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Ahmadreza Ghasemi
Assistant Professor, Industrial Management, Faculty of Management and Accounting, College of Farabi, University of Tehran, Iran.
e-mail: ghasemiahmad@ut.ac.ir
***Mohsen Seyghali*[b]**
Assistant Professor, Financial Management, Faculty of Financial Management, University of Tehran, Iran, e-mail: seighali@ut.ac.ir
Maryam Moradi
MSc. in Business Management Financial, Ershad Damavand University, Tehran, Iran, e-mail: maryam.morady1369@yahoo.com

PREDICTION OF FINANCIAL DISTRESS, USING METAHEURISTIC MODELS

Abstract. Investors need to assess and analyze the financial statement, to make the logical decision. Using financial ratios is one of the most common methods. The main purpose of this research is to predict the financial crisis, using ratios of liquidity. Four models, Support vector machine, neural network back propagation, Decision trees and Adaptive Neuro–Fuzzy Inference System has been compared.Furthermore, the ratios of liquidity considered in a period of 89_93. The research method is qualitative and quantitative and type of casual comparative. The result indicates that the accuracy of the neural network, Decision tree, and Adaptive Neuro–Fuzzy Inference System showed that there is a significant differently 0/000 and 0/005 years this is more than support vector machine result. Therefore the result of support vector machine showed that there is a significant differently 0/001 in years. This has been shown that neural network in 2 years before the bankruptcy has the ability to predict a right thing. Therefore, the results have been shown that all four models were statistically significant. Consequently, there are no significant differences. All models have the precision to predict the financial crisis.

Keywords: financial crisis, neural network, Decision tree, Adaptive Neuro–Fuzzy Inference System, support vector machine.

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Ахмадреза Гасемі
доцент,
факультет менеджменту та бухгалтерського обліку, промисловий менеджмент, Коледж Фарабі, Тегеранський університет, Іран;
e-mail: ghasemiahmad@ut.ac.ir
Мохсен Сейгалі
доцент, Фінансовий менеджмент,
факультет фінансового менеджменту, Тегеранський університет, Іран, e-mail: seighali@ut.ac.ir
Марій Мораді
магістр у сфері управління фінансами,
Університет Ершад Дамаван, Тегеран,
Іран, e-mail: maryam.morady1369@yahoo.com

ПРОГНОЗ ФІНАНСОВИХ ПРОБЛЕМ, ВИКОРИСТОВУЮЧИ МЕТАЕВРИСТИЧНІ МОДЕЛІ

Анотація: Інвесторам необхідно оцінити та проаналізувати фінансову звітність, прийняти логічне рішення. Використання фінансових показників є одним з найпоширеніших методів. Основна мета цього дослідження – прогнозувати фінансову кризу, використовуючи співвідношення ліквідності. Чотири моделі: векторні машини підтримки, зворотне розповсюдження нейронних мереж, дерево рішень та адаптивна система нейро–нечіткого висновку. Крім того, коефіцієнти ліквідності розглянуті в період 2011–2015 рр. Метод дослідження є якісним та кількісним, а також тип випадкової порівняльної. Результат показує точність нейронної мережі, дерево рішень, і система Adaptive Neuro–Fuzzy Inference показала, що значно відрізняється від 0/000 і 0/005 років, це більше, ніж підтримка векторної машини. Тому результат підтримки векторної машини показав, що існує значно по–різному 0/001 років. Це показало, що нейронна мережа за 2 роки до банкрутства має можливість прогнозувати правильну річ. Тому результати показали, що всі чотири моделі були статистично значущими. Отже, істотних відмінностей немає. Всі моделі мають точність прогнозування фінансової кризи.

Ключові слова: фінансова криза, нейронна мережа, дерево рішень, адаптивна система нейро–нечіткого висновку, векторна машина підтримки.

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Ахмадреза Гасеми

доцент, факультет менеджмента и бухгалтерского учета,
промышленный менеджмент,
Колледж Фараби, Тегеранский университет,
Иран; e-mail: ghasemiahmad@ut.ac.ir

Мохсен Сейгали

Доцент, Финансовый менеджмент,
Факультет финансового менеджмента,
Тегеранский университет, Иран
e-mail: seighali@ut.ac.ir

Марий Моради

Магистр в сфере управления финансами, Университет Эршада Дамаван, Тегеран,
Иран; e-mail: maryam.morady1369@yahoo.com

ПРОГНОЗ ФИНАНСОВЫХ ПРОБЛЕМ, ИСПОЛЬЗУЯ МЕТАЭВРИСТИЧЕСКИЕ МОДЕЛИ

Аннотация: Инвесторам необходимо оценить и проанализировать финансовую отчетность, принять логическое решение. Использование финансовых показателей является одним из самых распространенных методов. Основная цель этого исследования – прогнозировать финансовый кризис, используя соотношение ликвидности. Четыре модели: векторные машины поддержки, обратное распространение нейронных сетей, дерево решений и адаптивная нейро–нечеткая система вывода. Кроме того, коэффициенты ликвидности рассмотрены в период 2011–2015 гг. Метод исследования является качественным и количественным, а также тип случайной сравнительной. Результат показывает точность нейронной сети, дерево решений, и система Adaptive Neuro–Fuzzy Inference показала, что значительно отличается от 0/000 и 0/005 лет, это больше, чем поддержка векторной машины. Поэтому результат поддержки векторной машины показал, что существует значительно по–разному 0/001 лет. Это показало, что нейронная сеть за 2 года до банкротства имеет возможность прогнозировать правильно. Поэтому результаты показали, что все четыре модели были статистически значимыми. Итак, существенных различий нет. Все модели имеют точность прогнозирования финансового кризиса.

Ключевые слова: финансовый кризис, нейронная сеть, дерево решений, адаптивная нейро–нечеткая система вывода, векторная машина поддержки.

Формул: 2; рис.: 4; табл.: 5; библ.: 19

Introduction. Bankruptcy is an objective and practical issue facing businesses and firms and because of its frequency, it has found a special niche in financial and investment literature following the motto "prevention is better than cure".

Prediction of bankruptcy is so important for organizations at all, and agencies because it has a profound impact on the economy and raises prices causing many social problems. There are many methods and techniques through which investors and economic analysts can predict bankruptcy (Salehi and Davoudipour, 2016).

Financial crisis prediction, which is based on financial information, aims at diagnosing and predicting the potential financial crisis in enterprises' operation. It has been attracting wide attention since the 1960s. Odom is the first to apply the neural network model to financial crisis prediction of banks; the neural network is inclined to local optima in the course of study and optimization. And support vector machine (SVM) performs better in solving nonlinear approximation and local optimum than neural network, thus SVM has been drawing wide attention in the field of financial crisis prediction recently And support vector machine (SVM) performs better in solving nonlinear approximation and local optimum than neural network, thus SVM has been drawing wide attention in the field of financial crisis prediction recently (Han and Zhao, 2015).

Both neural networks and fuzzy logic principles are two part of adaptive networks that incorporate, ANFIS is one of them. Furthermore, in historical data set for the prediction of future values, neural networks have supervised learning algorithms. In fuzzy logic, the control signal is generated from firing the rule base. This rule base is drawn on historical data and is random in nature (Mathur and others, 2016).

In this study, five important ratios used for bankruptcy prediction and classification models can help to select financial ratios and increase prediction accuracy. The results of this research can be basic criteria for evaluating a performance of an enterprise and to sustain its activities. The need or lack of need for continuity provides firm, assess their actions.

Research History. Many statistical and mathematical models have been used to predict financial distress since the first publications in the 1960s. Uni variate model in 1966 presented by beaver and two years later Altman pioneered the use of discriminant analysis in the field. Altman's work has been the subject of much later research, including that of Deakin who increased the number of explanatory variables and Edminster who focused on small businesses. Agarwal and Taffler 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. As well as interesting to note that Agarwal and Toffler recommend that once models become out–of–date, which can take a long time; it is preferable to build a completely new model rather than simply re–estimate coefficients of existing models (Gepp and Kumar, 2015).

Altman (1968). First to use multiples Discriminant Analysis (MDA) methodology, to predict distress. Moreover, He set out to integrate 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. Accordingly, 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.

Consequently, Altman's 1968 model took the following form:

$$Z = 0.012X1 + 0.014X2 + 0.33X3 + 0.006X4+X5 \tag{1}$$

Where:

X1=Working capital/total assets;

X2=Retained earnings/ total assets;

X3=Earnings before interest and taxes/total assets;

X4=Market value of equity/book value of total liabilities;

X5=Sales/total assets.

The usefulness of financial ratio analysis for prophesying small business failure has been tested by Robert O.E. His research has shown that analysis of selected ratios is useful for predicting failure of medium and large asset–size firms. However, previous studies have largely ignored small businesses because of the difficulty of obtaining data (Robert, 1972).

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.

In 1993, Theodossiou 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 (Williams and Rasmussen, 1996).

Eleftherios Giovanis in his study two approaches is used able for the prediction of the economic recession or development periods in the USA. The First approximation comprises Logit and probit models, the second is an Adaptive Neuro–Fuzzy Inference System (ANFIS) use of Gaussian and Generalized Bell membership functions. The results show that the ANFIS model outperforms the Logit and Probit model. This mention that neuro–fuzzy model provides a better and more credible signal on whether a financial distress will take place (Giovanis, 2010).

More recently in 2011, du Jardin and Severinoutlined an approach using a Kohonen map that has shown promise in making predictions over longer periods. There are also many other techniques that have been used to predict financial distress, including support vector machines and nearest neighbor, survival analysis and decision trees (Jardin, 2011).

Since the literature on corporate distress in African contexts is rather economical, this study makes an important contribution to the global discourse on corporate distress prediction in an increasingly globalized world (Appiah, K, 2011).

Accordingly to Lopez Mas, A, Have developed a statistical business distress prediction model specifically for cooperative societies and identifies the most powerful predictive agricultural cooperatives with financial indicators as explicative variables. The prediction models procure variables. This is done by applying logistic regression to a sample of Spanish, proficient of predicting distress one or two years before they actually happen, reached an exactness level of more than %94. The best predictors confirmed the importance to cooperatives of having a minimum amount of capital available to ensure their financial independence, which could be put at risk by virtue of the cooperative principle of ―voluntary and open membership‖, especially when financial problems appear on the horizon. Consequently, the importance of the results–based indicators was also shown, which could be considered as obvious, given that the objectives of cooperative societies are to obtain the greatest possible advantage from the activities carried out by their members(Mateo and et al., 2011).B–Sherrod’s Failure Prediction Model One of the most modern models to predict financial distress, this model rely on the six independent financial indicators, in addition to the relative weights of discrimination function coefficients given for these variables, according to the following formula(Abu Orabi,2014).

$$Z = 17X1 + 9X2 + 3.5X3 + 20X4 + 1.2X5 + 0.10X6 \quad (2)$$

Where as:

X1 = Working capital to total assets.

X2 = cash assets to total assets.

X3 = total shareholders' equity to total assets.

X4 = earnings before interest and taxes to total assets.

X5 = total assets to total liabilities.

X6 = total shareholders' equity to tangible fixed assets.

Neophytou E. et al improved a distress classification model for UK public industrial companies using logit and Neural Networks analysis. They consume a dataset consists of 51 matched–pairs of failure and non– failure UK public industrial firms over the period 1988–1997.Research results exhibit that a parsimonious model that includes three financial ratios, a profitability, an operating cash–flow and a financial leverage ratio can yield an overall correct classification preciseness of %83 one year prior to failure(Abu Orabi,2014).

Financial distress and then the consequent failure of a business is generally a highly costly and disruptive event. Statistical financial distress prediction models assay to predict whether a business will experience financial distress in the future. Discriminant analysis and logistic regression have been the most well–liked approaches, but there is also a large number of alternative cutting – edge data mining techniques that is able to be used. The results show that decision trees and survival analysis models have good prediction accuracy that vindicate their use and supports further investigation (Gepp and Kumar, 2015).

Han and Zhao in their research describe that, forecasting financial distress is generally researched by means of the kernel principal component analysis (KPCA) and the support vector machine (SVM) model. However, kernel functions utilization in these methods is fundamentally single. In fact, hybrid kernel functions are superior to the component kernel functions in referring to nonlinear issues, for they can make full use of the feature mapping capability of different kernel functions. Based on bi–orthogonal wavelet kernel functions CDF9/7 and linear kernel functions, a new kind of bi–orthogonal wavelet hybrid kernel functions are assembled. Besides, KPCA–SVM models based on hybrid kernel functions are also proposed for forecasting financial distress. The empirical research on the listed companies in China's securities market is conducted at last. The results display that the new type of bi–orthogonal wavelet hybrid kernel function can enhance the feature taking out of KPCA and enhance the forecasting accuracy of SVM model, and then the accuracy of the forecast financial distress can be improved (Han and Zhao, 2015).

Wang and Wu in their study adopts manifold learning algorithm to choose feature subsets, and employs the kernel–based FSOM (KFSOM) to create base classifiers, and recommend the two–stage selective ensemble model for business distress prediction. At First, three manifold learning algorithms, which are Isomap, Laplacian Eigen maps and Locally Linear insert, are adopted to choose three feature subsets from original financial data. Then, KFSOM uses three kinds of kernel functions correspondingly, which is Gaussian, Polynomial, and Sigmoid, to obtain three classifiers. Hence, three feature subsets are calculated by KFSOMs with three kernel functions respectively to acquire nine base classifiers. At Last, nine base classifiers are merged by the two–stage selective ensemble method. The first stage, nine base classifiers are classification according to three standards. The stepwise forward choose approach is adopted to selectively integrate nine base classifiers according to different standards. In the second stage, three chosen ensembles in the first stage are merged again to acquire the result. In the empirical research, employs financial data from Chinese listed companies to forecasts business distress, and makes a comparative analysis with previous methods. It is the result that the two–stage chosen ensemble with manifold learning algorithm and KFSOM is good at forecasting business distress (Wang and wu, 2016).

Mathur and et al. in their research said that surveillance of the interface temperature at skin level in lower–limb prosthesis is notoriously hard to understand. It is because the flexible nature of the interface liners used impeding the requirement consistent positioning of the temperature sensors during donning and doffing. Forecasting the in–socket remainder limb temperature by monitoring the temperature between socket and liner rather than skin and liner could be an arrogant step in alleviating complaints on raised temperature and perspiration in prosthetic sockets. In this paper, we tender to implement an adaptive neuro fuzzy inference strategy (ANFIS) to predict the in–socket residual limb temperature. ANFIS suit to the family of fused neuro fuzzy system in which the fuzzy system is incorporated in a framework which is adaptive in nature. The tender method is compared to our earlier work using Gaussian processes for machine learning. By comparing the forecasted and actual data, results show that both the modelling techniques have similar performance metrics and can be efficiently used for non–invasive temperature supervision (Mathur and et (Mathur and et al.,2016).

Sun and et al. in their research titled" Dynamic financial distress prediction with concept drift based on time weighting combined with Adaboost support vector machine ensemble" said that, Dynamic financial failure prediction (DFDP) is important for enhancing corporate financial risk management. However, recent studies refuse the time weight of samples when constructing ensemble FDP models. Their study recommend two new DFDP approaches based on time weighting and AdaBoost support vector machine (SVM) ensemble. One of them is the double expert voting ensemble based on AdaBoost–SVM and Timeboost–SVM (DEVE–AT), which exterior integrated the outputs of an error–based decision expert and a time–based decision expert. The other one is AdaBoost SVM internally combined with time weighting (ADASVM–TW) that uses a novel error–time–based sample weight updating function in the AdaBoost repetition. Empirical research is accomplish with sample data of 932 Chinese listed companies' 7 financial ratios, and time moving procedure is simulated by separating the sample data into 13 batches with one year as a time step. The results show that both DEVE–AT and ADASVM–TW have significantly better DFDP performance than single SVM, the batch–based ensemble with a local weighted scheme, AdaBoost–SVM, and Timeboost–SVM, and they are more appropriate for disposing of concept drift of financial failure (Sun and et al., 2016).

Li and et al. in their research titled "Dynamic prediction of financial distress using malmquist DEA" in banks said that, banks are often required to provide the rationale behind their decisions in addition to being able to predict the performance of companies when assessing corporate applicants for loans. They used Data Envelopment Analysis (DEA) to evaluate multiple decision–making units. A linear programming algorithm is occupied to estimate corporate efficiency as a measure to recognize healthy companies from those in financial distress. Their research extends the cross–sectional DEA models to time–varying Malmquist DEA. They used 742 sample of Chinese listed companies showed over 10 years suggest that Malmquist DEA offers insights into the competitive situation of a company in addition to accurate financial failure predictions based on the DEA efficiency measures. They showed other DEA algorithms such as standard DEA, Network DEA or Window DEA does not completely fit the bankruptcy prediction paradigm. A weakness of Malmquist DEA is that it is calculation intensive and cannot handle very large datasets (Li and et al., 2017).

Salehi and Davoudipour have investigated Iran Khodro companies using the Neural Network prediction model. They use the neural network–based predictive model used in their study to confirm the model, prediction of failure among 14 auto parts companies was undertaken for 2011. This forecasting was based on data collected for the past ten years. At last, the proposed model furnish accurate predictions for auto parts manufacturers using failure and not failure classifications. Iran Khodro Diesel Company as a non–failure company, the models forecasting was wrong. Zamiyad Company was a failing company but the model illegally classified it as a non–failure company. The result shows overall information of the model. The model also provided an incorrect forecasting for Iran Khodro Company which was non–failure, but the model wrongly classified it as a failed company. Finally, based on companies' classification into non–failure and failure companies, the final model of the neural network was able to predict not failure and failure auto parts manufacturers with the accuracy of %87.5 (Salehi and Davoudipour, 2016).

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 five independent variables and the dependent variable. Background the research has been penetrated independent variables used in this study, five financial ratios, according to the study being used Soleimani's research (2010). As well as the validity and reliability of the variables were tested in this study. The dependent variable in this research is qualitative nature is the firm's financial crisis. analyze should be based on theory and empirical evidence in this regard by selected financial ratios. As well as, data have been collected in the five–year period since 1389–1393.We were chosen financial ratios as an input in each model.

Independent variables include:

- Working Capital/Total Assets
- Earnings before Interest and Taxes/ Total Assets
- Total Stockholders' Equity/ Total Assets
- Sale/ Total Assets
- Current Asset /Total Assets

Accordingly, 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.

Consequently, 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.

Hypothesis. Therefore, the neural network model is highly predictive of the financial crisis.

1. An Adaptive Neuro–Fuzzy Inference System is highly predictive of the financial crisis.
2. A Support Vectors Machines model is highly predictive of the financial crisis.
3. A Decision tree model is highly predictive of the financial crisis.

Adaptive Network–Based Fuzzy Inference System. This implies that the controller's output is also random which may prevent optimal results. The use of ANFIS can make the selection of the rule base more adaptive to the situation. In this technique, the rule base is selected utilizing the neural network techniques via the back propagation algorithm. To enhance its applicability and performance, the properties of fuzzy logic, i.e. approximating a nonlinear system by setting IF–THEN rules are inherited in this modeling technique. This integrated approach, makes ANFIS be a universal estimator (Kusagur and et al., 2010).

One of a hybrid system's family is ANFIS, called as the term 'neuro fuzzy networks 'inheriting the properties of both neural networks and fuzzy logic. Neural networks can easily learn from the data. However, it is difficult to interpret the knowledge as– queried by it, as meaning associated with each neuron and each weight it quite complexes to comprehend. In contrast, fuzzy logic it– self cannot learn from the data. But fuzzy–based models are easily understood as it utilizes linguistic terms rather than numeric and the structure of IF–THEN rules (Mathur and et al., 2016).

A well– founded tool within machine learning that has become is supported vectors machines.In practice they work Excellent and have been used across a wide range of applications from acknowledging handwritten digits, to face identification, text categorization, bio informatics and database marketing. The whole approach is systematic and properly inspired by statistical learning theory(Campbell and Ying, 2011).

consequently, decision trees, or classification trees, are a non–parametric data – mining technique. The trees are built by a recursive process of splitting data when moving from higher–to–lower levels. There are different algorithms that be able used to build decision trees, and the selection of algorithm can make a difference to performance. Decision tree software called THAID was developed for classification tasks by Morgan and Messenger in the 1970s.

Model generation and prediction. The ANFIS model is designed using MATLAB's Fuzzy Logic Tool– box. The optimized sets of rules were generated using the grid partition method. The architecture of the realized ANFIS model had the following specifications; number of nodes: 92,

Number of linear parameters: 32
Number of nonlinear parameters: 40
Total number of parameters: 72
Number of training data pairs: 165
Number of fuzzy rules: 32

The number of iterations required for mapping is known as epochs. It is observed from Fig.1

That 50 iterations (epochs) are required to train the model on data set, with a minimal error of 0.38062.

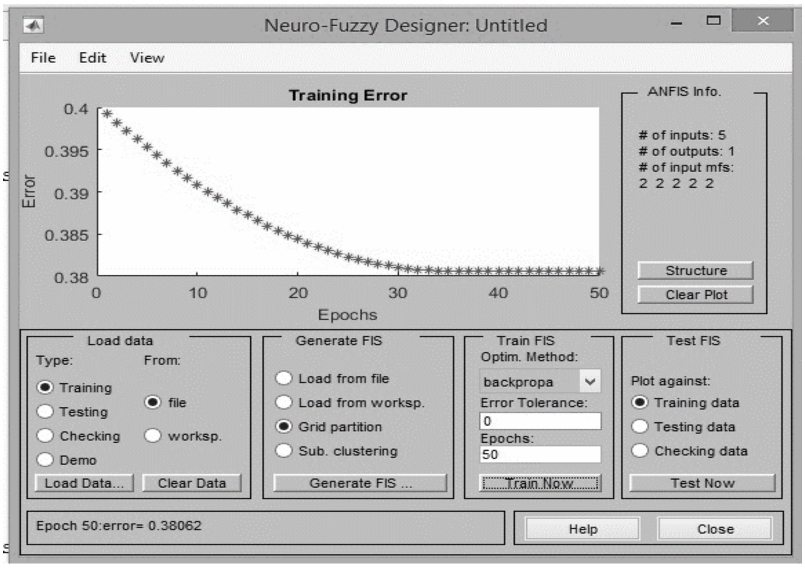

Fig.1. Epochs and training error in ANFIS
(Source: The result of the research)

Consequently, after the data were collected as time series, the neural network is designed using MATLAB software in such a way that it receives data from the beginning up to time t and then it is trained by the data. In this way, the network is able to provide its predictions in the considered time interval. This prediction is known a test for designed model performance. To examine the neural network, the back propagation neural network (BPNN), we used one of the most popular algorithms for training multilayer neural network and result of neural the network has been shown in fig.2. Validation shows how well the model performed the forecast correctly. Here, the %97 network has done the right thing.

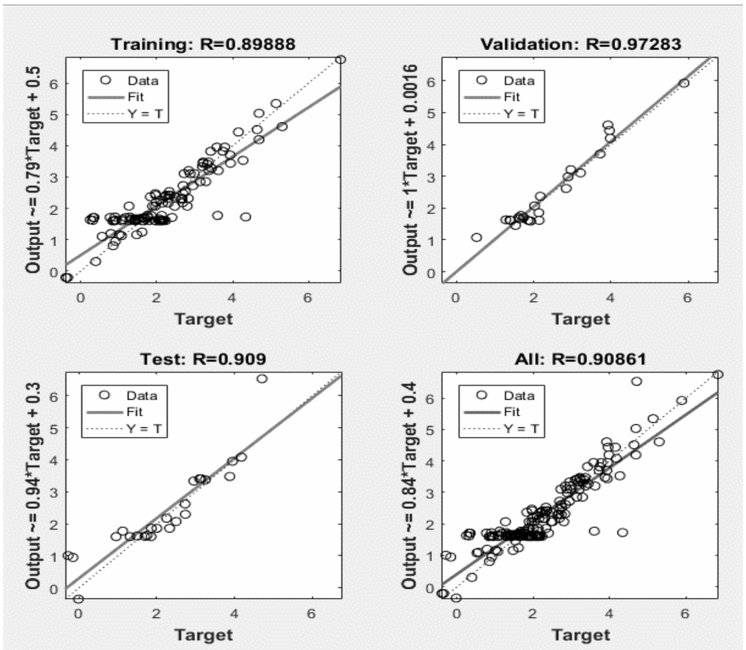

fig.2. the result of neural network
(Source: The result of the research)

As well as for test support vector machine, we used kernel function (RBF) that it is most accurately than other models of support vector machine. The result of support vector machine has been shown in Fig. 3. And the result of decision trees has been shown in Fig.4.

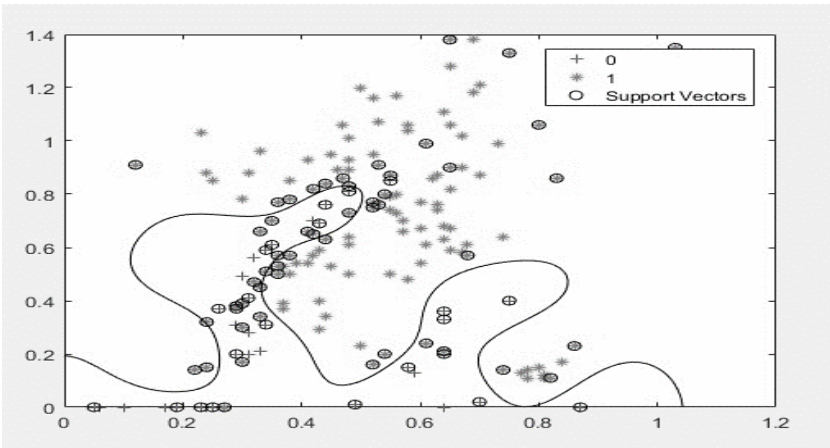

Fig.3.Result of support vector machine (RBF)
(Source: The result of the research)

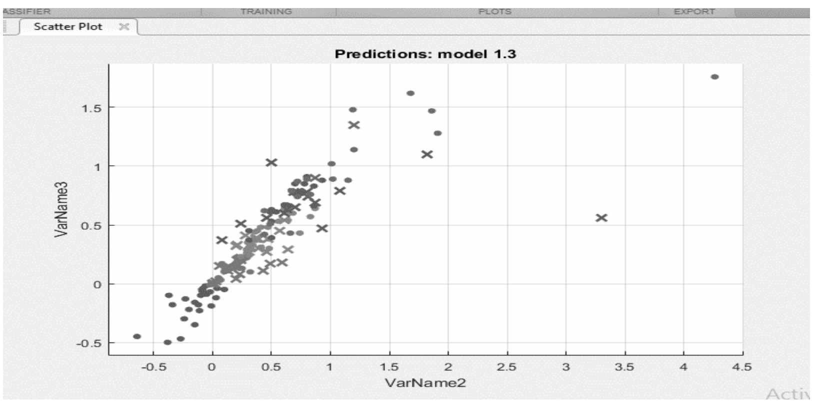

Fig.4.Result of Decision trees Result
(Source: The result of the research)

Result. Consequently, after the overall results of the models were obtained, we selected a group of 10 companies, which included 5 healthy companies and 5 unhealthy companies, as the testing group. We trained a total of 33 companies that comprise our entire sample. Then we introduced 10 companies as the test groups into the model. The results of the models are summarized in table 1.

Table 1

The results of models

Validation				Error				
DECISION TREES	ANFIS	SVM	BPNN	DECISION TREES	ANFIS	SVM	BPNN	
%87	%85	%75	%97	0.46	0.38	0.40	0.08	Train
%83	%70	%77	%97	0.39	0.53	0.22	0.03	Test

(Source: The result of the research)

Moreover, as you can see, the neural network with a confidence of %97 is more accurate.

Testing of models based on year t According to the table2, the neural network, with a total error of %1, and %99 is the best prediction accuracy. Decision trees with a total error of %29 and %80.6 accuracy are in the second rating. ANFIS with a total error of %28 and %80 accuracy is the third rating and the Support vector machine with a total error of %29 and %58.2 accuracy is the last one.

Table 2

Testing of models based on year t

Error	Validation	
0.01	%99	BPNN
0.68	%58.2	SVM
0.28	%80	ANFIS
0.29	%80.6	DECISION TREES

(Source: The result of the research)

Table 3 shows the results of a year before bankruptcy it shows that in a year before bankruptcy, the neural network model is the best one.

Table 3

Testing of models based on year t–1

Error	Validation	
0.01	%99	BPNN
0.68	%57	SVM
0.28	%80	ANFIS
0.55	%73.3	DECISION TREES

(Source: The result of the research)

Table 4 shows the results of two years before bankruptcy. According to the results, as we see, as far as year t is concerned, the difference between the two models is greater. So the neural network can predict well, bankruptcy two years before, according to the financial ratios.

Table 4

Testing of models based on year t–2

Error	Validation	
0.02	%98	BPNN
0.69	%56.1	SVM
0.40	%85	ANFIS
0.22	%77	DECISION TREES

(Source: The result of the research)

Hypothesis test. According to the results, we discuss the hypotheses as follows:

Table 5

The result of T independent model

Models	T statistic	P–Value	Mean	Std. deviation
BPNN	174/413	0/000	78/00000	1/00000
ANFIS	21/909	0/000	44/66000	6/12372
SVM	9/600	0/001	60/00000	10/40279
DT	25/421	0/000	60/18000	5/29358

(Source: The result of the research)

All four hypothesis with confidence level are less than %5. Therefore, the assumption H0 is rejected and the correlation between these two variables is confirmed. This means that the neural network, An Adaptive Neuro–Fuzzy Inference System, Support Vectors Machines and Decision tree has high power in predicting a financial crisis.

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, neural network, an Adaptive Neuro–Fuzzy Inference System and decision trees.

The results showed that financial ratios are a suitable tool for predicting bankruptcy. In sum, it should be noted that using the results of this study as a first step in preventing the bankruptcy of companies.

Although the results of this research are similar to the results of other researcher such as: Ting Hang, Qiu chen Zhao (2015), Abu Orabi (2014), Neha Mathur, Ivan Glesk, Arjan Buis (2016) and Mahdi Salehi, Mojdehs Davoudi Pour (2016).

Література

1. Salehi, M. Bankruptcy prediction of listed companies in Tehran Stock Exchange [Text] / Mahdi Salehi, Mojdeh Davoudi Pour // International Journal of Law and Management. – 2016. – Vol. 58, Issue 5. – P. 545–561.
2. Han, T. T. Financial crisis predictions based on biorthogonal wavelet hybrid kernel support vector machine [Text] / Ting–ting Han, Qiu–chen Zhao // 11th International Conference on Natural Computation (ICNC), 15–17 Aug. 2015. – P. 719–724.
3. Mathur, N. Comparison of adaptive neuro–fuzzy inference system (ANFIS) and Gaussian processes for machine learning (GPML) algorithms for the prediction of skin temperature in lower limb prostheses [Text] / Neha Mathur, Ivan Glesk, Arjan Buis // Medical engineering & physics. – 2016. – Vol. 38, Issue 10. – P. 1083–1089.
4. Gepp, A. Predicting financial distress: A comparison of survival analysis and decision tree techniques [Text] / Adrian Gepp, Kuldeep Kumar // Procedia Computer Science. – 2015. – Vol. 54. – P. 396–404.
5. Altman, E. I. The success of business failure prediction models: An international survey [Text] / Edward I. Altman // Journal of Banking and Finance. – 1984. – Vol. 8, Issue 2. – P. 171–198.
6. Ohlson, J. A. Financial ratios and the probabilistic prediction of bankruptcy [Text] / James A. Ohlson // Journal of Accounting Research. – 1980. – Vol. 18, № 1. – P. 109–131.
7. Edmister, R. O. An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction [Text] / R. O. Edmister // The Journal of Financial and Quantitative Analysis. – 1972. – Vol. 7, № 2. – P. 1477–1493. – Supplement: Outlook for the Securities Industry.
8. Williams, C. K. I. Gaussian processes for regression [Text] / Christopher K. I. Williams, Carl Edward Rasmussen // Advances in Neural information processing systems 8 : Proceedings of the 1995 Conference / Eds David S. Touretzky, Michael C. Mozer, Michael E. Hasselmo. – MIT press, 1996. – P. 514–520.

9. Giovanis, E. Study of Discrete Choice Models and Adaptive Neuro–Fuzzy Inference System in the Prediction of Economic Crisis Periods in USA [Text] / Eleftherios Giovanis // Economic Analysis and Policy. – 2012. – Vol. 42, Issue 1. – P. 79–95.
10. Jardin, P. Predicting Corporate Bankruptcy Using a Self–Organizing Map: An Empirical Study to Improve the Forecasting Horizon of a Financial Failure Model [Text] / Philippe du Jardin, Eric Séverin // Decision Support Systems. – 2011. – Vol. 51, Issue 3. – P. 701–711.
11. Appiah, K. O. Corporate Failure Prediction: Some Empirical Evidence from Listed Firms in Ghana [Text] / Kingsley Opoku Appiah // China–USA Business Review. – 2011. – Vol. 10, № 1. – P. 32–41.
12. Mateos–Ronco, A. Developing a business failure prediction model for cooperatives: Results of an empirical study in Spain [Text] / Alicia Mateos–Ronco, Ángela López Mas // African Journal of Business Management. – 2011. – Vol. 5, № 26. – P. 10565–10576.
13. Orabi, M. M. A. Empirical Tests on Financial Failure Prediction Models [Text] / Marwan Mohammad Abu Orabi // Interdisciplinary journal of contemporary research in business. – 2014. – Vol. 5, № 9. – P. 29–43.
14. Wang, L. Business failure prediction based on two–stage selective ensemble with manifold learning algorithm and kernel–based fuzzy self–organizing map [Text] / Wang Lu, Wu Chong // Knowledge–Based Systems. – 2017. – Vol. 121. – P. 99–110.
15. Dynamic financial distress prediction with concept drift based on time weighting combined with Adaboost support vector machine ensemble [Text] / J. Sun et al. // Knowledge–Based Systems. – 2017. – Vol. 120. – P. 4–14.
16. Li, Z. Dynamic prediction of financial distress using Malmquist DEA [Text] / Li Zhiyong, Jonathan Crook, Galina Andreeva // Expert Systems with Applications. – 2017. – Vol. 80. – P. 94–106.
17. Soleymani Amiri, Gh. Investigating of the efficiency of financial distress prediction models in Iranian Companies [Text] / Gholamreza Soleimany Amiri // Journal of Accounting Knowledge. – 2010. – Vol. 1, № 2. – P. 139–158.
18. Kusagur, A. Modeling, design &simulation of an adaptive neuro fuzzy inference system (ANFIS) for speed control of induction motor [Text] / Ashok Kusagur, S. F. Kodad, B V. Sankar Ram // International Journal of Computer Applications. – 2010. – № 12.
19. Campbell, C. Learning with support vector machines [Text] / Colin Campbell, Yiming Ying. – Morgan & Claypool Publishers, 2011. – 100 p. – (Synthesis lectures on artificial intelligence and machine learning).

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References

1. Salehi, M., & Pour, M. D. (2016). Bankruptcy prediction of listed companies in Tehran Stock Exchange. *International Journal of Law and Management, 58(5)*, 545–561.
2. Han, T. T., & Zhao, Q. C. (2015, August). Financial crisis predictions based on biorthogonal wavelet hybrid kernel support vector machine. *11th International Conference on Natural Computation (ICNC)*, 719–724.
3. Mathur, N., Glesk, I., & Buis, A. (2016). Comparison of adaptive neuro–fuzzy inference system (ANFIS) and Gaussian processes for machine learning (GPML) algorithms for the prediction of skin temperature in lower limb prostheses. *Medical engineering & physics, 38(10)*, 1083–1089.
4. Gepp, A., & Kumar, K. (2015). Predicting financial distress: A comparison of survival analysis and decision tree techniques. *Procedia Computer Science, 54*, 396–404.
5. Altman, E. I. (1984). The success of business failure prediction models: An international survey. *Journal of Banking and Finance, 8(2)*, 171–198.
6. Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of accounting research, 18(1)*, 109–131.
7. Edmister, R. O. (1972). An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction. *The Journal of Financial and Quantitative Analysis, 7(2)*, 1477–1493.
8. Williams, C. K. I., & Rasmussen, C. E. (1996). Gaussian processes for regression. *Advances in Neural information processing systems 8 : Proceedings of the 1995 Conference*, 514–520.
9. Giovanis, E. (2012). Study of Discrete Choice Models and Adaptive Neuro–Fuzzy Inference System in the Prediction of Economic Crisis Periods in USA. *Economic Analysis and Policy, 42(1)*, 79–95.
10. Jardin, P., & Séverin, E. (2011). Predicting Corporate Bankruptcy Using a Self–Organizing Map: An Empirical Study to Improve the Forecasting Horizon of a Financial Failure Model. *Decision Support Systems, 51(3)*, 701–711.
11. Appiah, K. O. (2011). Corporate Failure Prediction: Some Empirical Evidence from Listed Firms in Ghana. *China–USA Business Review, 10(1)*, 32–41.
12. Mateos–Ronco, A., & Mas, A. L. (2011). Developing a business failure prediction model for cooperatives: Results of an empirical study in Spain. *African Journal of Business Management, 5(26)*, 10565–10576.
13. Orabi, M. M. A. (2014). Empirical Tests on Financial Failure Prediction Models. *Interdisciplinary journal of contemporary research in business, 5(9)*, 29–43.
14. Wang, L., & Wu, C. (2017). Business failure prediction based on two–stage selective ensemble with manifold learning algorithm and kernel–based fuzzy self–organizing map. *Knowledge–Based Systems, 121*, 99–110.
15. Sun, J. (2017). Dynamic financial distress prediction with concept drift based on time weighting combined with Adaboost support vector machine ensemble. *Knowledge–Based Systems, 120*, 4–14.
16. Li, Z., Crook, J., & Andreeva, G. (2017). Dynamic prediction of financial distress using Malmquist DEA. *Expert Systems with Applications, 80*, 94–106.
17. Soleymani Amiri, Gh. (2010). Investigating of the efficiency of financial distress prediction models in Iranian Companies, *Journal of Accounting Knowledge, 1(2)*, 139–158.
18. Kusagur, A., Kokad, S. F., & Ram, B. V. S. (2010). Modeling, design &simulation of an adaptive neuro fuzzy inference system (ANFIS) for speed control of induction motor. *International Journal of Computer Applications, 12*.
19. Campbell, C., & Ying, Y. (2011). *Learning with support vector machines*. Morgan & Claypool Publishers.

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