Original Article

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Development of a Fraud Detection Model Using an Integrated Approach Based on the Factor Analysis Model and the Artificial Neural Network Method in Firms Listed in Tehran Stock Exchange

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Abstract

In today's world, fraud,which is euphemistically called economic crimes, is frequently seen in the business environment. Fraud is followed by enormous losses and irreparable damages for an organization. The main purpose of this research is to propose a fraud detection model using an integrated approach based on the factor analysis model and the artificial neural network method. The neural network used in this research is a feed forward neural network with backpropagation algorithm. The statistical population of this study is comprised of the companies listed in Tehran Stock Exchange in the time interval from 2013 to 2014. Out of these companies, 140 have been selected as the research sample. The Beneish M-Score model has been used in order to classify the companies with the likelihood offraudulent and non-fraudulent reporting. According to the Beneish M-Score Model, 78 companies were fraudulent in terms of their reports and 62 were non-fraudulent. For the final selection of the input variables (financial ratios) in the artificial neural network, the confirmatory factor analysis model and the principal component analysis model have been used. The results obtained from the aforementioned models have shown that the reported structure of the neural network model has 7 hidden layer neurons and the momentum learning algorithm has been used for training the network. This algorithm was more precise and functioned better than other reviewed structures. Therefore, it was selected as the final adjustment of the neural network. Then, the performance of the neural networks model was estimated and it was compared with the logistic regression method in order to review the precision of the neural network. The obtained results indicated that the artificial neural network method had a higher performance in this regard; in that the precision of classification of fraudulent and non-fraudulent firms and the overall performance of the artificial neural network method was 57.69%, 72.73% and 62.16%, respectively. On the other hand, the precision of classification of fraudulent and non-fraudulent firms and the overall performance of the logistic regression method was 54.55%, 50% and 54.05%, respectively.

Key words: Fraud, Fraudulent financial reporting, Artificial neural network, Confirmatory factor analysis

INTRODUCTION

In today's world, fraud, which is euphemistically called economic crimes, is frequently seen in the business environment. Fraud is followed by enormous losses and irreparable damages for an organization. Annually, due to frauds, business units all over the world have faced hundreds of millions of dollars of losses. The continuous promotions and rumors resulting from such misconducts and indecencies can be followed by large-scale disastrous consequences in the long run (Rezayi, et al. 2011). Accounting experts define accounting fraud as: "false and deliberate manipulation of the data of financial statements with the purpose of acquiring operational profit and presenting a better image of the firm than the reality" (Sharma and Panigrahi, 2013). Audits believe that there are two type of deliberate distortions when it comes to investigating fraud:

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a- Distortions resulting from fraudulent financial reporting
b- Distortions caused by misuse of assets.

The issue of fraud in financial statements has received a great deal of attention from communities, media, investors, financial society and legislators and this was due to multiple infamous frauds in large companies such as Enron, Lucent and WorldCom over the past years (Yue and Else, 2007). In the past few years, in the world's auditory literature, we have observed efforts that have been made with the purpose of proposing models for predicting frauds committed by managers; models that are quite efficient as far as detection of fraud in financial statements is concerned and guide the auditor in detecting the frauds in the financial statements in a shorter period of time and with lower costs than the common traditional methods (Kadkhodayi and Elyadarani, 2010).

Some motives that makes managers commit fraud in their financial reporting are rewards that are based on the reported profit, maintaining or increasing the stock market prices, getting access to domestic and international forecasts, minimizing tax liabilities, preventing violations in debt covenants and being able to finance the firm in the cheapest way possible (Safarzadeh, 2010).

OBJECTIVES OF THE RESEARCH

The main purpose of this research is to propose a fraud detection model using an integrated approach based on the factor analysis model and the artificial neural network methodin order to reassure investors, creditors and financial analysts for them to be able to make decisions in the capital market. The specific objectives of the research are:

- Identifying factors affecting fraud
- Measuring factors affecting fraud
- Ranking factors affecting fraud
- Proposing a fraud detection model using the artificial neural network model.

LITERATURE REVIEW AND RESEARCH QUESTIONS

- In 2014, Yeganeh et al. used the probabilistic neural networksfor detecting the type of auditor's opinion in an article. The results of this research were indicative of the high explanatory power of the probabilistic neural networks in terms of predicting auditor's reports. In connection with the evaluation of the relative importance of the input variables and also in order to analyze their role in the process of auditing, sensitivity analysis was used.
- In 2014, Vosoogh et al. wrote an article and reviewed fraud detection in credit cards using the artificial neural network. By comparing the criteria of the evaluation of performance calculated in this research with the results of the models proposed in other studies, it became clear that the performance evaluation criteria of this research were properly valid and reliable.
- In 2014, Moradi et al. wrote an article and investigated the recognition of the risky factors that affected the likelihood of commitment of fraud in financial statements from the perspective of auditors and their impact on financial performance. The findings of this research indicated that there is a significant relationship between management features, management's adherence to internal controls and enforceable standards, risk factors associated with the conditions of the market and industry, operating characteristics, cash flow and financial stability with the likelihood of commitment of fraud. In addition, the results were also indicative of the presence of a significant relationship between firm performance (variables: rate of return on assets, operating cash flow, return on equity and return on the firm) and the risk of fraud.
- Etemadi and Zelghi, in 2013, reviewed the application of logistic regression in detectingfraudulent financial reporting in an article. The obtained results showed that this model plays an effective role in detecting fraud in financial statements and can be of significant help to investors, official accountants, internal accountants, tax authorities, public institutions and banking systems.
- In 2012, Forooghi et al. wrote an article and reviewed the effect of the importance of auditing on the attention paid by auditors in the process of detecting the fraud committed by managers. The research results indicated that the importance of auditing the financial statements makes auditors less attentive in the process of detecting the fraud committed by managers. By reviewing the auditory reports, it became clear that the process of auditing financial statements revealed that the managers had probably committed a fraud in a maximum of 6.3% of the reviewed cases.
- In 2011, Amini et al. wrote an article and reviewed the factors affecting the issuance of audit reports using the neural network method. The results showed that the ratio of after-tax profit to sales had the most significant relationship with the issuance of qualified audit opinions and after that, in order of preference, there is: current ratio, ratio of total debt to total assets, firm size, qualification of the auditory reports of the previous year, ratio of accounts receivables to total assets, the number of inventory turnover, quick ratio and the type of the audit firm and these factors all affect the issuance of qualified audit opinions.
- In 2016, Edmond Ofori wrote an article and reviewed detection of financial fraud in Enron firm using an

integration of Altman Z-score model and Beneish M-score. This firm has used fraudulent financial reports to mislead investors, shareholders, creditors, employees of the firm, government and the legislating institutions of the financial markets. The results showed that the financial reports of the firm in 1997 were fraudulent. The eigenvalue of Beneish M had increase to 36.18% in 1998 in comparison with that in the year 1997 which means that profit manipulation had started at that time.

- In 2015, Roshayani et al. wrote an article and predicted the business failure and fraudulent financial reports based on Beneish M-score model and Altman Z-score in 24 bankrupted firms and 24 non-bankrupted firms among the firms listed in Malaysia Stock Exchange. By using 10 financial ratios, they attempted to predict business failure and to detectfraudulent financial reportand according to the obtained results, the classification of bankrupted firms was 96% accurate and the classification of fraudulent financial reports were 83.3% accurate.
- In 2015, Tarju and Neural wrote an article and reviewed the application of Beneish M-score model and data analysis for detecting financial fraud in the time interval from 2001 to 2014 for public services firm in Indonesia. The results showed that Beneish M-score model is able to detect financial fraud. The gross profit margin index, the depreciation index, sales, general and administrative expense index, and accruals have a significant effect on the detection of financial fraud. but the sales index, the asset quality index and the lever index do not have a statistically significant impact on the detection of financial fraud.
- In 2012, Lei and Ghorbani used the advanced comparative learning neural networks in order to detect fraud and network intrusion. The results showed that both of the used networks (SCLN and ICLN)had high performances and the performance of SCLN was better than the unsupervised traditional clustering algorithms.
- In 2009, Veri and Kullanimi used the data analysis techniques for detecting frauds in the financial statements of productive companies. The ratio of financial lever to return and the ratio of important financial assets to one another in detecting fraud in financial statements were some of the results of their study.
- In 2007, Kirkos and else used financial ratios as the input variables and used the data analysis method and reviewed the way the frauds in financial statements. The decision tree model, the neural network method and Bayesian belief network were 96%, 100% and 95%-accurate predictions, respectively. The obtained results indicated that these frauds can be detected by analyzing the data obtained from financial statements.

In this research, a model was developed for detecting fraud in firms listed in Tehran Stock Exchange using an integrated approach based on the factor analysis model and the artificial neural network method. Given the research literature and the theoretical principles of previous studies, the following questions must be answered:

1. How can a model for detecting fraud in firms listed in Tehran Stock Exchange be developed by using an integrated approach based on the factor analysis model and the artificial neural network method?
2. Is the accuracy of prediction and classification of the artificial neural network method different for firms that probably have fraudulent and non-fraudulent financial reporting?
3. Is the artificial neural network method better at predicting the fraud in firms listed in Tehran Stock Exchange and at classifying them than the traditional statistical methods?

RESEARCH METHODOLOGY

Selecting the Sample and Time Period

In the present study, the systematic elimination method has been used for sampling; in such a way that the statistical population (all of the firms listed in the Stock Exchange in the time interval from 2013 to 2014) and the relevant criteria have been taken into consideration and then the 140 firms that had all of the necessary criteria were selected as the research sample.

Research Models

In this research, in order to analyze the research data and to estimate the models, an integration of approaches has been used. The "Beneish M-Score" model has been used for classifying firms as those that have likely committed frauds and those that haven't. In this model, 8 indexes have been used for evaluating financial statement accruals. The results obtained from the indexes in the Beneish Model have been presented in the following formula:

M= - 4.84 + (0.92*DSRI[1]) + (0.528*GMI[2]) +(0.404* AQI[3]) + (0.892*SGI[4]) + (0.115*DEPI[5]) -(0.172* SGAI[6]) + (4.679*TATA[7]) - (0.327*LVGI[8])

1. DRSI = Days' Sales in Receivable Index.
2. GMI = Gross Margin Index.
3. AQI = Asset Quality Index.
4. SGI = Sales growth Index.
5. DEPI = Depreciation Index.
6. SGAI = Sales, General and Administrative Expenses Index.
7. TATA = Total Accruals to Total Assets.
8. LVGI = Leverage Index.

The constant number in this model is −4.84 and the coefficients of each of these eight indexes are way higher than the constant number. When the result obtained from the model show a number higher than −2.22, it indicates that the financial statements of the firm might have been manipulated. According to this model, the calculations associated with the 140 firms selected as the statistical sample of the research have been done using the formula above and the obtained results indicate that the reports of 78 firms were probably fraudulent and the reports of 62 firms were probably non-fraudulent. Then, in order to obtained the fraud detection model, the ratios of the financial statements of the firms with the likelihood of fraud and firms without the likelihood of fraud were selected by taking into considerationprevious researches and the opinions of experts and specialists and these ratios were ranked as the input variables using the "factor analysis model" and were used in the "artificial neural network" and the results of the artificial neural network were compared with those of the "logistic regression".

RESEARCH FINDINGS

Descriptive Statistics

Descriptive statistics include mean, standard deviation, minimum, and maximum of the variables under study. The descriptive statistics of the companies with the likelihood offraudulent reporting and companies with the likelihood of non-fraudulent reporting have based on Beneish M-score model, have been presented in Table 1:

Table 2 shows mean, minimum and maximum value and standard deviation of the research variables with the separation of the financial years (2013 and 2014).

As the article goes on, in order to compare the mean of research variables in the financial years 2013 and 2014, the measurement scales of the variables were matched so that the comparisons between them would be as clear as possible.

Normality Test of Research Variables

One of the most used tests in this field is the Kolmogorov-Smirnov test for a population. By using this test, normal, uniform and Poisson distribution can be reviewed. In this test, the H_0 and H_1 are defined as follows:

$$\begin{cases} H_0: & \text{variable has normal distribution} \\ H_1: & \text{variable does no have normal distribution} \end{cases}$$

Table 3 shows the results obtained from the Kolmogorov-Smirnov test for the research variables. These results are based on the data associated with the financial year 2014.

According to the information presented in Table 3, the significance level of the (Sig.) test for most of the variables of the research is lower than 0.05 at the confidence level of 95%. Therefore, H_0 of the test, which suggests that the distribution of the aforementioned variables is normal, is rejected and the other hypothesis is confirmed. Accordingly, all of the research variables have abnormal distribution, except for "working capital to asset ratio".

Factor Analysis Model

Table 4 shows the results of implementing the factor analysis method on all of the 25 identified financial ratios. As it can be seen, the eigenvalue, the communality value and the factor loading value have been reported for each variable (financial ratio).

Table 1: Descriptive statistics of the variables of Beneish M-Score model

Fraud (1) nonfraud (0)		N	Minimum	Maximum	Mean	Standard deviation
0	DSRI	62	0.10638364	2.18815040	0.9226052263	0.35919805763
	GMI	62	−4.13800860	5.23427600	0.9767488097	1.0206565351
	AQI	62	0.03540154	2.99931670	0.8717142781	0.42891903558
	SGI	62	0.41953400	1.99648550	1.1546302481	0.28672168050
	LVGI	62	0.46039975	2.74118660	1.0820292077	0.35841952415
	TATA	62	−0.3486991000	0.3593599000	006054533387	0.14646876092
	DEPI	62	0.051809250	1.229067700	0.85584749032	0.27783283221
	SGAI	62	0.15873665	6.65811160	1.5047688440	1.1078683809
	Valid N (listwise)	62				
1	DSRI	78	0.12107932	4.95803400	1.6542324597	1.0417515377
	GMI	78	−0.35318306	11.49505700	1.5346762233	1.3917687461
	AQI	78	0.45335570	8.37996600	1.2379636706	1.0004492277
	SGI	78	0.39217168	7.54283860	1.3378648156	0.92905645910
	LVGI	78	0.33467380	1.47846960	1.0371223003	0.18340766231
	TATA	78	−0.5577372300	0.3619623800	0.007668368107	0.13761743496
	DEPI	78	0.021666525	22.945206000	1.16859235391	2.5125941597
	SGAI	78	−3.75863360	2.44008610	0.8672918963	0.93770380569
	Valid N (listwise)	78				

Source: Researcher's calculations (2016)

Table 2: Descriptive statistics of the research variables

Variable	Financial year	Minimum	Maximum	Mean	Standard deviation
EPS	2013	−1183	6942	1107.47	1390.741
	2014	−1367	7152	679.70	1108.08
Debt to equity	2013	−23.30	74.66	2.32	7.57
	2014	−489.73	25.28	−1.10	41.75
Sales to total asset	2013	0.169	2.90	0.94	0.50
	2014	0.117	3.36	0.95	0.57
Net profit to sales	2013	−1.09	2.03	0.17	0.30
	2014	−1.20	0.96	0.12	0.21
Receivables to sales	2013	0.001	1.50	0.26	0.28
	2014	0.0004	1.25	0.26	0.21
Inventory to sales	2013	0.002	4.39	0.35	0.41
	2014	0.004	3.55	0.35	0.33
Inventory to asset	2013	0.001	0.74	0.25	0.13
	2014	0.003	0.80	0.26	0.12
Gross profit to sales	2013	−0.27	0.58	0.25	0.14
	2014	−1.02	0.80	0.21	0.18
Gross profit to asset	2013	−0.25	0.60	0.21	0.12
	2014	−0.37	0.50	0.17	0.11
Net profit to asset	2013	−0.31	0.56	0.13	0.13
	2014	−0.43	0.35	0.08	0.11
Working capital to asset	2013	−0.60	0.75	0.14	0.21
	2014	−1.17	0.73	0.11	0.25
Asset log	2013	4.57	7.98	6.04	0.56
	2014	4.82	8.05	6.10	0.55
Working capital	2013	−3130402	6999957	291110	1008925
	2014	−4147878	5345941	207272	979530
Fixed asset to asset	2013	0.013	078	0.31	0.18
	2014	0.008	0.83	0.32	0.18
Current ratio	2013	0.39	4.65	1.42	0.70
	2014	0.26	4.41	1.37	0.67
Net profit to fixed asset	2013	−1.22	7.30	0.63	0.97
	2014	−1.04	5.14	0.42	0.72
Cash to asset	2013	0.0009	0.42	0.04	0.06
	2014	0.0003	0.28	0.03	0.03
Quick ratio	2013	0.03	2.75	0.66	0.49
	2014	0.04	2.59	0.62	0.44
EBIT	2013	–223752	16274991	552195	1942048
	2014	–179420	13550907	515006	1653862
Long term debt to asset	2013	0.00	0.57	0.08	0.09
	2014	0.00	0.47	0.08	0.09
Debt to asset	2013	0.11	1.32	0.62	0.22
	2014	0.19	1.84	0.64	0.23
Working capital to asset	2013	–1.50	51.76	1.49	4.97
	2014	–2.05	52.10	1.43	5.00
Working capital to sales	2013	–1.38	4.43	0.21	0.53
	2014	–3.22	3.23	0.17	0.52
Net profit to equity	2013	–10.40	3.82	0.30	0.99
	2014	–3.25	27.02	0.40	2.30

Source: Researcher's calculations (2016)

As it can be seen in Table 4, the communality value and also the factor loading value of a number of variables (financial ratios) is lower than accepted. Variables that must be eliminated from the selection list in the first stage of the factor analysis test are: EPS, working capital, working capital to fixed assets, cash to asset, asset Log, EBIT, debt to equity, net profit to equity and finally sales growth.

Following the elimination of the previously cited variables, the second stage of the factor analysis test must be implemented on the remaining variables. Table 5 illustrates the results obtained from the second stage of the factor analysis method.

As it can be observed in Table 5, the eigenvalue, the factor loading value and the communality value are all acceptable. Accordingly, a final list of the variables can be developed consisting of financial ratios for predicting companies' fraud. By implementing the factor analysis test on the research variables, some financial ratios with the necessary power for prediction were selected to enter the neural network (Table 6).

Designing the Neural Network Model

In this stage of data analysis, given the results obtained from the previous stages, the artificial neural network method is used for predicting the likelihood of financial fraud in

Table 3: Testing normality of distribution of variables

Research variables	Kolmogorov-Smirnov Z	Sig.
EPS	0.20	0.000
Debt to equity	0.47	0.000
Sales to total asset	0.17	0.000
Net profit to sales	0.15	0.000
Receivables to sales	0.12	0.000
Sales growth	0.22	0.000
Inventory to sales	0.21	0.000
Inventory to asset	0.07	0.046
Gross profit to sales	0.10	0.001
Gross profit to asset	0.08	0.021
Net profit to asset	0.08	0.016
Working capital to asset	0.07	0.074
Asset log	0.08	0.015
Working capital	0.23	0.000
Fixed asset to asset	0.08	0.010
Current ratio	0.17	0.000
Net profit to fixed asset	0.20	0.000
Cash to asset	0.22	0.000
Quick ratio	0.14	0.000
EBIT	0.34	0.000
Long term debt to asset	0.233	0.000
Debt to asset	0.088	0.010
Working capital to asset	0.31	0.000
Working capital to sales	0.17	0.000
Net profit to equity	0.43	0.000

Source: Researcher's calculations (2016)

Table 4: Outputs of the "first" stage of the factor analysis test

Factor	Financial ratio	Factor loading	Communality	Eigen value
1	EPS	0.62	0.77	7.60
	Net profit to sales	0.74	0.83	
	Gross profit to sales	0.74	0.86	
	Gross profit to asset	0.68	0.87	
	Net profit to asset	0.81	0.94	
	Working capital to asset	0.78	0.95	
	Working capital	0.55	0.78	
	Current ratio	0.72	0.93	
	Net profit to fixed asset	0.81	0.86	
	Quick ratio	0.55	0.81	
	Working capital to fixed asset	0.71	0.77	
	Altman Z-Score	0.76	0.86	
2	Inventory to asset	0.41	0.89	4.25
	Fixed asset to asset	0.61	0.93	
	Cash to asset	0.31	0.33	
3	Inventory to sales	0.57	0.91	2.23
	Asset log	0.57	0.77	
	EBIT	0.40	0.70	
4	Debt to equity	0.46	0.76	2.07
	Sales to total asset	0.63	0.89	
	Debt to asset	0.49	0.94	
5	Receivables to sales	0.57	0.80	1.50
6	Long term debt to asset	0.67	0.86	1.39
	Net profit to equity	0.41	0.69	
7	Sales growth	0.49	0.69	1.23

Source: Researcher's calculations (2016)

firms using the set of financial ratios which was finalized in the previous stage. For this purpose, given the results

Table 5: Outputs of "second" stage of the factor analysis test

Factor	Financial ratio	Factor loading	Communality	Eigen value
1	Net profit to sales	0.81	0.85	6.24
	Gross profit to sales	0.88	0.88	
	Gross profit to asset	0.89	0.91	
	Net profit to asset	0.91	0.92	
	Net profit to fixed asset	0.82	0.84	
	Altman Z-Score	0.66	0.88	
2	Working capital to asset	0.89	0.95	3.26
	Current ratio	0.92	0.95	
	Quick ratio	0.86	0.85	
	Working capital to sales	0.87	0.89	
3	Sales to total asset	0.92	0.90	1.88
	Receivables to sales	0.67	0.80	
4	Inventory to sales	0.78	0.94	1.48
	Inventory to asset	0.92	0.92	
5	Fixed asset to asset	0.85	0.94	1.42
	Debt to asset	0.55	0.95	
6	Long term debt to asset	0.95	0.95	1.05

Source: Research's calculations

of the previous stage, the financial ratios that were proven to be powerful in terms of predicting the decision variable (likelihood of fraud of firms) were selected as the input of the neural network and the "firms' fraud condition", which is a binary variable (0=non-fraud, 1=fraud) was used as the output variable. Then, the collected data was used to train and to test the network. For this purpose, the Rapidminer software Ver.6.4 has been used. The Rapidminer software is a powerful software in the field of data analysis, machine learning, analyzing and predicting businesses. As the article goes one, the results of this stage of data analysis will be discussed.

Assessing neural network

The number of neurons in the middle layer or the hidden layer seriously affects the efficiency of the network and the accuracy of its prediction. In order to determine the number of hidden layer neurons, the trial and error method has been used; in such a way that after training the neural network with different structures, they would be evaluated by using the test data and the most accurate network with highest performance would be selected. In order to train the network, the input data are divided into three groups training data (70%), validation data (15%) and test data (15%). The validation data is used for preventing network saturation and the test data is used for measuring the performance and accuracy of the trained network.

In order to determine the number of neurons in the hidden layer of the designed network, the trial and error method has been used and the most accurate network with highest performance has been selected. In order to compare the performance of neural networks with different structures

Table 6: Financial ratios selected by the factor analysis test for entering the neural network

Row	Selected financial ratios			
1	Net profit to sales	Gross profit to sales	Gross profit to asset	Net profit to asset
2	Net profit to fixed asset	Altman Z-Score	Working capital to asset	Current ratio
3	Quick ratio	Working capital to sales	Sales to total asset	Receivables to sales
4	Inventory to sales	Inventory to asset	Fixed asset to asset	Debt to asset
5	Long term debt to asset			

Source: Researchers' calculations (2016)

Table 6: Structure and accuracy of the trained network for predicting the condition of fraud in firms

Row	Structure of the network	Learning algorithm	Accuracy of the model (%)
1	17-3-1*	Momentum	54
2	17-5-1	Momentum	51
3	17-7-1	Momentum	63
4	17-9-1	Momentum	54
5	17-12-1	Momentum	51
6	17-14-1	Momentum	48

*Right to left: The number of input, hidden and output layer neurons,
Source: researchers' calculations (2016)

network accuracy and confusion matrix have been used and the structure of the network with lowest error and highest accuracy has been selected. Table 8 shows learning algorithms and structures of the neural network with a higher accuracy and a higher performance than other tested networks.

Given the information presented in the table above, all of the tested neural network structures and algorithms predict the condition of fraud of firms with a proper and acceptable level of accuracy. Nonetheless, the structure reported in third row, which has 7 neurons in the hidden layers and has used the momentum learning algorithm for training the network, has a higher performance and accuracy than other reviewed structures and that is why it has been selected as the final adjustment of the neural network. The information presented in Table 6 is indicative of the high accuracy and performance of the designed neural network in terms of predicting and modeling the likelihood of fraud in firms based on the selected explanatory variables (the selected financial ratios) in the research. In other words, the designed and trained neural network is able to predict the condition of financial fraud of firms based on the selected financial ratios with a proper level of accuracy by using the data collected from the Stock Exchange. Figure 1 shows the final neural network model after training with the collected data and the estimation of synaptic weights.

Table 7 shows the synaptic weights associated with the connections between the input layer and the hidden layer neurons.

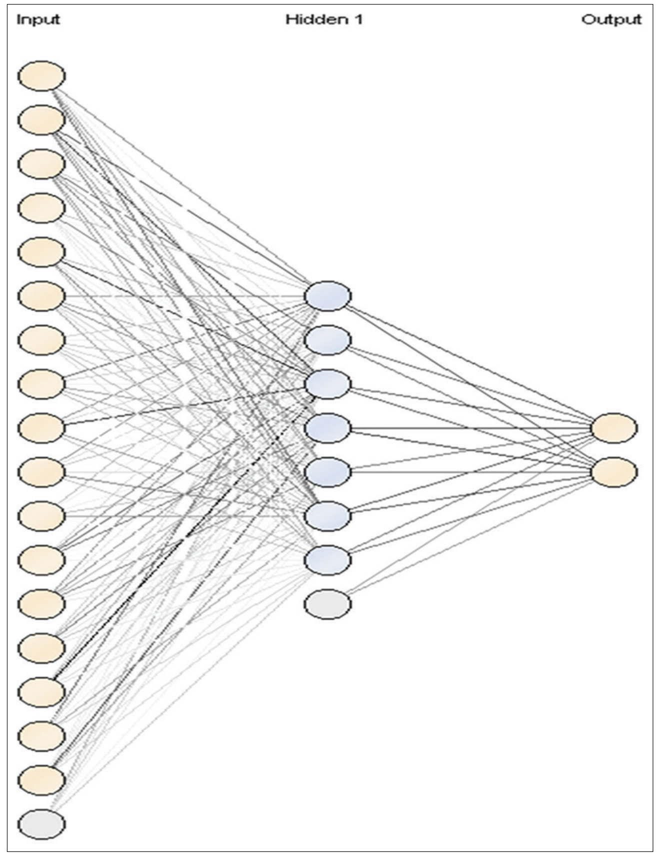

Figure 1: The neural network model proposed in the research

It is noteworthy that due to using a nonlinear transfer function and also existence of a hidden layer in the structure of the trained neural network, the synaptic weights cannot be considered as equal with the effect coefficient in common statistical methods.

Reviewing the performance of the proposed neural network

One of the most used criteria for evaluating classification algorithms including the neural network model is the confusion matrix. This matrix is a N×N square matrix. N is the number of classes in the classification (fraudulent and non-fraudulent). In order to evaluate the proposed neural network model, the test data, from which the decision variable was eliminated, for reviewing the accuracy of the network. For this purpose, the test data enter the trained neural network for the network to classify them

Table 7: Synaptic weights associated with the connections that exist in the neural network

Hidden layer neurons Input layer	Neuron 1	Neuron 2	Neuron 3	Neuron 4	Neuron 5	Neuron 6	Neuron 7
Sales to total asset	–5.245	0.650	–1.260	3.791	–3.789	6.182	0.547
Net profit to asset	–8.127	–1.670	8.550	–2.301	–3.706	5.110	–0.317
Receivables to sales	2.260	6.749	–3.364	–5.468	1.036	4.125	3.633
Inventory to sales	2.458	0.478	5.868	0.752	1.299	1.184	–0.742
Inventory to asset	0.155	2.891	–9.827	–0.968	–1.731	–5.517	–2.745
Gross profit to sales	4.290	–0.465	3.810	–5.124	–2.360	–1.768	–3.824
Gross profit to asset	2.092	0.872	2.307	–1.978	–2.299	–3.149	–1.639
Net profit to asset	–6.551	–1.991	–0.716	4.052	–3.329	–3.122	–0.457
Working capital to asset	–4.841	1.748	–9.210	–0.088	0.087	–4.297	–2.736
Fixed assets to assets	5.056	1.689	–2.445	–0.214	1.598	5.186	2.577
Current ratio	2.996	–0.930	–0.079	–0.847	2.728	–4.133	0.417
Net profit to fixed assets	–1.761	–5.222	–7.578	–6.155	0.413	0.304	0.835
Quick ratio	4.267	1.295	5.132	3.327	5.460	–1.425	1.078
Long-term debt to asset	–0.167	–2.058	3.261	6.172	1.356	2.653	1.050
Debt to asset	1.399	–3.475	11.143	2.535	–0.500	1.764	1.463
Working capital to sales	–6.161	0.677	–2.240	–0.409	–0.822	–4.073	–2.194
Altman Z-Score	–0.959	0.920	–0.989	7.540	–4.021	–1.398	–1.815

Source: Researchers' calculations (2016)

based on the estimated synaptic weights and put them either in the fraudulent or non-fraudulent classes. Then the classification done by the network is compared with the actual classification. This comparison is made by the confusion matrix. Table 8 shows the confusion matrix for the proposed neural network model after the classification of the test data.

Table 8: Confusion matrix for testing the accuracy of the classification of the proposed neural network model

Condition	Actual classification		Accuracy of classification
	Fraudulent	Non-fraudulent	
Predicted			
Fraudulent	15	11	57.69%
Non-fraudulent	3	8	72.73%

Source: Researchers' calculations

As the information presented in Table 8 shows, the proposed neural network is more accurate in predicting non-fraudulent firms than fraudulent ones; in that the proposed model has been able to accurately predict about 73% of the existing non-fraudulent firms in the test data. On the other hand, this model has not been as accurate in predicting fraudulent firms and has been able to accurately detect about 58% of the reviewed samples.

CONCLUSION

By implementing the factor analysis test on the research variables, some financial ratios with the necessary power for prediction were selected to enter the neural network. The17 financial ratios are as follows:

Net profit to sales – gross profit to sales – gross profit to total asset – net profit to total asset – net profit to fixed assets – Altman-s Z – working capital to total assets – current ratio – quick ratio – working capital to sales – sales to total asset –receivables to sales – inventory to sales – inventory to total asset –fixed assets to asset – debt to total asset – long-term debt to total asset.

Given the reported information, all of the tested neural network structures and algorithms predict the condition of fraud of firms with a proper and acceptable level of accuracy. Nonetheless, the structure reported in third row, which has 7 neurons in the hidden layers and has used the momentum learning algorithm for training the network, has a higher performance and accuracy than other reviewed structures and that is why it has been selected as the final adjustment of the neural network. The information presented in table 6 is indicative of the high accuracy and performance of the designed neural network in terms of predicting and modeling the likelihood of fraud in firms based on the selected explanatory variables (the selected financial ratios) in the research. In other words, the designed and trained neural network is able to predict the condition of financial fraud of firms based on the selected financial ratios with a proper level of accuracy by using the data collected from the Stock Exchange.

The confusion matrix has been used for evaluating the classification algorithms including the neural network model. The obtained results indicate that the proposed neural network is more accurate in predicting non-fraudulent firms than fraudulent ones; in that the proposed model has been able to accurately predict about 73% of the existing non-fraudulent firms in the test data. On the other hand, this model has not been as accurate in predicting fraudulent firms and has been able to accurately detect about 58% of the reviewed samples.

The performance of the estimated neural network model has been compared with that of the logistic regression method with the purpose of reviewing the level of accuracy of the neural network. According to the logistic regression method, five of the most important financial ratios in predicting the condition of fraud in firms are:

1- Net profit to fixed assets
2- Gross profit to asset
3- Debt to asset
4- Altman Z
5- Fixed assets to assets.

The results also indicate that that the artificial neural network method had a higher performance in this regard; in that the precision of classification of fraudulent and non-fraudulent firms and the overall performance of the artificial neural network method was 57.69%, 72.73% and 62.16%, respectively. On the other hand, the precision of classification of fraudulent and non-fraudulent firms and the overall performance of the logistic regression method was 54.55%, 50% and 54.05%, respectively.

The findings of the present research comply with the results obtained from researches conducted by Yeganeh et al. (2014), Vosoogh et al. (2014), Etemadi and Zelghi (2013), Amini et al. (2011), Safarzadeh (2010), Chi-Chen Lin (2015), Sharma and Panigrahi (2013), Lei and Ghorbani (2012), Chen et al. (2009), Chen and Du (2009), Kirkos et al. (2007) and Kirkos (2005).

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