International Business Research; Vol. 9, No. 12; 2016
ISSN 1913-9004 E-ISSN 1913-9012
Published by Canadian Center of Science and Education

A Comparison of Jordanian Bankruptcy Models: Multilayer Perceptron Neural Network and Discriminant Analysis

Yusuf Ali Khalaf Al-Hroot[1]

[1]Department of Accounting, Philadelphia University, Jordan

Correspondence: Yusuf Ali Khalaf Al-Hroot, Department of Accounting, Philadelphia University, Jordan. E-mail: yhroot@philadelphia.edu.jo

Received: October 17, 2016 Accepted: November 14, 2016 Online Published: November 16, 2016

doi:10.5539/ibr.v9n12p121 URL: http://dx.doi.org/10.5539/ibr.v9n12p121

Abstract

The main purpose of this study is to develop and compare the classification accuracy of bankruptcy prediction models using the multilayer perceptron neural network, and discriminant analysis, for the industrial sector in Jordan. The models were developed using the ten popular financial ratios found to be useful in earlier studies and expected to predict bankruptcy. The study sample was divided into two samples; the original sample (n=14) for developing the two models and a hold-out sample (n=18) for testing the prediction of models for three years prior to bankruptcy during the period from 2000 to 2014.

The results indicated that there was a difference in prediction accuracy between models in two and three years prior to failure. The results indicated that the multilayer perceptron neural network model achieved a higher overall classification accuracy rate for all three years prior to bankruptcy than the discriminant analysis model. Furthermore, the prediction rate was 94.44% two years prior to bankruptcy using multilayer perceptron neural network model and 72.22% using the discriminant analysis model. This is a significant difference of 22.22%. On the other side, the prediction rate of 83.34% three years prior to bankruptcy using multilayer perceptron neural network model and 61.11% using discriminant analysis model. We indicate there was a difference exists of 22.23%. In addition, the multilayer perceptron neural network model provides in the first two years prior to bankruptcy the lowest percentage of type I error.

Keywords: multilayer perceptron neural network (MLPNN), discriminant analysis (DA), bankruptcy, financial ratios, Jordan

1. Introduction

It is now more than 80 years since the first study by Fitzpatrick (1932) on bankruptcy. Researchers use statistical techniques, such as logistic regression, discriminant analysis and neural networks to build prediction models for assessing and predicting bankruptcy (business failure), with a very high accuracy rate reached in many studies. Prediction models that were developed using statistical methods to predict bankruptcy can help companies reduce losses for the internal or external users of the finances, by sending warnings prior to bankruptcy.

Since the late 1980s, researchers in Jordan have been working to build prediction models using statistical techniques for assessing and predicting business failure, such as discriminant analysis or by applying the Altman model.

The main objective of the current study is to build two prediction models with data from the Jordanian Industrial Sector during the period 2000 to 2014 for a total of 32 companies, using the multilayer perceptron neural network (MLPNN) and discriminant analysis (DA) to predict the risk of bankruptcy three years prior to the event and compare the performance of the two models.

This study is organized as follows. The first section provides an introduction and literature review. In section two, we discuss the research hypothesis. Section three describes the research methodology. Section four discusses empirical results, and the final section presents the findings of the study and the conclusion.

2. Literature Review

The first study regarding bankruptcy was undertaken by Fitzpatrick (1932), more than three decades after the Fitzpatrick study, Beaver (1967) used in his study the t-tests to evaluate five prior years to bankruptcy, the accounting ratios are independent variables of the study. In 1968, Altman applied a new technique known as discriminant analysis and it is recorded as the most common and important study in the field of bankruptcy. The logit regression statistic was undertaken by Ohlson's (1980) for a large sample that did not include the same size of bankrupt and non-bankrupt companies.

Another technique that can be used to predict bankruptcy is known as neural networks and is used by many researchers. Odom and Sharda's (1990) study compared two statistical tools; the neural networks (NN) and the discriminant analysis technique to compare the prediction rate of both techniques. The results show that a neural network (NN) has better prediction rate. A study by Koh and Tan (1999) showed that the neural network model reached 100% classification accuracy for all tested cases.

In Jordan, the first study on bankruptcy was undertaken by Gharaibeh and Yacoub (1987). The researchers developed a model using the discriminant analysis technique, and this study had a 100% accuracy rate. Also, the same results were found by Alomari (2000) and Al-Hroot (2015). Al-Hroot's (2016) study was recorded as the first study in Jordan related to using the neural network (NN). This study developed a model using the neural network (NN) and reached a 100% accuracy rate for one-year pre to bankruptcy. The study of Alkhatib and Al Bzour (2011) applied Altman and Kida models in the Jordanian non-financial service and manufacturing firms during (1990-2006), results of the study show that the prediction rate for Altman model (93.8%) is better than Kida's model prediction rate (69%). also the study of (Gharaibeh et al., 2013) applied the Altman Z-score (1968) and Kida models in Jordan between 2005and 2012 on a sample included 38 companies in the Jordanian industrial companies, Altman's model shows for three years before bankruptcy prediction rate 89.5%, 65.8% and 52.6% (one, two and three years before bankruptcy) respectively, while Kida's model for three years before bankruptcy prediction rate 76.3%, 52.6%, and 44.7% (one, two and three years prior bankruptcy) respectively. Another study by Alareeni and Branson (2012) applied the Altman models to the service sector in Jordan, the researchers concluded that the Altman Z-score could not give a warning as soon as before bankruptcy and could not differentiate between bankrupt and non- bankrupt companies. They recommended that to obtain high accuracy, another statistical method must be used.

We can conclude that studies inside and outside of Jordan show differing results. While the neural network models and discriminant analysis shows high predictive ability in classification in many studies, researchers in this field reached a high classification rate and a satisfactory result. A neural network model was not applied in earlier studies conducted in Jordan, except in the study of Al-Hroot (2016). In other words, the number of studies that test statistical prediction models that have been done in Jordan are limited, especially the neural network models, when compared with other countries such as the USA or European Union countries.

2.1 Hypotheses Development

To achieve the objective of the study, and after reviewing the related literature, the following hypotheses will be tested:

Hypothesis 1: The MLPNN model will not predict bankruptcy of industrial firms in Jordan for the three years before bankruptcy.

Hypothesis 2: The DA model will not predict bankruptcy of industrial firms in Jordan for the three years before bankruptcy.

3. Research Methodology

This study is to develop and compare the classification accuracy of bankruptcy prediction models using the multilayer perceptron neural network, and discriminant analysis. The study population consisted of companies in the Industry sector in Jordan, over a 14-year period (2000-2014). The sample contains 32 industrial companies in Jordan, Out of 32 industrial companies, 14 are used for estimation sample comprise a similar pair-matched sample of bankrupt and non-bankrupt firms, and 18 are a holdout for model effectiveness comprise a similar pair-matched sample of bankrupt and non-bankrupt firms. Once the sample was selected, the financial ratios can be seen in (Appendix) Table 1; financial ratios includes the ten most popular financial ratios found to be useful in earlier studies and expected to predict financial distress (Jodi, Don and Michael, 2007). Table 1 shows the accounting ratios; calculated accounting ratios are entered then into SPSS to estimate the MPLNN and DA models.

Table 1. List of popular financial ratios in earlier studies

Variable Code	Financial ratios	Number of Studies used the Factor*
X1	Current Ratio	51 studies
X2	Return on Assets	54 studies
X3	Cash/Total Assets	18 studies
X4	Debt Ratio	27 studies
X5	Cash Flows from Operating Activities/Total Liabilities	14 studies
X6	Current Assets to Total Assets Ratio	26 studies
X7	Long -term Debt/Total Assets	8 studies
X8	Margin Before Interest and Tax	9 studies
X9	Sales /Total Assets	32 studies
X10	Working Capital /Total Assets	45 studies

* Jodi, Don and Michael, 2007

3.1 Neural Network and Discriminant Analysis

3.1.1 The Neural Network

Figure 1 shows that the neural network (NN) have three layers; the *input layer* is 10 ratios (from X1 to X10), the number of *hidden layers* is 1, which includes 7 units in this layer using the activation sigmoid function, and the *output layer* is the status of the company (bankrupt or non-bankrupt), We chose the NN to classify bankrupt and non-bankrupt industrial companies on the basis of ten variables.

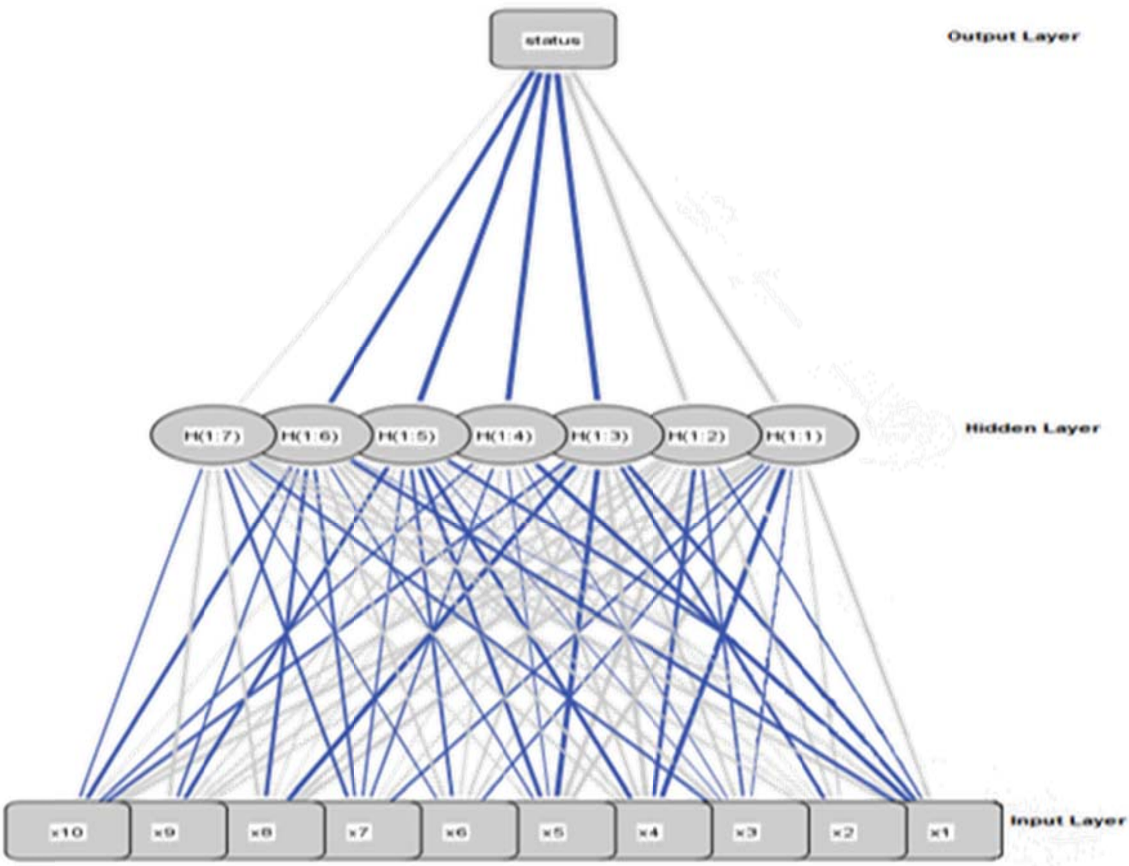

Figure 1. MPLNN model design

Table 2 shows the parameter estimates (also called beta coefficients, or synaptic weights) shows the relationship between the input units in a given layer (X_1, X2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, X_{10}) and the units in the following layer (Hidden Layer). The values of synaptic weights can become rather high and these values (weights) are not used to interpret neural network results because they are not actual values.

Table 2. The Synaptic weights

		Input Layer (x)										Output Layer
	Codes	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	z(j)
Weights to Hidden h(I,j)	h(1:1)	1.05	0.26	-0.06	-1.81	1.53	-0.26	-0.38	1.92	0.26	1.47	2.9
	h(1:2)	-0.22	0.34	-0.26	-0.78	1.51	0.26	0.15	1.16	0.95	0.70	3.7
	h(1:3)	-1.27	-0.69	0.50	1.72	-1.65	0.40	0.04	-2.76	0.21	-0.86	-5.1
	h(1:4)	-2.57	0.004	-0.10	0.42	-0.12	0.15	-0.25	0.03	0.21	-0.36	-2.8
	h(1:5)	0.18	0.14	-0.05	-1.26	-0.95	-0.37	-0.20	0.12	-1.11	0.02	-4
	h(1:6)	-1.30	0.11	0.67	0.48	-0.19	0.36	-0.36	-0.63	-0.26	-1.10	-1.9
	h(1:7)	0.96	0.27	-0.52	0.37	0.13	-0.18	-0.42	0.44	0.55	-0.20	0.1

The steps to calculate the prediction score are as follows:

1- Converting input nodes to a hidden node *f* (j), the equation is given by (Schmidhuber, 2015):

$$f(j) = \sum_{i=1}^{10} x(i) \times h(i,j) \qquad (1)$$

f (j): is the hidden node.

x (i): is the input node.

h (i,j) : is the weights to hidden.

The values shown in Table 4 are not final and the algorithm cannot use these values because they are not actual values. The results in Table 4 show the application of the above equation shown in number 1.

Table 3. Hidden nodes *f* (j)

Codes	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	**∑ *f* (j)**
f(1)	x1×1.05	x2×0.26	x3×-0.06	x4×-1.81	x5×1.53	x6×-0.26	x7×-0.38	x8×1.92	x9×0.26	x10×1.47	**∑ *f* (1)**
f(2)	x1×-0.22	x2×0.34	x3×-0.26	x4×-0.78	x5×1.51	x6×0.26	x7×0.15	x8×1.16	x9×0.95	x10×0.70	**∑ *f* (2)**
f(3)	x1×-1.27	x2×-0.69	x3×0.50	x4×1.72	x5×-1.65	x6×0.40	x7×0.04	x8×-2.76	x9×0.21	x10×-0.86	**∑ *f* (3)**
f(4)	x1×-2.57	x2×0.004	x3×-0.10	x4×0.42	x5×-0.12	x6×0.15	x7×-0.25	x8×0.03	x9×0.21	x10×-0.36	**∑ *f* (4)**
f(5)	x1×0.18	x2×0.14	x3×-0.05	x4×-1.26	x5×-0.95	x6×-0.37	x7×-0.20	x8×0.12	x9×-1.11	x10×0.02	**∑ *f* (5)**
f(6)	x1×-1.30	x2×0.11	x3×0.67	x4×0.48	x5×-0.19	x6×0.36	x7×-0.36	x8×-0.63	x9×-0.26	x10×-1.10	**∑ *f* (6)**
f(7)	x1×0.96	x2×0.27	x3×-0.52	x4×0.37	x5×0.13	x6×-0.18	x7×-0.42	x8×0.44	x9×0.55	x10×-0.20	**∑ *f* (7)**

2-Converting the values to actual values:

The values in Table 4 must be converted to threshold values (theta) to be actual values. The theta values fall between 0 and 1 (Gosavi, 2015), using the sigmoid function which refers to the logistic function to convert

3- Calculating the weights on the link from the hidden node to the output node

Table 4 shows the equations for weights on the link from hidden nodes ∑ *f* (j) to the continuous output v (j); the v (j) is the weights on the link from the hidden node to the output node o (j). The results in Table 4 show the application of the below equation number 2.

$$v(i) = \frac{1}{1+e^{-f(i)}} \qquad (2)$$

Table 4. Converting hidden node ∑ *f* (j)

∑ *f* (j)	v(j)
∑ *f* (1)	$1/(1+e^{-f(1)})$
∑ *f* (2)	$1/(1+e^{-f(2)})$
∑ *f* (3)	$1/(1+e^{-f(3)})$
∑ *f* (4)	$1/(1+e^{-f(4)})$
∑ *f* (5)	$1/(1+e^{-f(5)})$
∑ *f* (6)	$1/(1+e^{-f(6)})$
∑ *f* (7)	$1/(1+e^{-f(7)})$

$$o(j) = \sum_{i=1}^{10} v(i) \times z(i,j) \qquad (3)$$

Table 5 shows the results of the application of the equation number 3.

Table 5. The output nodes o (j) calculation

v(j)	z (j)	o (j)
$1/(1+e^{-f(1)})$	2.9	v(1) × z(1)
$1/(1+e^{-f(2)})$	3.7	v(2) × z(2)
$1/(1+e^{-f(3)})$	-5.1	v(3) × z(3)
$1/(1+e^{-f(4)})$	-2.8	v(4) × z(4)
$1/(1+e^{-f(5)})$	-4	v(5) × z(5)
$1/(1+e^{-f(6)})$	-1.9	v(6) × z(6)
$1/(1+e^{-f(7)})$	0.1	v(7) × z(7)
Total ($\sum_{i=1}^{10} v(i) \times z(i,j)$)		Value [1]

Finally, we have to convert the value of o(j) similar to the prediction score as a calculation in step 2. The equation is given by (Schmidhuber, 2015):

$$Predection\ score(p\ score) = \frac{1}{1 + e^{-o(i)}} \tag{4}$$

3.2 Discriminant Analysis (DA)

Discriminant Analysis (DA) is a statistical technique (discrete prediction), and this technique usually used when the dependent variable has two or more than three categories, in this study the dependent variable (bankrupt or non-bankrupt) is predicted on the basis of two or more independent variables (financial ratios), the financial ratios are interval numerical variables in DA. The final equation of DA is:

DA score = M1 X1 + M2 X2+M3 X3... M_i X_i +a

Where DA is the discriminate function or score

M = the discriminant coefficient or weight for that variable

X = the independent variables (e.g., financial ratios)

a = a constant

i = the number of predictor variables

DA score = 0.25X1 + 3.92X2 - 8.9X3 + 9.94X4 -7.46X5 - 8.6X6 + 0.8X7 + 7.62X8 - 6X9 + 1.95X10 +4.3

In the above function (DA function) the cut-off point or value is -0.0071, the cut-off point means that companies with a DA score greater than or equal to -0.0071 are predicted as solvent and companies with a DA score less than -0.0071 are predicted as being bankrupt. The performance of the model is evaluated using the overall accuracy rate and accuracy is based on the total number of the correct classification shown in table 7. Furthermore, the most important financial ratios that investors can use for making their decisions based on the DA model are; Return on Assets (ROA), Debt Ratio and Margin before Interest and Tax.

Table 6. DA model classification summary

Actual observed	Bankrupt	Non-bankrupt	Total	Percent Correct	Type I error	Type II error
Bankrupt	7	0	7	100%	0%	0%
Non-bankrupt	0	7	7			

4. Results

Table 8 shows the results after testing the PLMNN and DA models on the original sample. The PLMNN model cut-off point is 0.5; using a cut-off level of 0.5 to classify the output values, the cut-off point means that companies with a PLMNN score greater than or equal to 0.5 are predicted as solvent and companies with a PLMNN score less than 0.5 are predicted as being bankrupt. The performance of the model is evaluated using the overall accuracy rate and accuracy is based on the total number of the correct classification shown in table 7.

[1]The value varies due to the financial ratios of company selected.

Table 7. Classification Results for PMLNN and DA models (Original Sample)

PLMNN model				DA model			
Number of correct classifications	Percent of correct classifications	Percent of error classification		Correct classification rate	Percent of correct classifications	Percent of error classification	
		Type I error	Type II error			Type I error	Type II error
7	100%	0%	0%	7	100%	0%	0%

The holdout sample was used to assess the PLMNN and DA models. The results obtained by using the PLMNN and DA models on the holdout sample are presented in Tables 8 and 9. Comparative classification results of PLMNN and DA models are summarized in Table 10.

Table 8. Classification Results for PMLNN model (holdout sample)

Year prior to bankruptcy	Actual observed	Predicted		Percent Correct	Percent of error classification	
		Bankrupt	Non- bankrupt		Type II error	Type I error
Year -1	Bankrupt	9	0	100.0%		0%
	Non- bankrupt	0	9	100.0%	0%	
	Overall Percent			100.0%		
Year -2	Bankrupt	8	1	88.89%		11.11%
	Non- bankrupt	0	9	100.0%	0%	
	Overall Percent			94.44%		
Year -3	Bankrupt	7	2	77.78%		22.22%
	Non- bankrupt	1	8	88.89%	11.11%	
	Overall Percent			83.34%		

As indicated in Table 8, the PMLNN model is extremely accurate in classifying 100% of the total sample correctly for one year prior to bankruptcy, but the accuracy rate declined to 94.44% for the second year prior to bankruptcy. The Type I error proved to be only 11.11%, while the Type II error was not recorded. For the third year prior to bankruptcy, the accuracy rate dropped to 83.34% with the Type I error proved to be only 22.22%, while the Type II error increased to 11.11% in this test. Nevertheless, the PMLNN achieved high overall classification accuracy for two years prior to bankruptcy, with an accuracy rate of 100% and 94.44% respectively.

Table 9. Classification Results for DA model (holdout sample)

Year prior to bankruptcy	Actual observed	Predicted		Percent Correct	Percent of error classification	
		Bankrupt	Non- bankrupt		Type II error	Type I error
Year -1	Bankrupt	9	0	100.0%		0%
	Non- bankrupt	0	9	100.0%	0%	
	Overall Percent			100.0%		
Year -2	Bankrupt	5	4	55.56%		44.44%
	Non- bankrupt	1	8	88.89%	11.11%	
	Overall Percent			72.22%		
Year -3	Bankrupt	4	5	44.44%		55.56%
	Non- bankrupt	2	7	77.78%	22.22%	
	Overall Percent			61.11%		

As indicated in Table 9, the DA model is extremely accurate in classifying 100% of the total sample correctly for one year prior to bankruptcy, but the accuracy rate falls from 100% one year prior to bankruptcy to 72.22% two years prior to bankruptcy. The Type II error proved to be 44.44% while the Type I error was lower at 11.11% in this test. For the third year prior to bankruptcy, the accuracy rate dropped to 61.11%, with the Type I error proved to be only 22.22%, while the Type II error was slightly larger at 55.56% in this test. Nevertheless, the DA achieved high overall classification accuracy for one year prior to bankruptcy with an accuracy rate of 100%.

5. Discussion

Table 10 presented the results of two methods used in this study. The results indicated that the MLPNN model achieved the highest overall classification accuracy rate for all three years prior to bankruptcy than the DA model. Furthermore, the results indicate that the accuracy rate of the MLPNN model increased from 77.78% for the third year prior to bankruptcy to 100% for the first year prior to bankruptcy. This result supports the rejection of the first hypothesis which states that the MLPNN model is unable to predict bankruptcy of industrial companies in Jordan during the three years prior to bankruptcy.

As Table 10 shows that the accuracy rate of the DA model increased from 61.11% for the third year prior to bankruptcy and reached 100% for the first year prior to bankruptcy. These results support the rejection of the second hypothesis which states that the DA model is unable to predict bankruptcy of industrial companies in Jordan during the three years prior to bankruptcy.

It is also noted from Table 10 and Figure 2 that the MLPNN model achieved the highest overall classification accuracy rate for all three years prior to bankruptcy, with an average classification rate of 92.59% while the DA model achieved an average classification rate of 77.78%.

Table 10. Comparative Classification Results

Year prior to bankruptcy	MLPNN model	DA model	MLPNN model		DA model		Altman model	
			Type I error	Type II error	Type I error	Type II error	Type I error	Type II error
Year -1	100%	100%	0%	0%	0%	0%	10%	25%
Year -2	94.44%	72.22%	11.11%	0%	44.44%	11.11%	15%	60%
Year -3	83.34%	61.11%	22.22%	11.11%	55.56%	22.22%	16%	48%
Average rate	92.59%	77.78%	11.11%	3.70%	33.33%	11.11%	13.67%	44.33%

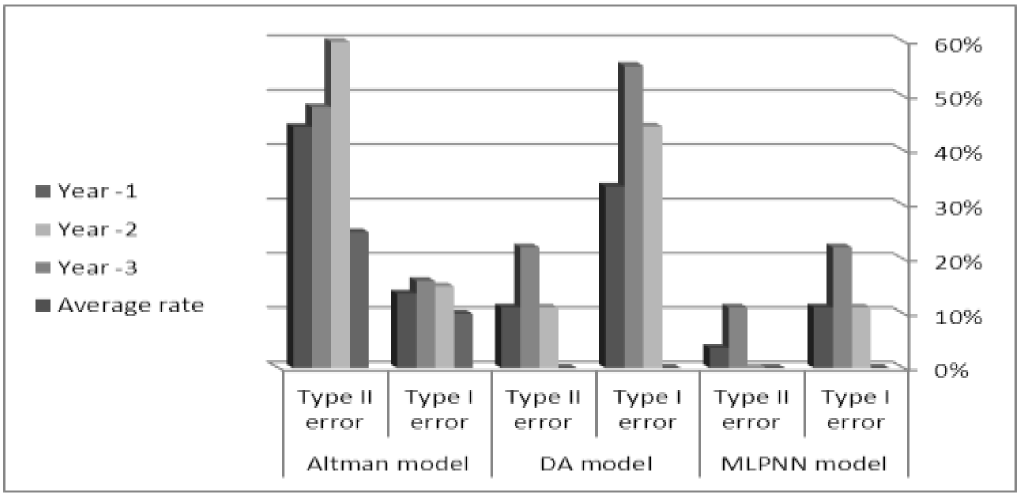

Figure 2. Classification rates over the three years tested

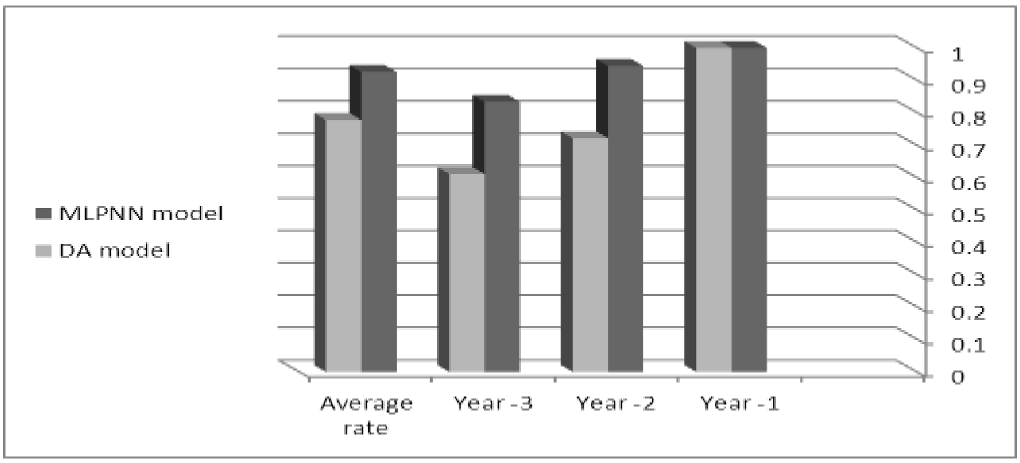

Figure 3. Type I and type II errors for each model

Furthermore, since the type I error is more costly than the type II error (Charitou et al., 2004), Altman et al. (1977) and Charitou et al. (2004). In addition, if models minimize type I error rates they consider to be superior. Table 10 and Figure 3 shows that the MLPNN model provides the lowest type I error percentage in the first two years prior to bankruptcy. However, type II error rates are highly low (3.70% on average) and this model may consider reliable for practical application purposes. These results support the rejection of the first hypothesis which states that the MLPNN model is unable to predict bankruptcy of industrial companies in Jordan during the three years prior to bankruptcy.

6. Conclusion

The comparison of the multilayer perceptron neural network (MLPNN) and discriminant analysis (DA) in terms of ability to predict bankruptcy in Jordan, The study population consisted of companies in the Industry sector in Jordan, over a 14-year period (2000-2014). The sample contains 32 industrial companies in Jordan to develop two models using the MLPNN and DA.

The MLPNN and DA models can predict bankruptcy of Industry sector in Jordan, with the accuracy of 100% for one year before bankruptcy, and this is the same prediction rate accuracy for the DA model. On the holdout sample, the results indicated that the MLPNN model achieved the highest overall classification accuracy rate for all three years prior to bankruptcy than the DA model, and the MLPNN model result in low type I error rates. The results are associated with the findings of Odom & Sharda (1990) and Raghupathi & Schkade and Raju (1991), Koh & Tan (1999) and Charitou et al. (2004). They also found that the models developed with neural networks (NN) can achieve a better classification accuracy rate than other statistical methods. Furthermore, the MLPNN model provides the lowest type I error percentage in the first and second years before bankruptcy. Nonetheless, type II error rates are highly low (3.70% on average) and this model may consider reliable for practical application purposes in Jordan. On the other hand, the most important financial ratios that investors can use for making their decisions based on the two models are; Return on Assets (ROA), Debt Ratio and Margin before Interest and Tax.

Finally, we recommended that the proposed model must apply by the Jordanian Companies Control Department (CCD) in the Ministry of Industry & Trade, so the CCD will be able to take an appropriate action and necessary corrective decisions in the industrial sector. Furthermore, CCD must publish a guide to using these statistical models such as MLPNN model. For future research other statistical methods can also be used to predict bankruptcy such as the Radial basis neural network (RBNN) in order to compare the results with the multilayer perceptron neural network (MLPNN) model.

Acknowledgments

The author would like to thank the editorial team and reviewers for their comments that greatly improved the manuscript.

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Appendix A

Table 1. Financial ratios (Independent variables)

	Current ratio	Return on assets	Cash assets ratio	Debt ratio	Cash Flow Coverage Ratio	Current assets to total assets ratio	Long -term debt/total assets	Margin Before Interest and Tax	Asset Turnover Ratio	Working Capital Ratio
Company name	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}
Jordan Kuwait For Agriculture & Food Products	0.12	-0.96	0.00	0.97	-0.09	0.12	0.00	-0.52	0.23	-0.85
Nayzak Dies & Moulds Manufacturing	0.92	-0.06	0.00	0.71	0.07	0.35	0.33	-0.23	0.26	-0.03
Jordan Medical Corporation	0.20	-0.35	0.11	3.11	-0.04	0.62	0.01	-2.45	0.14	-2.49
International Textile Manufacturing	1.64	0.08	0.01	0.45	-0.03	0.37	0.23	-0.68	0.06	0.14
United Glass Industries	33.49	0.01	0.53	0.02	0.49	0.53	0.00	0.33	0.02	0.52
Arab Investment & International Trade	1.84	-0.07	0.02	0.23	-0.23	0.30	0.07	-0.21	0.26	0.14
Arab Food & Medical Appliances	0.13	-0.20	0.00	1.04	-0.14	0.14	0.00	-0.96	0.10	-0.91
Arab Center For Pharmaceuticals & Chemicals Industries	15.00	0.12	0.23	0.05	2.85	0.80	0.00	0.27	0.50	0.74
Arab Aluminium Industry	4.04	0.08	0.01	0.12	1.92	0.36	0.00	0.18	0.61	0.27
Middle East Pharmaceutical & Chemical Industries	4.80	0.02	0.17	0.13	-0.06	0.60	0.00	0.02	0.83	0.47
Jordan Paper & Cardboard Factories	3.61	0.07	0.06	0.12	0.36	0.42	0.00	0.11	0.69	0.30
Al-ekbal Printing & Packaging	3.08	0.04	0.09	0.14	0.21	0.44	0.00	0.07	0.61	0.30
National Aluminium Industrial	2.91	0.07	0.09	0.26	0.42	0.42	0.43	0.17	0.46	0.28
Universal Modern Industries	2.35	0.04	0.01	0.13	0.10	0.26	0.00	0.22	0.30	0.11