crisis. Selected financial ratios used to analyze should be based on theory and empirical evidence in this regard. Also data have been collected in five-year period since 1389-1393 .We were chosen financial ratios as an input in each models.

In this paper, the statistical community is cement companies that are listed on the Tehran Stock Exchange, the general statistical community the list of 41 companies. The samples were taken following restrictions:

Companies that had changed during the period 89-93, the samples were removed.

Companies that did not provide financial information to the stock exchange during the period of 89-93 were excluded.

The companies that entered the stock during the period of 93- 89 were excluded.

Finally, the number 33 of 41 cement companies that were chosen as samples. The samples consisted of 12 healthy and 22 unhealthy companies.

It should be noted that the above hypothesis has been investigated in the form of three statistical hypotheses in years t, t-1 and t-2.

H0 = There is no significant difference between two models of support vector machine and neural network.

H1 = There is a significant difference between two models of support vector machine and neural network.

Considering the aim of this study is to compare the method of the Support vector machine and neural network. Therefore, in order to test the hypotheses, first, the data extracted from the financial statements of the companies into the Excel software, and finally used to analyze the data from MATLAB software.

Finally, we were used SPSS software for Wilcoxon test and single sample T test, to test statistical hypothesis. In this study, we assessed the recognition of healthy firms from unhealthy ones using Altman's model. The analysis of the Altman model is as follows:

$Z < 1/23$ bankrupt company

$1/23 < Z < 2/9$ suspended company

$Z > 2/9$ non-bankrupt company

3. RESULT

The support vector machine model and artificial neural network were tested using liquidity ratios. We first introduced the entire sample companies into the model education group. As you can see in Table 1, the neural network with a total accuracy of 98% and a supporting vector machine with 83.3% can be said that the neural network is more accurate. Then we considered 10 companies that included 5 healthy companies and 5 unhealthy companies

as testing groups. The neural network was able to accurately represent 99 percent accuracy of the backup machine, which is 5.85 percent higher. We divide each group into two subgroups. Which is called Healthy and Unhealthy Group, which includes 22 healthy companies and 11 unhealthy companies, and separately reviewed each of them. The results are presented in Table 1.

Table 1. General outcomes of models

The correct prediction percent			
Support Vector Machine	Neural Network		
%83/4	%99	Healthy	Train
%81/3	%98	Unhealthy	
%83/3	%98	Total	
%87	%99	Healthy	Test
%85	%98	Unhealthy	
%85/5	%99	Total	

According to the hypothesis, we examine the hypothesis in year t. Year t is the last year of the study, which is 93 years old. As you can see in Table 2, the neural network has 100% predicted yearly bankruptcy. And the backup carriers with a precise accuracy of 87.5% had a precise prediction. Referring to these results, it could be said that the neural network was more accurate.

Table 2. The results of the models are based on year t

Support Vector Machine	Neural Network	
10 companies	11 companies	Train
%86/5	%100	
21 companies	22 companies	Test
%88	%100	
31 companies	33 companies	Total
%87/5	%100	

Fig.1. shows the regression output of the neural network model. The Network training section shows 99% of the correct prediction. Also in the data testing section, the network is considered as test data, which indicates that 99% of our test data is correct. The correctness part is also a validation of the model and shows how well the model has made the prediction correct.

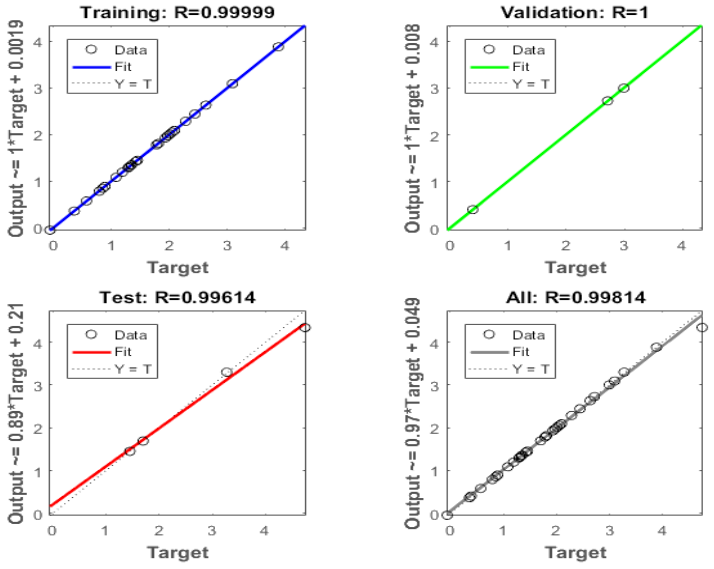

Fig.1. The output of the neural network model in year t

To test the research hypothesis of year t, the paired comparison test was used. Using this test, the performance of each model is examined based on statistical models. Table 3 shows the results of the paired comparison test. According to Table 3, the overall accuracy of the prediction of the neural network model is higher than the 95% confidence level of the overall accuracy of the supporting vector machine. As it is seen, the significance level is 0/001 <0/05. So our zero assumption is rejected. The hypothesis is confirmed for the year t.

Table 3. Paired comparison test

	SVM_ANN
Z statistic	-28/825
Sig.	0/001

According to the hypothesis, we consider the hypothesis in year t-1.

As you can see in Table 4, the neural network managed to correctly identify 32 companies from the total of 33 companies with accuracy of 99%. The support vector machine with a total of 29 companies and a prediction accuracy of 83.3% was correct. You see, in the year before bankruptcy, the neural network has been shown to be more accurate.

Table 4. The results of the models are based on year t-1

SVM	ANN	
9 companies	11companies	Healthy
%82	%99	
20 companies	21 companies	Unhealthy
%85	%99	
29 companies	29 companies	Total
%83/3	%99	

Fig. 2 shows the regression output of the neural network model. The network training section, which represents 99% of the correct prediction. Also in the data testing section, the network is considered as test data, which shows that 99% of our test data is correct. In the correctness of the results, the validation of the model shows how well the model performed the forecast accurately. That's where the 99% network is doing right.

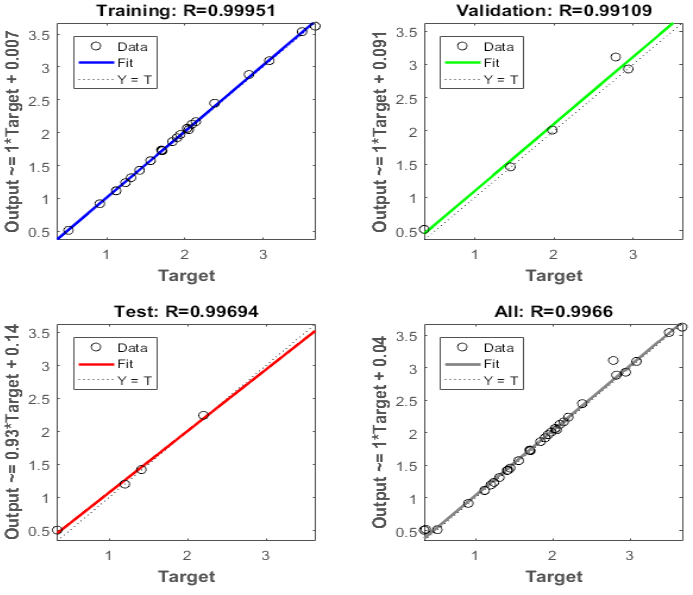

Fig. 2. the output of the neural network model is t-1

To test the t-1 research hypothesis, the paired comparison test was used. Using this test, the performance of each model is examined based on statistical models. Table 5 shows the results of the paired comparison test.

Table 5. Paired test results

	SVM_ANN
Z statistic	-13/571
Sig.	0/005

According to Table 5, the general accuracy of the prediction of the neural network model is higher than 95% confidence level of the overall accuracy of the support vector machine. As it is seen, the significance level is 0/005 <0/05. So our zero assumption is rejected. And the hypothesis is confirmed for year t-1.

According to the hypothesis, we consider the hypothesis in year t-2. As shown in Table 6, the neural network managed to identify 31 companies with 96% accuracy from the total of 33 companies. In the case of backup machines with a total of 27 companies and a precision forecast of 75%, the prediction was correct.

Table 6. The results of the models are based on year t-2

SVM	ANN	
8 companies	10 companies	Healthy
%75	%95	
19 companies	21 companies	Unhealthy
%77	%98	
27 companies	31 companies	Total
%75	%96	

Fig.3 shows the regression output of the neural network model. In the training section of the network, it shows that 99% of the predictions are correct. Also in the data testing section, the network is considered as test data, which indicates that 99% of our test data is correct. In the correctness section, the validation of the model also shows how well the model performed the forecast. Here, the network has done 96% of the predictions correctly.

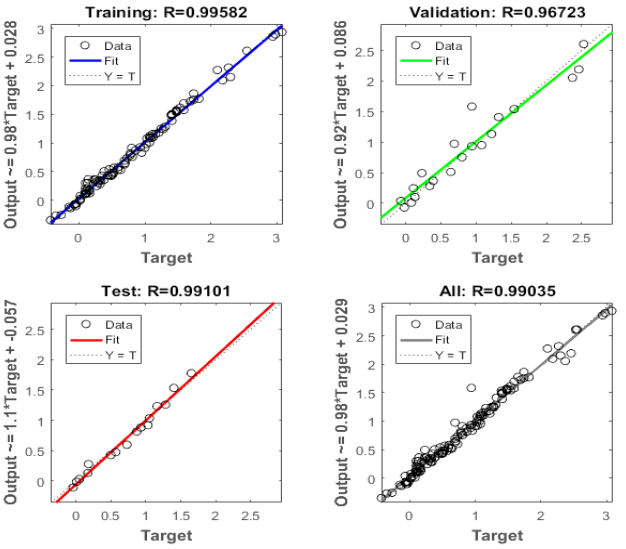

Fig.3. Neural network model output in year t-2

To test the hypothesis of year t-2, the paired comparison test was used. Using this test, the performance of each model is examined based on statistical models. Table 7 shows the results of the paired comparison test.

Table 7. Paired test results

	SVM_ANN
Z statistic	-62/000
Sig	0/000

According to Table 7, the general accuracy of the prediction of the neural network model is higher than the 95% confidence level of the overall accuracy of the supporting vector machine. As it is seen, the significance level is 0/000 <0/05. So our zero assumption is rejected. And the hypothesis is confirmed for year t-2.

4. CONCLUSION

Prediction of Financial crisis and corporate bankruptcy are one of the key issues in financial management. Given the fact that companies are influenced by internal and external factors, as well as the cement industry, which is also influenced by external factors such as economic conditions, as the mother industry. The importance and necessity of this research. In this study, the prediction of the financial crisis of cement companies was carried out using four models of support vector machine and neural network.

The results indicated that the neural network model was significantly higher than support vector machine model. And also liquidity ratios are effective in predicting financial crisis. And Ratio of working capital, including liquidity ratios, which has the highest impact among these ratios. The results of this study were compared with previous studies. The results of this study were similar to those of similar studies. In similar internal investigations, the neural network model was more accurate than the support vector machine. The results showed that liquidity ratios are an appropriate tool for predicting bankruptcy.

Researchers can achieve different and better results by employing different industries and raising the statistical community. Because of the limited difficulty of the statistical community in the investigator. And it's also possible that different industries will have different results. And the use of inflation rates in the prediction of bankruptcy and the use of other ratios such as leverage ratios and activity can also result in different and more precise results.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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