Credit risk prediction: A comparative study between discriminant analysis and the neural network approach

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Abstract: Banks are concerned with the assessment of the risk of financial distress before giving out a loan. Many researchers proposed the use of models based on the Neural Networks in order to help the banker better make a decision. The objective of this paper is to explore a new practical way based on the Neural Networks that would help the banker to predict the non payment risk the companies asking for a loan. This work is motivated by the insufficiency of traditional prevision models. The sample consists of 86 Tunisian companies and 15 financial ratios were calculated, over the period from 2005 to 2007. The results were compared with those of discriminant analysis. They show that the neural networks technique is more accurate in term of predictability.

Keywords: credit risk, prediction, discriminant analysis, artificial neural networks

JEL codes: B41, C14, C45, C53

1. Introduction

The evolution of banking in recent decades also led to the appearance of new risks and deepening of existing ones. Thus, risk management in the field of credit is an important issue; it has significantly improved and helped to strengthen the financial reliability of credit institutions: it is the central theme of the new Basel II. The Basel II is a step towards international harmonization of banking regulations. It

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allows among others to correct some obvious weaknesses of Basel I. The evolution of prudential Cooke ratio to the Mc Donough ratio is mainly aimed at maintaining the financial stability and reliability of the banking system. This way the new guidelines of the three fundamental pillars of Basel II: credit, market and operational risks encourage the intensification of effective and sound risk management, taking into account the rapid evolution of financial markets. But to what extent will the new rules actually ensure the safety and stability of the international financial system?

Several types of risks can affect a bank. However, the counterparty risk, or credit risk, is simultaneously the first, the most dangerous and the common risk that face a financial institution. Generally, credit risk is defined as the risk that a borrower will default: they are unable to keep their promise to pay interest payments on time or repay the principal at maturity.

Banks are competitive financial institutions of vital importance that seek profit by providing various financial services to households and businesses while managing different types of risk. Therefore, risk-taking is often regarded as the basic driver of financial performance and profitability (Bekhet & Eletter, 2014). From this fact, and because risk taking is a synonym for profitability, banks make a large part of their profits out of their lending activities and are therefore very interested in developing credit risk assessment models always more accurate to optimize the performance of granted loans .

Several methods have been proposed to predict the risk of credit. The most used technique is the credit scoring from discriminates analysis. This operation is completed by the engagement of a score function which helps decision making in granting credit to companies that borrow. Many researches were based on discriminant analysis (Altman, 1968; Altman *et al.*, 1977; Conan & Holder, 1979). However, the method of discriminates analysis has been criticized by several authors (Eisenbeis, 1977; Deakin, 1976; Joy & Tollefson , 1975) because the validity of the results found by this technique depends on their restrictive assumptions in case of the assumption of normality of the distribution of each of the variables used and the assumption of independence between them .

To overcome the shortcomings of the discriminant analysis method, other models of risk analysis have emerged. Neural networks are powerful nonlinear data processing techniques, which have proven their reliability in many areas. The neural network is a new approximation method of complex systems, especially useful when these systems are difficult to model by means of conventional statistical methods.

The first implementation of neural networks to estimate the risk of financial failure was conducted by Bell & Alii (1990). The use of this technique was then intensified with work by Tam (1991) and Altman *et al.* (1994). Several studies have shown that the neural approach offers improved predictive accuracy compared to discriminant analysis (Odom & Sharda, 1990; Abdou *et al.*, 2008). However, Altman *et al.* (1994) recommended using both methods (neural approach and discriminant analysis).

In this context, this paper's main objective is to determine a discrimination model to detect financial distress of companies requesting credit from banks by means of a new approach based on artificial neural networks and compare the method to discriminant analysis to improve decision support for Tunisian bankers.

2. Literature review

2.1. The Discriminant analysis

Discriminant analysis is a statistical technique used to discriminate between observations given their individual characteristics. It is used to classify and / or predict a phenomenon and make the dependent variable qualitative. Its empirical application started since the 1930s with the work of Fisher (1936) and Mahalanobis (1936).

The discriminant analysis is to find a weighted average of several ratios (discriminate function), calculated for each company, which best ensures the distinction between firms in financial distress and successful ones. This is a method used by banks especially for Scoring.

The discriminant analysis requires that data are independent and normally distributed. Therefore, the general equation is as follows (Jackson & Wood, 2013)

$$Z_i = \propto + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_n X_{in}$$

Where Z represents the score of firm i, α is the constant, X_{i1} are the attributes (ratios, categorical or qualitative variables) of firm i and βi represents the coefficients of the linear combination of explanatory variables.

The pioneer of the Credit Scoring method is Beaver (1966). He used univariate analysis to distinguish between efficient firms and firms in difficulty up to 5 years before bankruptcy. This allows assigning companies to the group of healthy companies or those in difficulty with the lowest error rate. Although this method provides effective results, it was greatly criticized. On the one hand, this approach does not provide a comprehensive assessment of the situation of the company.

Treating ratio each separately does not simultaneously take into account the existing interdependence between the different financial ratios. On the other hand, the financial situation of a firm cannot be fully described through a single ratio regardless of the importance of this ratio. Despite all these criticisms, this method has been the starting point for the development of other models such as the z-score model published by Altman (1968) which brought about the prediction model of the most popular defects in literature. It calculates a score function Z is a linear combination of n financial ratios and whether the score of any business is above or below a certain threshold. It checks if the company is healthy or in distress.

However, the major problem in the application of these methods is that the validity of the results found by these techniques is dependent on their restrictive assumptions that are rarely met in real life, in this case the assumption of normality distribution of each of the variables used and the assumption of independence between them which can make these theoretically invalid methods (Huang *et al.*, 2004; Sustersic *et al.*, 2009).

Therefore, the constraint of the basic assumptions necessary for effective implementation of the discriminant analysis has led some researchers to test the effectiveness of other statistical tools.

2.2. Artificial Neural Networks (ANNs)

ANNs are flexible and non-parametric tools inspired from biological neural systems. The field of artificial neural networks appeared in the 1940s with the work of Warren McCulloch and Walter Pitts who showed that with such networks we could, in principle, compute any arithmetic or logic function. The first practical application of artificial neural networks occurred in the late 1950s with the work of Frank Rosenblatt (1958) on the perceptron. ANN is a tool of artificial intelligence, commonly used in applied sciences (biology, physics, etc.), that was firstly used in finance at the early 1990s, in addition to the classic statistical methods, as a quantitative forecasting method.

ANN is based on learning, that is to say, these systems learn by themselves the relationships between different variables from a data sample, simulating human reasoning. They allow us to connect the inputs (the database) and the outputs (results) under the assumption that the relationship is nonlinear. In our case, we forecast the presence of credit risk or not, according to the diagram below:

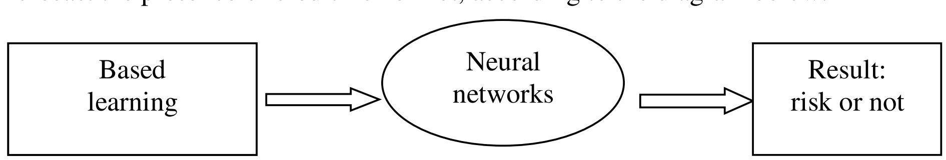

Figure 1 General scheme of treatment

ANN usually consisting of an input layer representing input neurons (input variables), an output layer with the vector of output variables that transfer information outside the network, and one or more hidden layers having all hidden nodes with connections incoming from the input neurons.

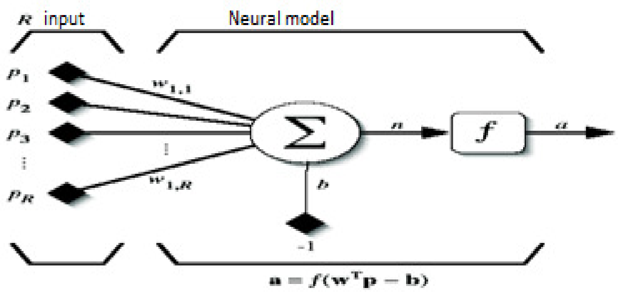

Figure 2 Model of artificial neural networks

The figure above has R inputs; each entry is assigned a $P_i$synaptic weight$w_{1,i}$. The neuron will start to make the weighted sum is the input function, which will give its internal state. The result n of this sum is transformed by a transfer function (also called activation function) f which produces the output $a$of neuron. This transfer function is very important and determines the operation of the neuron network. It can take different forms; it can be a linear or sigmoid function threshold. It can be considered a model neuron as a black box with inputs and outputs. In the case of McCulloch - Pitts neurons (1943), the transfer function is the "all or nothing" (bipolar threshold function) if the activation of the neuron is above the threshold , the final status will be one , if it is below the threshold, the final status will be -1 . Bipolar threshold functions are hardly used anymore. Generally, we use those sigmoid. Parameters (weight of arcs) of ANN need to be estimated before the model is used for predictive purposes. The process of determining these weights is the period of training or learning. For classification problems, learning is said supervised in the sense that the input-output combinations are known desired. Supervised learning is much faster than the other two existing algorithms (unsupervised or reinforcement) as the weight adjustment is made directly from the error, the difference between the output obtained by the ANN and desired output or observed. A popular supervised learning algorithm is the process error back propagation (back propagation of errors).

The ANNs were examined by Arminger *et al.* (1997), Desai *et al.* (1996), Lee *et al.* (2002), West (2000), Khashman (2010), Tsai *et al.* (2009), and Oreski *et al.* (2012) in the treatment of credit Scoring problems. The majority of studies have shown that neural networks are more accurate, flexible and robust than conventional statistical methods for the assessment of credit risk (Oreski *et al.*, 2012).

2.3. Comparison between discriminant analysis and the neural approach

The comparison of these two methods is presented through the results of several works. Numerous studies have attempted to demonstrate the effectiveness of one rather than the other.

Based on the importance of the neural approach in detecting problems in several areas, Paquet (1997) mentions that there are two main reasons why researchers became interested in this tool. First, this method is more flexible than some conventional statistical methods since no assumptions are required about the functional form of the relationship between the characteristics and the probability of default or about the distribution of the error terms and variables. Second, it is a suitable instrument for dealing with unstructured complex issues, making it impossible to specify a priori the shape of the relationship between the variables studied.

Angelini *et al.* (2007) find that the neural approach differs from the conventional method of credit scoring mainly in the nature of the black box and its ability to handle non-linear relationships between variables. In general, according to these authors, the neural networks are considered as a black box because of the inability to extract symbolic information from their internal configuration.

Studies by Odom & Sharda (1990) reported that neural networks are more efficient than conventional statistical methods. The network used in this study gives better results than discriminant analysis on the test sample. Indeed, it correctly classifies 81.81 % against 74.28 % companies for discriminant analysis.

Coats & Fant (1993), in the context of the prediction of business failures, recommend using both the discriminant analysis and neural networks method if the user problem is simply a correct classification. Meanwhile, neural networks perform better than the discriminant analysis method in terms of the type of error and associated cost.

The results obtained by Altman *et al.* (1994), making their study of 1000 Italian industrial companies between 1982 and 1992, concluded that achieving the best results require the use of both methods of neural networks and the technique of discriminant analysis.

However, Swales & Yoon (1992) confirm that the simultaneous use of methods of neural networks and discriminant analysis would be quite difficult to implement in the current tests, since both methods are based on different theoretical backgrounds.

Hoang (2000) , in his doctoral thesis , says the methods of discriminant analysis can achieve better performance than the methods of neural networks when linear patterns are involved in the classification task , but the methods by neuron networks are more likely to detect non-linear patterns in the classification task .

As part of the credit risk prediction, Abdou *et al.* (2008) conducted a comparative analysis between the neural network and discriminant analysis. The sample for the study that was provided by a commercial bank in Egypt consisted of 581 management credit records. Individuals in the sample were classified into two groups: group of companies in good financial health (1) and companies in financial distress group (0). An initial batch composed of 20 independent variables was selected by the bank, but some variables were identical for all the samples, thus they were excluded, such as the duration of the loan that was four years in all cases and all the clients had a credit card. Therefore, the selected variables were reduced to 12. Thus, these variables were used in the discriminant analysis. The number of highly ranked companies in this model is equal to 86.75 %. From this batch of 12 variables, the authors applied the method of stepwise regression. The results of this method showed that only nine variables showed a significant discrimination power. Variables found are then used in the discriminant analysis. This method allowed having a good ranking rate of about 86.92 %. Abdou *et al.* (2008) kept the 12 variables to build the neural model. The results of this approach show good classification rates of about 93.98 % using the neural network with 4 hidden nodes, and a correct classification rate of about 94.84 % using the neural network with 5 hidden nodes. These authors concluded that the neural approach dominates the technique of discriminant analysis because neural networks have the highest right ranking.

3. Methodology: presentation of the sample, selected variables and approach to score model constructing

3.1. Presentation of the sample

The database was composed of 86 Tunisian client companies of a Tunisian commercial bank from various sectors over three years from 2005 to 2006 and 2007. To test the predictive power of the discrimination method, the sample was divided into two sub-samples called base sample and test sample comprising information about 2005 - 2006 and 2007 respectively.

Companies were classified according to two groups with reference to the opinion of the lending operations manager at the bank: efficient companies group (class 1) and inefficient companies group (class 0).

The base sample comprised 60 efficient companies and 26 inefficient companies over 2005 and 2006 with a total of 120 efficient and 52 inefficient observations. Data from 2007 included 60 efficient and 26 inefficient companies used for the test sample.

The choice to analyze situations of Tunisian firms is explained by the fact that in Tunisia, according to financial statistics conducted by the central bank in 2013, the credit risk has increased given the growth of credit to the economy. Indeed, the overall volume of credit increased from 14,451.221 MTD in 1998 to 53,127 MTD in 2012, with an increase of about 267.630%. In addition, a general problem identified by all Tunisian banks is the constant increase of the number of non performing loans.

3. 2. Selected variables

An initial batch containing ratios 15, encoded R01 to R15, was selected. These ratios were used by the bank and considered relevant in explaining the financial situation of enterprises.

Table 1. The variables of the study

	Title variables	Measure variables
R01	Added value rate	Added value / Turnover
R02	Operating profitability	EBITDA / Turnover
R03	Operating margin	EBIT / Turnover
R04	Debt ratio	Financial expenses / Turnover
R05	Profit Margin Ratio	Net profit / Turnover
R06	Financial profitability	Net income / Net Equity
R07	Solvency ratio	Net equity / Total assets
R08	Financial dependence	Long-and medium-term loan / Permanent Capital
R09	Repayment capacity	Long-and medium-term debt/ Net cash flow
R10	Economic profitability	Net income / Total assets
R11	Ratio of capital assets	Capital assets / Total assets
R12	Financial autonomy	Equity / Permanent capital
R13	Cash flow from operations	Cash flow/ Turnover
R14	Change in working capital	Working capital / Turnover
R15	Synthesis ratio	Permanent capital/ Net capital

3.3. Approach to score model construction

We applied an approach to study the variables and select the most discriminating one to determine score equations using the conventional scoring method i.e. discriminant analysis and the artificial intelligence techniques based on neural networks that identify companies in difficulty and non-difficulty ones.

To do so, we first considered the variables dependence according to a correlation test and then developed the variable selection aspect.

3.3.1. Correlation analysis

We define the intensity of binding between the different variables, relying on the correlation measure. To detect whether two variables are collinear, we examined the Pearson coefficients according to the correlation matrix.

Table 2. Matrix of correlation

	R01	R02	R03	R04	R05	R06	R07	R08	R09	R10	R11	R12	R13	R14	R15
R01	1														
R02	**0,977**	1													
R03	**0,959**	**0,986**	1												
R04	**0,979**	**0,984**	**0,978**	1											
R05	0,319	0,362	0,359	0,255	1										
R06	-0,002	0,010	0,017	0,001	0,091	1									
R07	-0,028	-0,026	-0,026	-0,068	0,280	0,117	1								
R08	-0,015	-0,015	-0,011	-0,009	-0,042	0,013	-0,132	1							
R09	-0,013	-0,011	-0,010	-0,007	-0,003	0,004	-0,051	-0,010	1						
R10	-0,002	0,032	0,029	-0,024	0,428	0,131	0,120	-0,059	-0,028	1					
R11	-0,026	-0,038	-0,043	-0,040	-0,025	0,016	0,029	-0,013	0,017	0,445	1				
R12	0,015	0,015	0,011	0,009	0,043	-0,012	0,132	-1,000	0,010	0,060	0,013	1			
R13	0,106	0,100	0,098	0,094	0,046	-0,031	-0,069	-0,017	-0,015	-0,044	-0,064	0,017	1		
R14	0,827	0,786	0,755	0,791	0,213	0,006	0,009	-0,012	-0,018	-0,023	-0,060	0,012	0,111	1	
R15	0,105	0,092	0,095	0,091	0,096	0,061	0,260	-0,020	-0,023	0,047	-0,122	0,020	0,029	0,227	1

Presence of collinearity

If the absolute value of the Pearson coefficient between two variables exceeds 0.8, which is the boundary drawn by Kennedy (1985) (cited by Marrakchi, 2000), we suspect collinearity.

Under this rule, and from table 2, we may suspect a problem of collinearity between variables R01 and R02, R01 and R03, R02 and R03, R01 and R04, R02 and R04, as well as R03 et R04.

3.3.2. Automatic variable selection

To construct a score for the early detection of the company's difficulties, the choice of explanatory variables is an important step that determines the effectiveness of the score function. For this reason, we used a stepwise selection analysis of the most relevant ratios to discriminate between the two company groups defined by the respective values of the indicator of financial hardship.

The objective of the "Stepwise" method is to choose the model with the best predictive value, and retain the most discriminating variables.
It first calculates the empty model, consisting solely of the constant and then the variables are introduced one by one. The process stops when it is no longer possible to enter a variable capable of improving the model performance in a "statistically significant" way.

The selection variables to be used later in this work are as follows: R02, R03, R04, R05, R06, R08, R09, R10 and R12.

4. Results

4.1. Results of the discriminant analysis

Test of equality of group means is necessary to check the existence of a strong relationship between the ratios used and their belonging to a group. Moreover, the most discriminating variables in the analysis should have high values in the Fisher test and, of course, a significance which tends towards zero.

Table 2. Test of equality of group means

	Wilks' Lambda	F	ddl1	ddl2	Signification
R02	0,992	1,36	1	170	0,245
R03	0,993	1,15	1	170	0,285
R04	0,989	1,87	1	170	0,174
R05	0,979	3,64	1	170	0,058
R06	0,999	0,16	1	170	0,693
R08	0,952	8,57	1	170	0,004
R09	0,984	2,7	1	170	0,102
R10	0,986	2,34	1	170	0,128
R12	0,953	8,38	1	170	0,004

Table 2 shows the relevance of the R08 ratio "Long-and medium-term debt / Permanent capital" with the highest discriminate power (F 8, 57 Fisher), which shows that this variable deeply influences the situation of the company and allows to differentiate between the two categories of firms (efficient and inefficient). Debt plays an important role in assessing the current and future financial situation of a company. This result is confirmed by the works of St. Cyr & Pinsonneault (1997). These authors argue that the more a company's debt, there is more risk that it would experience solvency problems over time. According to these authors, the use of debt induces risks relating to the variability of performance and increases the probability of insolvency. R12 ratio "Equity / Permanent Capital" also have a high discriminative power. According to the bank standard, this ratio must be greater than or equal to 0.5. Otherwise, we say that the long-term debt capacity of the company is saturated. In financial terms, companies in distress suffer from high debt burden in the short term and low financial autonomy (Lelogeais, 2003). From the results, we note that some variables had a very low discriminatory power and a significance level of error that exceeded 0.05. Indeed, the ratio R06 "Net income / Net Equity" had the lowest discriminate power. The study by Vernimmen (2002) confirms this result. According to this author, this criterion although attractive in terms of simplicity of calculation, is not perfect. Indeed, and in contrast to other indicators, it does not take account of the risk. It is often limited to one year. Moreover, it should be compared to the rates required to be significant. The R02 ratio "EBITDA /turnover" has a low discriminatory power. However, Stili (2002) mentioned that the EBITDA is the first balance obtained at the end of the production process and marketing. This concept is the main component in the calculation of the ratio of operating profitability. It is the first direct measurement of the industrial and commercial performance of the company and an indicator, usually significant, about its earnings capacity.

To make the discriminate equation and determine a score, discriminate function coefficients were estimated from Table 3.

Table 3. Coefficients of canonical discriminate functions

	Function 1
R02	1,671
R03	-0,779
R04	-0,566
R05	-6,151
R06	0,087
R08	1,364
R09	0,008
R10	0,005
R12	0,037
(Constant)	-0,188

This establishes the following discriminant function:

D1 (i0) = - 0,188+ 1,671R02 - 0,779R03 - 0,566R04 - 6,151R05 + 0,087R06+ + 1,364R08+ 0,008R09+ 0,005R10+ 0,037R12

One of the discriminating power measures is the rate of right classification. It is equal to the number of companies well classified in two groups divided by the total number of companies.

Table 4. Classification results of the base sample

		Class (es) of expected allocation (s)		Total
Y		**0**	**1**	
Original Number	0	10	42	52
	1	2	118	120
%	0	19,231	80,769	100
	1	1,667	98,333	100

at 74.4% of the original correctly classified observations.

As the table shows, the rate of correct classification of inefficient firms is equal to 19.231 % and the rate of correct classification of successful companies is equal to 98.33 %. Thus, the number of companies classified by the model is equal to 74.4 %.

4.2. Results of artificial neural networks

To create, manipulate and visualize results of neural networks, we used the Matlab 7.1 software that contains an application of "neural network toolbox", which allows the modeling of artificial neural networks.

The architecture of the multilayer perceptron neural network is used to build models for predicting financial distress. To determine the best architecture, we used the function "trainrp" as a learning function. In our case, the selected algorithm was the back gradient propagation algorithm trained through the entire learningdataset. In addition, the activation function selected for our application was the sigmoid "logsig" function for the hidden neurons in the hidden layers and the linear function "purelin" for the output neuron. The function of creating a network was "newff" for feedforward neural inputs which were not connected with those of output. This command creates the network and initializes its weight. Finally, we selected as a function of performance the meansquared error (MSE):

$$E = \frac{1}{2}\sum_{i=1}^{n}(d_i - y_i)^2$$

With d_i: desired value of output, y_i: calculated value of the output and n: number of observations in the sample

This equation determines the mean square error of the neural model. It is from this indicator that the network decides whether to continue to seek the desired solution or not. The ideal result is to have a very low or even zero error. Function "sim" is used to calculate the MSE of the test sample. We took as input of the learning function the 9 identified relevant variables and one output variable that takes a value 1 or 0 depending on whether the company is considered healthy or struggling during the learning process.

Therefore, in this work, we tried to do several tests on the network by varying the number of hidden layers and the number of hidden neurons in each layer in order to choose the best architecture that provides a minimal error rate since there is no rule, or theorem that would determine the number of hidden layers and the number of neurons to place in the hidden layer to get an optimal network of neurons. Indeed, in our program, we set a number of iterations equal to 500 and a minimum number of hidden layers equal to 1 to 5. The following table summarizes the results we reached:

Table 5. Summary of results of neural networks

Multilayer networks: Feed forward architecture	Number of layers	Number of hidden layers	Total Number of hidden layers MSE[1]	MSE learning sample test
Net1_1 [9 1 1]	3	1	0,1485	0,16038
Net1_2 [9 3 1]	3	1	0,1249	0,14437
Net1_3 [9 4 1]	3	1	0,1013	0,1053
Net1_4 [9 6 1]	3	1	0,1046	0,11895
Net1_5 [9 7 1]	3	1	0,0807	0,1257
Net1_6 [9 4 6 1]	4	2	0,0569	0,09744
Net1_7 [9 6 8 1]	**4**	**2**	**0,0086**	**0,0608**
Net1_8 [9 2 4 5 1]	5	3	0,1298	0,14756
Net1_9 [9 5 6 7 1]	5	3	0,0671	0,08604
Net1_10 [9 2 3 4 3 1]	6	4	0,1384	0,1523
Net1_11 [9 3 4 4 4 1]	6	4	0,0846	0,11891
Net1_12 [9 1 2 3 4 1 1]	7	5	0,1106	0,16454

From this table, we notice that the optimal number of layers is 4, including 2 intermediate. This network enabled us to get a least high MSE for the training sample and the test sample which are respectively 0.00868 and 0.0608 mean square error.

In this work, the correct classification rate of the test sample of the best architecture is determined using a threshold value of 0.5 for the business holding (Khashman, 2011). If the output result of the neural network is greater than or equal to 0.5, the case is assigned to a class (good, acceptance); otherwise, it is assigned to the other category (bad, rejection). Thus, the network output y_i is interpreted as follows:

Seeker_i ∈ Good credit class if: $y_i \geq 0.5$

Seeker_i ∈ Bad credit class if: $y_i < 0.5$

Table 6. Results of ranking the best architecture

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
desired **d_i**	1	1	1	1	1	1	1	1	1	1	1	1
real **y_i**	0,852	0,785	0,798	0,795	0,791	0,85	0,808	0,896	0,799	0,008	0,892	0,865
	1	1	1	1	1	1	1	1	1	0	1	1
	13	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
desired **d_i**	1	1	1	1	1	1	1	1	1	1	1	1
real **y_i**	0,516	0,873	0,848	0,008	0,785	0,882	0,818	0,803	0,785	0,791	0,785	0,852
	1	1	1	0	1	1	1	1	1	1	1	1
	25	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**
desired **d_i**	1	1	1	1	1	1	1	1	1	1	1	1
real **y_i**	0,884	0,809	0,832	0,828	0,785	0,743	0,304	0,864	0,873	0,887	0,785	0,876
	1	1	1	1	1	1	0	1	1	1	1	1
	37	**38**	**39**	**40**	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**
desired **d_i**	1	1	1	1	1	1	1	1	1	1	1	1
real **y_i**	0,262	0,151	0,899	0,039	0,872	0,191	0,817	0,617	0,785	0,859	0,869	0,54
	0	0	1	0	1	0	1	1	1	1	1	1
	49	**50**	**51**	**52**	**53**	**54**	**55**	**56**	**57**	**58**	**59**	**60**
desired **d_i**	1	1	1	1	1	1	1	1	1	1	1	1
real **y_i**	0,833	0,926	0,95	0,835	0,85	0,877	0,785	0,563	0,862	0,897	0,868	0,041
	1	1	1	1	1	1	1	1	1	1	1	0
	61	**62**	**63**	**64**	**65**	**66**	**67**	**68**	**69**	**70**	**71**	**72**
desired **d_i**	0	0	0	0	0	0	0	0	0	0	0	0
real **y_i**	0,523	0,333	0,325	0,466	0,788	0,072	0,27	0,069	0,433	0,192	0,366	0,371

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
	1	0	0	0	1	0	0	0	0	0	0	0
	73	**74**	**75**	**76**	**77**	**78**	**79**	**80**	**81**	**82**	**83**	**84**
desired $\mathbf{d_i}$	0	0	0	0	0	0	0	0	0	0	0	0
real $\mathbf{y_i}$	0,162	0,111	0,132	0,878	0,287	0,008	0,558	0,441	0,445	0,812	0,821	0,611
	0	0	0	1	0	0	1	0	0	1	1	1
	85	**86**										
desired $\mathbf{d_i}$	0	0										
real $\mathbf{y_i}$	0,008	0,24										
	0	0										

Misclassified Company

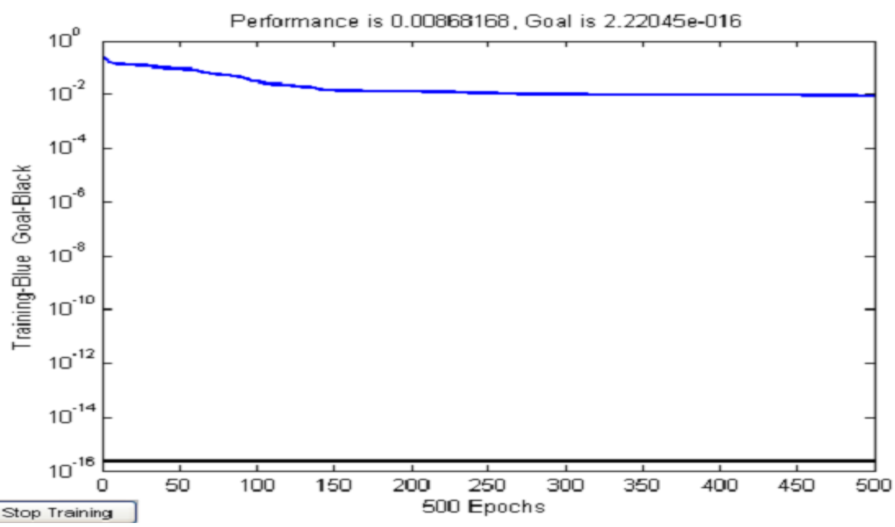

Figure 3. Learning curve of the optimal network with two hidden layers and one output

4.3. Comparison of model performance

The comparison of the two models (discriminates analysis and neural approaches) in terms of predictability shows to the efficiency of neural technique as compared to discriminates analysis. Indeed, the percentage of correct classification, resulting from the application of artificial neural networks is better than discriminates analysis.

Result of the discriminates analysis	results of neural networks
74,4%	82,55%

Thus, artificial neural networks appear to be a powerful tool for the prediction of the financial distress of companies. This work goes hand in hand with the empirical studies already established (Kerling & Podding, 1994; Oden & Sharada, 1990; Abdou *et al.*, 2008; Khashman, 2011).

Artificial neural network models are increasingly used in scoring with varying success. According to some statisticians, although these new methods are interesting and sometimes more efficient than traditional statistical techniques, they are also less robust and less well founded. Furthermore, neural networks are unable to explain the results they provide. Finally, they are as black boxes with unknown operating rules. They create their own representation in learning. In terms of interpretation of weights, discriminates analysis seems to be more efficient. Indeed, in an artificial neural network, internal links do not have any economic significance. Weight ratios appearing in the discriminates functions are rather transparent and easily interpretable in terms of the financial analysis.

To conclude, it is clear that the neural approach and discriminant analysis are two complementary techniques. Discriminates analysis allows us to select the most relevant variables and the neural network can resume variables and calculates the lowest error rate.

5. Conclusion

At this level, we can say that the neural approach outperforms discriminant analysis in terms of credit risk prediction. According to the results of this study, we can make the following major criticisms:

• The present work could be extended by taking into account a larger number and greater variety of variables, including qualitative ones. Bauer *et al* (1998) note that the financial ratios analysis is not an exact science because the priorities in terms of calculation vary from one examination to another. These authors refer to the use of quantitative factors as a guide for the orientation of institutions face to credit risk, which remains unequivocally partially unpredictable.

• The assessment of the Tunisian bank's lending is biased. First, the ratios used by the bank to assess the companies do not give a comprehensive view of the financial situation as there are other variables that are not operated by the bank even though they may reflect the reality of financial situation of companies. Second, Tunisian bank actually grants loans without theoretical or scientific solid reference. Sometimes, there are records of credits that are accepted even if they have financial difficulties either because the client has relations with the bank staff or because they are custodian customers which lead to problems of insolvency. Finally, banks in Tunisia assess their clients only through the criteria of its financial situation. However, Coats & Fant (1993) took the opinion of the auditors on the financial position of companies as a criterion to identify companies in distress. But this advice may lead to misleading results, since according to Altman *et al.* (1994); this criterion is very subjective and prone to misunderstanding.

Several extensions to the discriminant analysis and artificial neural networks are considered. They are likely to improve prediction and to overcome the drawbacks of the latter. This includes genetic algorithms and large margin separators which are also applied to the prediction of financial distress of companies.

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[1] Mean square error in the classification of companies of the training sample
Mean square error in the classification of companies in the test sample