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USAGE OF THE ARTIFICIAL NEURAL NETWORK IN THE PREDICTION OF FINANCIAL FAILURE AND APPLICATION IN ISTANBUL STOCK EXCHANGE*

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ABSTRACT

The need for the efficient use of a country's resources has, in many countries, increased the attention given to the studies of performance evaluation and pre-determination of financial failures. This study seeks to develop a model, that is able to predict which enterprises will fail one, two and three years into the future. Herein we compare the artificial neural network technology to the logistic regression model, the classification methodology typically used in finance. We find that for our sample of Turkish firms, the artificial neural network technology provides a higher proportion of correct financial failure classifications than does the logistic regression model.

Keywords**: Financial Failure Prediction; Artificial Neural Networks; Logistic Regression Model**

FİNANSAL BAŞARISIZLIĞIN TAHMİN EDİLMESİNDE YAPAY SİNİR AĞININ KULLANILMASI VE İSTANBUL MENKUL KIYMETLER BORSASI'NDA UYGULAMASI

ÖZET

Bir ülkenin kaynaklarının etkin kullanılmasına duyulan gereksinim, birçok ülkede, performans değerlendirme ve mali başarısızlıkların önceden tespit edilmesine ilişkin araştırmalara verilen önemi artırmıştır. Bu çalışma, hangi işletmelerin başarısızlığa uğrayacağının bir, iki ve üç yıl öncesinden tahmin edilebilmesini sağlayan bir model geliştirmeyi amaçlamaktadır. Bu çalışmada, yapay sinir ağı teknolojisiyle, finansmanda yaygın olarak kullanılan bir sınıflandırma metodolojisi olan lojistik regresyon modelini karşılaştırmaktayız. Türk firmaları için yapılan örnek uygulamada, yapay sinir ağı

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teknolojisinin sağladığı doğru mali başarısızlık sınıflandırması, lojistik regresyon modelinin sağladığından daha yüksek bir orandadır.

Anahtar Kelimeler: Finansal Başarısızlık Tahmini; Yapay Sinir Ağları; Lojistik Regresyon Modeli

1. INTRODUCTION

Increasing numbers of Turkish enterprises are now finding themselves in difficult financial straits. Many of these firms have no choice but to liquidate. In addition to becoming a burden to the economy, such enterprises' problems weaken the financial positions of their lenders and investors who may in time become bankruptcy candidates themselves. The need to enhance the efficient use of a country's resources has increased attention to studies of performance evaluation and pre-determination of financial failures. Such a study would be of benefit to credit analysts, intermediaries as well as corporate and individual investors.

Various approaches to bankruptcy prediction are discussed in the U.S. literature. Typically, an assortment of financial ratios are used as the predictor variables and standard statistical models such as discriminant analysis and logistic regression are applied to forecast financial failure (e.g., Altman, 1968; Altman and Loris, 1976; Altman, Haldeman and Narayanan, 1977). Both discriminant analysis and logistic regression however, have limitations in approximating a nonlinear relationship between the dependent variable and the independent variables. Other important studies that used multiple variable statistical models Deakin (1972) who used the multi discriminant model. Taffler and Tisshaw (1977); Ohlson (1980) who used the Logit model, Zavgren (1985), Hing and Lau (1987), Zmijevski (1984) who used the Probit model, Meyer and Pifer (1970) who used the multi regression model. In Turkey; Göktan (1981), Agaoglu (1989), Aktas (1993), Ganamukkala and Karan (1996), Kısa (1997).

Recently, researchers have begun to investigate the usage of artificial neural networks in finance application due to the flexibility of neural networks in capturing nonlinear mappings. For example, Tam and Kiang (1992) report that neural networks improved the accuracy of financial failure prediction; Maher and Sen (1998) find that the neural network based models perform significantly better than the logistic regression model in predicting bond ratings. Cheh, Weinberg, and Yook (1999) find neural networks exhibited a highly successful rate in predicting takeover targets. In Turkey Yıldız (2001) where the artificial neural network model was used, are important on forecasting financial failures.

The objective of this article is to propose and illustrate the use of feed forward neural network (Nnet), the most popular type of neural network, as an alternative method to predict financial failure in Turkey. The models we develop are able to predict which enterprises will fail one, two and three years before they do so, utilizing both a Nnet and a logistic regression methodologies. We find that for our sample of Turkish firms, the artificial neural network technology generates a higher proportion of correct financial failure classifications than does the logistic regression model.

The remainder of the article is organized as follows. In section 2 we present a brief review of logistic regression. In section 3, we introduce Nnet and explain why Nnet is more powerful in capturing nonlinearity than is logistic regression. In section 4, we develop both models to predict financial failure in Istanbul Stock Exchange. Our conclusion is presented in section 5.

2. LOGISTIC REGRESSION MODEL

Assuming we have two predictor variables (e.g., financial ratios), a simple logistic regression would model the probability for a firm to be successful (not fail) given the observed predictor variables as

$$P(y=1 \mid X) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2)}} \quad (1)$$

Where $y=1$ for successful firms, $y=0$ for failed firms.

If $\beta_0+\beta_1 x_1+\beta_2 x_2<0$, then $P(y=1 \mid X)<0.5$, then the observation is classified as a member of the about-to-fail group; Otherwise, the observation is classified as a member of the not-about-to-fail group. In other words, the two classes are distinguished by a decision boundary:

$$\beta_0+\beta_1 x_1+\beta_2 x_2=0 \quad (2)$$

as illustrated in Figure 1.

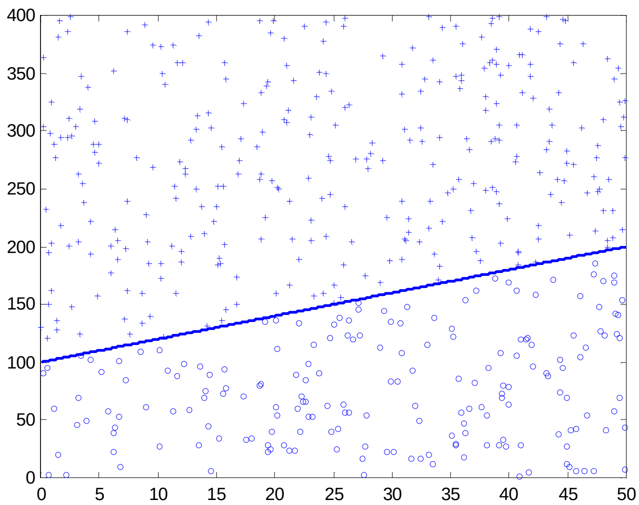

Figure 1. Simulated Example of Logistic Regression Model

Note to Figure 1: We represent firms that are about to fail as "+", firms that are not about to fail as "o". The straight line going through the graph represents the function $\beta_0+\beta_1 x_1+\beta_2 x_2=0$, known as the decision boundary. Observations above the line are classified as about to fail firms, those below the line are classified as successful firms. X1 and X2 are independent variables such as current ratio, debt ratio.

Note that the decision boundary based on a simple logistic regression model is a linear function of the predictor variables. We can of course add polynomial or other nonlinear terms to the simple logistic regression to capture certain kinds of nonlinearities. Such a model, however, has to be pre-specified by the investigator. In contrast, neural network picks up the nonlinearity automatically.

3. FEED FORWARD NEURAL NETWORK

A neural net links the dependent variable with the independent variables via a multilayer network structure: input layer, hidden layer and output layer. Feed forward neural network (Nnet), also known as back propagation neural network, is the most popular and basic neural network. Its topology is constrained to feed forward (i.e. no loops). Figure 2. illustrates the architecture of a single hidden layer Nnet with *K* independent variables (denoted by vector $X = [x_1, x_2 \cdots x_K]'$), *J* hidden nodes (denoted by vector $M = [m_1, m_2, \cdots m_J]'$) and one dependent variable (denoted by *o*)

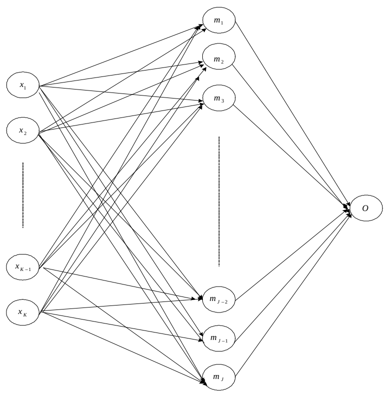

Figure 2. Schematic representation of single hidden layer feed forward neural network.

Figure 2 illustrates the structure of single hidden layer feed forward neural network. The input layer includes all of the independent variables, denoted as *X*. *X* goes to the hidden layer and gets transformed into *M*; *M* goes to the output layer and gets transformed into the dependent variable *o*.

The independent variable *X* goes to the hidden layer and is transformed into *M* by a certain transformation function[1] such as a linear function, threshold function, logistic function, etc.; *M* goes to the output layer and is transformed into the dependent variable *o*, which is the probability for a takeover attempt to go through in our case. Due to the network structure, Nnet is capable of parallel processing and thus is capable of capturing complicated non-linear relationship between the dependent variable and the independent variable.

[1] also known as a squasher function or an activation function.

Here we provide a simulated example to illustrate the superiority of Nnet at approximating nonlinear decision boundaries. Successful firms (denoted as "+") is distinguished from failed (denoted as dot) by a quadratic function: $x_2 = 0.5x_1^{\,2} - 25x_1 + 400$, as shown in Figure 3. X1 and X2 are independent variables such as current ratio and debt ratio. The fitted decision boundaries from a logistic regression (the dotted line) and a feed forward neural network (the dashed line) are also presented in Figure 3. Clearly, Nnet approximates the quadratic function more accurately.

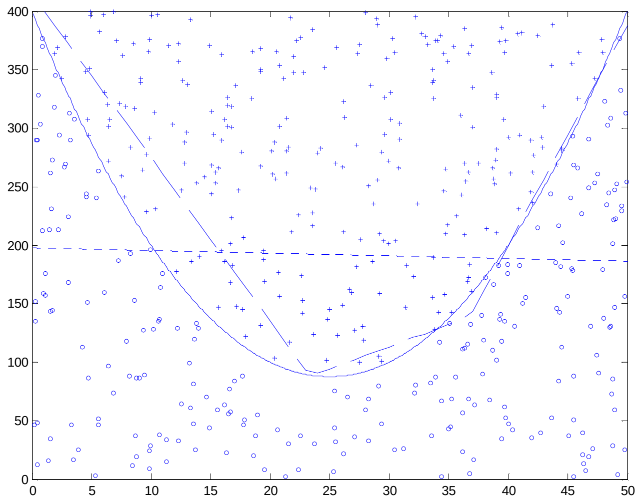

Figure 3. Simulated example of a nonlinear decision boundary

This figure provides a simulated example of a nonlinear decision boundary. Firms that succeed are represented as "+",firms that fall apart are represented as "o". The two groups are distinguished by a quadratic function, also known as the decision boundary: $x_2 = 0.5x_1^{\,2} - 25x_1 + 400$, denoted by the curved line going through the graph. The decision boundaries estimated by logistic regression, Nnet are also shown on the plot. The dotted line is the boundary estimated by logistic regression model, and the dashed line is the boundary estimated by Nnet model.

Specifying the architecture of the net is one major task in the process of fitting a Nnet. Unfortunately, no clear rule has yet been developed for determining the optimal number of hidden nodes. Usually the number of nodes is determined empirically through trial and error. One selects the number that gives the best result. As to the number of hidden layers, White (1992) indicated that a single hidden layer feed forward neural network can approximate any nonlinear function to an arbitrary degree of accuracy with a suitable number of hidden units. The most common net only has one hidden layer. The Nnet parameters could be estimated via maximizing the log-likelihood function, minimizing the sum of squared errors, etc.

4. FINANCIAL FAILURE PREDICTION IN ISTANBUL STOCK EXCHANGE

In this section, we develop both a logistic regression model and Nnet to predict financial failure for firms listed on the Istanbul Stock Exchange. We fit three models by each technique: failure prediction using financial information one, two and three year ahead of the failure, (Successful firms are only firms that are successful in year 1998, reasons will be provided in section 4.2. Thus the financial ratios one, two, three years ahead of the success would be those for year 1997,1996, and 1995).

4.1. Sample

In this study, the industrial firms, which were listed on the İstanbul Stock Exchange between the years of 1992-2001, were analyzed. Financial organizations, holding companies, and companies in the service and transportation sectors were not included because of their divergent financial characteristics. Failure determination criteria were defined as follows: going bankrupt; having negative "Net Profits" for three subsequent years; closure of the order of transaction in Istanbul Stock Exchange; or being discharged from the quote in Istanbul Stock Exchange. Thirty firms are identified as unsuccessful firms by these criteria. Firms that don't meet any of those three criteria are defined as successful. We only selected firms that are successful in year 1998, in which year the maximum number of failure occurred. Under this condition, 112 out of a total of 142 enterprises were taken as successful.

Our model's dependent variable is a binary (1, 0 for successful, unsuccessful firm). Twenty-eight financial ratios commonly used in the literature form our independent variable set. For example, to predict financial failure one year prior to failure, for unsuccessful firms, the independent variables are the financial ratios one year ahead of the failure, while for successful firms, the independent variables are the financial ratios for year 1997.

FINANCIAL RATIOS USED IN THE STUDY

A) Liquidity Ratios:

X_1) Curent Ratio: Curent Assets/Curent Liabilities
X_2) Acid-Test Ratio: (Current Assets -Inventory-Other Current Assets)/Current Liabilities
X_3) Cash Ratio: Liquid Assets/Current Liabilities

B) Financial Ratios:

X_4) Total Debt/Total Assets
X_5) Equity Capital/Total Assets
X_6) Equity Capital/Total Debts
X_7) Current Liabilities/Total Liabilities
X_8) Long Term Debt/Total Resources
X_9) Fixed Assets/Equity Capital
X_{10}) Fixed Assets/(Equity Capital + Long Term Debt)
X_{11}) Tangible Fixed Assets (net)/Equity Capital
X_{12}) Tangible Fixed Assets (net)/Total Assets
X_{13}) Current Assets/Total Assets

X_{14}) Fixed Assets/Current Assets

C) Activity Ratios:

X_{15}) Credit Turnover: Net Sales/Short -Term Commercial Credits
X_{16}) Stock Turnover: Costs of Sales/(Opening Stock + End of Period Stock)/2
X_{17}) Turnover of Current Assets: Net Sales/Current Assets
X_{18}) Turnover of Fixed Assets: Net Sales/Fixed Assets
X_{19}) Turnover of Tangible Fixed Assets: Net Sales/Tangible Fixed Assets (net)
X_{20}) Turnover of Assets: Net Sales/ Total Assets
X_{21}) Turnover of Equity Assets: Net Sales/Equity Assets

D) Profitability Ratios:

X_{22}) Gross Sales Profit/Net Sales
X_{23}) Basic Operation Profit/Net Sales
X_{24}) Operating Income/Net Sales
X_{25}) Profit Before Taxes/Net Sales
X_{26}) Net Income/Net Sales
X_{27}) Net Income/Equity Capital
X_{28}) Net Income/Total Assets

4.2. Methodologies

Fitting a logistic regression model is straightforward. We used an SPSS statistical package program and 28-predictor variables. The fitted model presented in the results section only contains the significant predictor variables.

Another package program (Neural Connection Version 2.0 Copyright 1995-1997. Recognition System Ltd.) was used to fit Nnet. In order to remove the effect of the measurement unit, the data are standardized by the package program (also called preprocessing) such that each data point contributes equally to the decisions. Then, the logistic function is selected as the transformation function for both the hidden layer and the output layer. The root mean square error (RMSE) is used as the performance function. The number of the hidden nodes is determined empirically. We tried one to seven hidden nodes for each model and found: five-node-Nnet performs the best for one year ahead prediction, four-node for two-year ahead prediction, and two-node for three-year ahead prediction, as shown in Table 1.

Table 1. Determining the Number of Hidden Nodes

Number of Hidden Nodes	Root Mean Square Error		
	One Year Ahead	Two-Year Ahead	Three-Year Ahead
1	**0.342752**	**0.540076**	**0.466623**
2	0.352060	0.500303	**0.402981****
3	0.431284	0.504473	0.433349
4	0.432923	0.343795**	0.434071
5	0.289960**	0.469179	0.408188
6	0.406475	0.447950	0.453705
7	0.314695	0.489401	0.437906

Five-node-Nnet performs the best for one year ahead prediction, four-node for two-year ahead prediction and two-node for three-year ahead prediction.

4.3. Research Findings

Empirical results are presented in the following subsections.

4.3.1. Financial Failure Prediction One Year Ahead of The Failure

Table 2 shows the logistic regression results for financial failure prediction one year ahead of the failure.

Table 2. Logistic Regression Model: Financial Failure Prediction One Year Ahead of Time

	Intercept X_0	Tangible Fixed Assets/ Total Assets X_{12}	Credit Turnover X_{15}	Net Income/ Total Assets X_{28}	R-Square
Parameter Estimates	-1.741**	5.940***	-0.286***	54.734***	43.39%
Standard Errors	0.82	2.26	0.083	12.20	

** represents statistical significance at the level of 0.05.
*** represents statistical significance at the level of 0.01.

The fitted logistic regression model can be written as:

$$P(Y=1 \mid X) = \frac{1}{1+\exp(-(-1.741+5.940X_{12}-0.286X_{15}+54.734X_{28}))} \quad (8)$$

Where $P(Y=1\,|\,X)$ is the probability for a firm to be successful given its financial ratios.

Table 3 shows the performance of the fitted logistic regression model (Panel A) and Nnet (Panel B) in predicting financial failure one year ahead of the failure.

Table 3. Financial Failure Prediction One Year Ahead of Time

Panel A: Logistic Regression Model				
	True Class			
Predicted Class	Unsuccessful	Successful	Overall	Accuracy Rate
Unsuccessful	23	7	30	76.7%
Successful	4	108	112	96.4%
Overall	27	115	142	92.3%
Panel B: Nnet				
	True Class			
Predicted Class	Unsuccessful	Successful	Overall	Accuracy Rate
Unsuccessful	26	4	30	86.7%
Successful	0	112	112	100.0%
Overall	26	116	142	97.2%

With the logistic regression model, we obtain an accuracy rate of 96.4% for the successful firms and 76.7% for the unsuccessful firms. The overall accuracy rate is 92.3%. With the Nnet, the accuracy rate for the successful firms is 100% while for the unsuccessful firms is 86.7%. The overall accuracy rate is 97.2%.

4.3.2. Financial Failure Prediction Two Years Ahead of The Failure

Table 4 shows the logistic regression results for financial failure prediction two years ahead of the failure.

Table 4. Logistic Regression Model: Financial Failure Prediction Two Years Ahead of Time

	Intercept X_0	Cash Ratio X_3	Basic Operation Profit/Net Sales X_{23}	Operating Income/Net Sales X_{24}	Net Income/ Total Assets X_{28}	R-Square
Parameter Estimates	-1.508***	-2.942***	-11.632***	10.576**	11.986**	28.58%
Standard Errors	0.56	0.98	3.28	4.65	5.55	

The fitted logistic regression model can be written as:

$$P(Y=1\,|\,X)=\frac{1}{1+\exp(-(1.508-2.942X_3-11.632X_{23}+10.576X_{24}+11.986X_{28}))} \quad (9)$$

Table 5 shows the performance of the fitted logistic regression (Panel A) and Nnet model (Panel B) in predicting financial failure two years ahead of the failure.

Table 5. Financial Failure Prediction Two Years Ahead of Time

Panel A: Logistic Regression Model				
	True Class			
Predicted Class	Unsuccessful	Successful	Overall	Accuracy Rate
Unsuccessful	17	13	30	56.7%
Successful	3	109	112	97.3%
Overall	20	122	142	88.7%
Panel B: Nnet				
	True Class			
Predicted Class	Unsuccessful	Successful	Overall	Accuracy Rate
Unsuccessful	25	5	30	83.3%
Successful	2	110	112	98.2%
Overall	27	115	142	95.1%

With the logistic regression model, the accuracy rate for the successful firms is 97.3% while for the unsuccessful firms is 56.7%. The overall accuracy rate is 88.7%. With Nnet, the accuracy rate is 98.2% for the successful firms, while 83.3% for the unsuccessful firms. The overall accuracy rate is 95.1%.

4.3.3. Financial Failure Prediction Three Years Ahead of The Failure

Table 6 shows the logistic regression results for financial failure prediction three years ahead of the failure.

Table 6. Logistic Regression Model: Financial Failure Prediction Three Year Ahead of Time

	Intercept X_0	Net Income/ Total Assets X_{28}	R-Square
Parameter Estimates	-0.249*	15.222***	35.29%
Standard Errors	0.45	8.38	

The fitted logistic regression model is

$$P(Y=1\,|\,X)=\frac{1}{1+\exp(-(-0.249+15.222X_{28}))} \quad \textbf{(10)}$$

Table 7 shows the performance of the logistic regression model (Panel A) and Nnet model (Panel B) in predicting financial failure three years ahead of the failure.

Table 7. Financial Failure Prediction Three Years Ahead of Time

Panel A: Logistic Regression Model				
	True Class			
Predicted Class	Unsuccessful	Successful	Overall	Accuracy Rate
Unsuccessful	6	24	30	20.0%
Successful	4	108	112	96.4%
Overall	10	132	142	80.3%
Panel B: Nnet				
	True Class			
Predicted Class	Unsuccessful	Successful	Overall	Accuracy Rate
Unsuccessful	20	10	30	66.7%
Successful	18	94	112	83.9%
Overall	38	104	142	80.3%

With the logistic regression model, we obtain an accuracy rate of 96.4% for the successful firms and 20.0% for the unsuccessful firms. The overall accuracy rate is 80.3%. With Nnet, the accuracy rate for the successful firms is 83.9%, while for the unsuccessful firms is 66.7%. The average accuracy rate is 80.3%.

4.3.4. Summary of The Performance of The Models Developed

Table 8 is a summarized table of the performance of the models developed.

Table 8. Summary of Predictive Accuracy of Logistic Regression and Nnet

	Years before the date of failure			
	1 year	2 years	3 years	Average
Successful Firms				
Logistic Regression	96.4%	97.3%	96.4%	96.7%
Nnet	100%	98.2%	83.9%	94.0%

Table 8

Failed Firms				
Logistic Regression	76.7%	56.7%	20.0%	51.1%
Nnet	86.7%	83.3%	66.7%	78.9%
Overall				
Logistic Regression	92.3%	88.7%	80.3%	87.1%
Nnet	97.2%	95.1%	80.3%	90.8%

As indicated by Table 8, the Nnet outperforms the logistic regression in predicting financial failure for the unsuccessful firms (78.9% vs. 51.1%), underperforms the logistic regression in predicting financial failure for the successful firms (94.0% vs. 96.7%), outperforms the logistic regression in predicting financial failure for the whole sample (90.8% vs. 87.1%). Because the loss on failed firms tends to be higher than the gain on investments in successful firms, the ability to predermine unsuccessful firms is more crutial to most investors. Accordingly, we should assign greater importance to the accuracy rate for predicting which firs are going to be unsuccessful as opposed to predicting which will be successful when comparing the two methodologies. Thus, we recommend Nnet as a superior alternative to logistic regression to predict financial failure in Istanbul Stock Exchange.

5. CONCLUSIONS

Logistic regression models are used widely in financial failure prediction models. On the other hand, logistic regression models have limitations in approximating nonlinearities exhibited in the data. Artificial Neural Network is an alternative technology to predict financial failure and is superior at capturing nonlinear mappings due to its network structure. This study suggest that neural networks provides more reliable results than logistic regression the in prediction of financial failure in Istanbul Stock Exchange.

6. REFERENCES

Agaoglu, A. (1989).“Türkiye’de Banka İşletmelerinin Ekonomik Analizi ve Gelişme Eğilimleri”. (Yayımlanmamış Doktora tezi), Ankara: Ankara Üniversitesi.

Aktas, R.(1993). ***Endüstri İşletmeleri İçin Mali Başarısızlık Tahmini***, Ankara, Türkiye İş Bankası Kültür Yayınları Yayın No:323.

Altman, E. (1968). “Financial Ratios, Discriminant Analysis and The Prediction of Corporate Bankruptcy”, ***The Journal of Finance***, 23, 589-609.

Altman, E., Loris, B.(1976). “A Financial Early Warning System for Over The Counter Broker- Dealers”, ***The Journal of Finance***, 31, 1201-1217.

Altman. E., Haldeman, R.G., Narayanan, P. (1977). “Zeta Analysis”, ***Journal of Banking and Finance***, 1, 29-54.

Cheh, J.J., Weinberg, R.S., Yook, K.C. (1999). “An application of an artificial neural network investment system to predict takeover targets”, ***The Journal of Applied Business Research,*** 15, 33-44.

Gallant, A., White, H. (1992). "On Learning the Derivatives of an Unknown Mapping with Multilayer Feedforward Network", ***Neural Networks,*** 5, 129-138.

Deakin, E.B.(1972). "A Discriminant Analysis of Predictors of Business Failure", ***Journal of Accounting Ressearch***, X, Spring, 167-179.

Ganamukkala, V.C., Karan, M.B. (1996). "Prediction of Financially Unsuccessful Companies Using MDA and MRA Techniques: An Empirical Study on İstanbul Stock Exchange", ***METU Studies in Development***, XXIII, 3: 357-376.

Göktan, E.(1981). "Muhasebe Oranları Yardımıyla ve Diskriminant Analizi Tekniğini Kullanarak Endüstri İşletmelerinin Mali Başarısızlığının Tahmini Üzerine Ampirik Bir Araştırma".(Yayınlanmamış Doçentlik tezi), Ankara.

Hing, A., Lau, L. (1987)."A Five-State Financial Distress Prediction Model", ***Journal of Accounting Research***, XXV, 1: 127-138.

Kısa, T.(1997). "Bankaların Mali Başarısızlığını Tahminine Yönelik Çok Boyutlu Model". (Yayınlanmamış Doktora tezi), Ankara: Gazi Üniversitesi.

Kline, D., Berardi, V. (2002). "Evaluating squared-error and cross-entropy functions for training neural network classifiers", ***Decision Sciences Institute 2002 Annual Meeting Proceedings***, 169-174.

Maher, J.J., Sen, T.K. (1998). "Predicting Bond Ratings Using Neural Networks: A Comparison with Logistic Regression", ***International Journal of Intelligent Systems in Accounting, Finance & Management,*** 6, 59-72.

Meyer, P.A., Pifer, H.W**.** (1970). "Prediction of Bank Failures", ***Journal of Finance***, XXV, 4: 853-868.

Ohlson, J.A. (1980). "Financial Ratios and the Probabilistic Prediction of Bankruptcy", ***Journal of Accounting Research***, XVIII, 1: 109-131.

Taffler, R.J., Tisshaw, H.(1977). "Going, Going, Gone- Four Factors Which Factors Which Predict" , ***Accountancy,*** March:50-54.

Tam, KY., Kiang, M.Y. (1992). "Managerial Applications of Neural networks: A Genetic Algorithm and Backpropagation Comparision", ***Decision Support Systems***, 30, 11-22.

Yıldız, B. (2001). "Finansal Başarısızlığın Öngörülmesinde Yapay Sinir Ağı Kullanımı ve Halka Açık Şirketlerde Ampirik Bir Uygulama." *İstanbul Menkul Kıymetler Borsası Dergisi*, V, 17,:51-67.

Zavgren, C.V. (1985)."Assessing the Vulnerability to Failure of American Industrial Firms: A Logistic Analysis", ***Journal of Business Finance and Accounting***, XII, 1: 19-45.

Zmijewski, M.E.(1984). "Methodological Issues Related to the Estimation of Financial Distress Prediction Models", ***Journal of Acounting Research***, Supplement: 59-82.