Using Neural Network to Detect Financial Statements Fraud of Tunisian Banks

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ABSTRACT

Fraud detection is a real problem hard to resolve given the multiple types and motivations a fraud can observe. Many financial institutions are deeply affected each year and the fraud loss growth is alarming. This study aims to detect managerial fraud in the Tunisian banks before its occurrence. We evaluate the use of Artificial Neural Networks (ANN), namely the Multilayer Perceptron Network (MLP) for fraud detection. MLP can solve problems that are not linearly separable and it is extensively used for pattern classification, recognition, prediction and approximation. Thus, this article introduces the subject and presents the MLP techniques used for fraud detection to recognize behavioral fraudulent patterns and to detect "suspicious" operations to predict banks that commit fraud. This study shows that performance ratios are the most important variables that detect Financial Statements Fraud of Tunisian Banks as well as the core capital (leverage) ratio.

INTRODUCTION

Garner [7] defines fraud as “A knowing misrepresentation of the truth or concealment of a material fact to induce another to act to his or her detriment”. Nevertheless, the professional and academic literature defines fraud in the financial statements differently. The American Institute of Certified Public Accountants (AICPA) in the Statement on Auditing Standard (SAS) N°99 -Consideration of Fraud in a Financial Statement Audit- refers to fraud as “an intentional act that results in a material misstatement of the financial statements that are the subject of an audit”. In the SAS 99, two types of fraud are considered. First type of fraud are misstatements arising from fraudulent financial reporting such as falsification of accounting records or intentional omission from the financial statements of events, transactions, or other significant information. The second types of fraud are misstatements arising from misappropriation of assets such as theft of assets, embezzling receipts or causing an entity to pay for goods or services that have not been received.

The International Federation of Accountants (IFAC) devoted a whole standard for auditor responsibility relating to fraud. In fact, the International Standard on Auditing (ISA) 240 [9] defines fraud as “an intentional act by one or more individuals among management, those charged with governance, employees, or third parties, involving the use of deception to obtain an unjust or illegal advantage”.

The results of the latest report published by the Association of Certified Fraud Examiners (ACFE) [1] are alarming. Indeed, the lighthouse observation of this report is that fraud costs 5% of revenues each year. This can be translated, if applied to the 2013 estimated Gross World Product, to a potential projected global fraud loss of nearly $3.7 trillion.

The Committee of Sponsoring Organizations of the Treadway Commission (COSO) [5], in its third report published in 2010, showed that for a sample of 347 fraudulent companies, the median fraud is $12.1 million. For 30 cases of fraud, each case includes anomalies or misappropriation of $500 million or more.
The study of fraud in financial statements of public companies in Tunisia is needed especially after 2011 revolution. In fact, cases of fraudulent financial reporting, misappropriation of assets or embezzlement are or had been in courts.

This study focuses on the Tunisian banks since it came out that the banking sector had been subject to misuse of funds in form of granting large credits for projects without securing them or at an interest lower than it should be.

This paper proceeds as follows. Section 2 presents a brief review of literature. Section 3 presents the methodology. Section 4 presents the results. Section 5 concludes.

LITERATURE REVIEW

The common motivations for companies to commit financial statements fraud are numerous. Economic incentives are common cases of fraud in the financial statements, as well as psychotic motivations, self-centered, or ideology. All these motivations can play an important role of fraud in the financial statements. Pressures and economic incentives to match analysts' forecasts are fundamental motivations for listed companies subject to financial fraud. The psychological motivations associated with criminal behavior are very rare in our case. Egocentric motivations are outlined up in the fact that through fraud the person increases his personal prestige. In reality, the desire of managers to fulfill a functional authority in society is this type of motivation. Ideological motivations encourage executives to think that through fraud, they can become market leaders and consequently, improve their position in the society. The managerial fraud and companies' performance have been separated, each one had its own theoretical framework. According to Griffin & Lopez [8], the research of management illegal behavior had produced a variety of models and definitions.

Fraud in the financial statements is made, if the company has strong incentives, as well as economic reasons to announce a more favorable financial performance than it really should be, in accordance with Generally Accepted Accounting Principles (GAAP). Empirical investigations [4] [12] identified two fundamental variables, managerial ownership and the debt limit, which affect the extent of fraud in the financial statements. These studies have shown that when managerial ownership is between 5-25%, the opportunistic behavior of managers is expected and that the likelihood of engaging in financial statement fraud is higher. Previous research ([3] [6] [13]) focused on examining measures of financial difficulties in terms of weak financial conditions and weak financial performance as motivational mechanisms. The conclusions reached by this researches, argue that the motivations of commitments of fraud in the financial statements increase when the firm encounters financial difficulties. The researchers found that the chance to engage in the financial statements fraud increase when the company financial conditions and performance deteriorate.

According to the COSO Report [5], the Securities and Exchange Commission (SEC) provided discussion in the Accounting and Auditing Enforcement Releases (AAERs) about the alleged motivation for the fraud. Among most commonly cited reasons summarized by the SEC in the AAERs include committing the fraud to 1.) Meet external earnings expectations of analysts and others, 2.) Meet internally set financial targets or make the company look better, 3.) Conceal the company's deteriorating financial condition, 4.) Increase the stock price, 5.) Bolster financial position for pending equity or debt

financing, 6.) Increase management compensation through achievement of bonus targets and through enhanced stock appreciation and 7.) Cover up assets misappropriated for personal gain.

Studies developed on banks financial statements fraud are very rare, although the 2014 report of the ACFE shows that the banking and financial services are leading organizations victim by generating 17.8% of fraud cases. Moreover, the report shows that the managerial fraud ranks first and second in the ranking of fraudsters. Indeed, there is a strong correlation between the fraudster function within the company that suffered from the fraud and the losses that are caused by the fraud. The median loss caused by the owner / manager is more than three times the loss caused by the managers, and more than nine times the losses caused by the employees. Ramage et al. [17] noted that financial institutions have different characteristics of errors than other sectors. Palmrose [16] and St. Pierre & Anderson [19] showed that about 30% of trials involved banks and loans institutions auditors. Kreutzfeldt & Wallace [10] [11] noted that the characteristics of inaccuracies in terms of error rate and false accounts vary across sectors. For example, banks are exposed to significantly higher error rates than other sectors companies in the liquidity accounts. In the same idea, Maletta & Wright [14] examined 36 commercial banks and 14 savings and loan institutions. They showed that they are assigned the highest error percentage that overstated net income of about 68.8%.

METHODOLOGY

The objective of this study is to detect managerial fraud before its occurrence. This study is to test the predictive ability of a battery of ratios one year before the occurrence of fraud. Different techniques have been developed to detect financial statement fraud ([18]). In this paper, we will use three groups of financial ratios produced by the Federal Deposit Insurance Corporation (FDIC) to detect managerial fraud ([15] [2]) using Artificial Neural Networks (ANN), namely the Multilayer Perceptron Network (MLP). Table 1 presents the detail of the ratios used in our study. This methodology is based primarily on fraud prevention so; there is a concern for the prediction-detection and prevention of fraud, an issue that seems to be relevant in regards to the risk of banks failure. The dependent variable is Fraud (having a value of 0 or 1) and the independent variables are listed in Table 1.

The period and selection of the sample

The period chosen is based on the year of fraud; it generally extends from 1999 to 2010. For our analysis, we took into account one-year period prior to the occurrence of the fraud for fraudulent and non-fraudulent bank. We consider that a bank commit a fraud when the Financial Market Council (the Tunisian equivalent of the SEC) or the Government Accountability Office announced the occurrence of the fraud or its external auditors issued an adverse opinion to the financial statements.

The data were collected directly from the web sites of the banks or from the printed annual reports available at the library of Central Bank of Tunisia (BCT). The sample consists of 10 Tunisian banks over a period of 12 Years. Table 2 gives details on the descriptive statistics of the sample chosen, including the number of observation, the minimum, the maximum, the mean and the standard deviation of each independent variable, presented in Table 1.

Table 1. Variables in the study

Variable	Definition
Performance ratios	
ASTEMPM_1	Assets per employee
EEFFR_1	Efficiency ratio
IDDIVNIR_1	Cash dividends to net income
IDLNCORR_1	Net loans and leases to core deposit
INATRESSR_1	Loss allowance to loans
INLSDEPR_1	Net loans and leases to deposits
INTEXPY_1	Cost of funding assets
INTINCY_1	Yield on earning assets
NIMY_1	Net interest margin
NOIJY_1	Net operating income to assets
NONIIY_1	Noninterest income to earning assets
NONIXY_1	Noninterest expenses to earning assets
ROA_1	Return on assets
ROE_1	Return on equity
ROEEINJR_1	Retained earnings to average equity
Growth ratios	
ASTEMPM_1	Assets per employee
EQV_1	Equity capital to assets
ROLLPS5TA_1	Growth ratio 1
Capital ratios	
EQV_1	Equity capital to assets
RBC1AAJ_1	Core capital (leverage) ratio

Table 2. Descriptive Statistics of the sample

	N	Minimum	Maximum	Mean	Std. Deviation
Total Asset	120	902,862,000	6,753,589,000	2,802,904,145	1,461,116,459
Number of Employees	120	781	5,826	1,645.2	832.21
ASTEMPM	120	786,516	4,578,061	1,807,938	787,827
EEFFR	120	-0.0071	0.0403	0.0083	0.0069
IDDIVNIR	120	0.0000	349.90	3.303	31.908
IDLNCORR	120	0.7660	1.5238	1.125	0.1815
INATRESSR	120	-0.0012	0.1178	0.0142	0.0142
INLSDEPR	120	0.7660	34.629	1.806	3.943
INTEXPY	120	0.0175	0.0548	0.0310	0.0062
INTINCY	120	0.0584	0.1231	0.0807	0.0100
NIMY	120	0.0320	0.0787	0.0492	0.0102
NOIJY	120	-0.1027	0.0377	0.0101	0.0151
NONIIY	120	0.0097	0.0506	0.0209	0.0059
NONIXY	120	0.0000	0.0041	0.0008	0.0007
ROA	120	-0.1035	0.4349	0.0152	0.0546
ROE	120	-0.0281	9.423	0.1720	0.8533
ROEEINJR	120	0.0000	0.2977	0.0617	0.0484
ASTEMPM	120	786,516	4,578,063	1,807,938	787,827
EQV	120	0.0330	0.1748	0.0958	0.0287
ROLLPS5TA	120	0.5168	0.9568	0.8502	0.0693
EQV	120	0.0330	0.1748	0.0958	0.0287
RBC1AAJ	120	4.720	29.348	10.485	4.144
Valid N (listwise)	120				

Multilayer Perceptron Network (MLP)

The MLP is one among the types of Artificial Neural Networks, which are basic input and output devices, with the neurons organized into layers. Multi Layer Perceptron can solve problems which are not linearly separable is widely used for pattern classification, recognition, prediction and approximation. Also known as multilayer feed-forward network (MLFF) the MLP has neurons arranged in a distinct layered topology: an input layer, one or more hidden layers and an output layer. The data flows forward from input to output layer. The input layer distributes the values to each of the neurons in the hidden layer. The outputs from the hidden layer are distributed to the output layer. The outputs of the output layer act as the output of the entire network.

Each neuron is a processing Unit that is connected to other processing Units. Simultaneously, one Unit is connected to another large number of Units (neurons) that carry out the processing. These neurons are interconnected typically in a highly complex manner between each other. That gives the structure of real NN which is called parallel and distributed structure. The signals flowing on the connections are scaled by adjustable parameters called weights, then the processing Units sum all these contributions and produce an output that is a nonlinear function of the sum The processing Units' outputs become either system outputs or are sent to the same or other processing Units.

All data pass through the network as signals. The signals are processed by an integration function to produce the Output activation signal. The output is simply the sum of the signal multiplied with the weights. Then this output activation signal is passed through an activation function (also known as a transfer function) to produce the output of the neuron. During network training, the weights and thresholds are first initialized to random values and adjusted directly from the training data according to the rule of the training algorithm used. A supervised learning process is aimed to fit the NN to the data: they learn how to transform data into the desired Output. During an iterative training process, the predicated output is compared to the given input and then, the weights are modified such that a classification as accurate as possible is achieved. The accuracy has to be quantified by an error criterion. The back propagation algorithm is widely used as a training algorithm.

The results

We used the 'Multilayer Perceptron Network' procedure in SPSS 22 to perform our analysis. In our case, we reserved 75 companies (68.2%) of the sample to the training, 25 companies (18.2%) for testing and 15 companies (13.6%) as a control sample. 10 companies were excluded for various raisons. Table 3 presents the case processing summary.

Table 3. Case Processing Summary

		N	Percent
Sample	Training	75	68.2%
	Testing	20	18.2%
	Holdout	15	13.6%
Valid		110	100.0%
Excluded		10	
Total		120	

Table 4 gives information about the results of training, testing and applying the final network to the holdout sample. The holdout sample is used to valid the results. From Table 4, we can see that the percentage of incorrect predictions is approximately equal across training, testing and holdout sample. This result makes us more confident about the future cases that would be scored by the network. The estimation algorithm stopped since the error didn't decrease after one step. As the output layer uses the

softmax activation function, Cross entropy error is displayed. This is the error function that the network tries to minimize during training.

Table 4. Model Summary

Training	Cross Entropy Error	18.970
	Percent Incorrect Predictions	8.0%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.02
Testing	Cross Entropy Error	5.177
	Percent Incorrect Predictions	10.0%
Holdout	Percent Incorrect Predictions	13.3%
Dependent Variable: Fraud		
a. Error computations are based on the testing sample.		

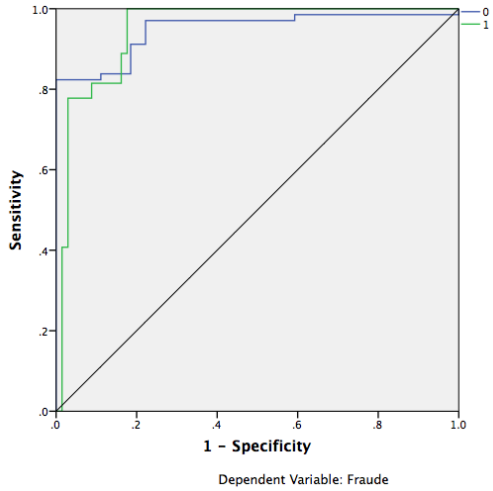
The classification table (Table 5) shows the practical results of using the network. For each case, the predicted response is 1 if that cases' predicted pseudo-probability is greater than 0.5. For each sample, the cells on the diagonal of the cross-classification of cases are correct predictions and the cells off the diagonal of the cross-classification of cases are incorrect predictions. Of the cases used to create the model, 17 of the 21 cases who previously had committed fraud are classified correctly. 52 of the 54 cases that had not committed fraud are classified correctly. Overall, 92% of the training cases are classified correctly, corresponding to the 8% incorrect prediction, shown in Table 4.

Table 5. Classification

		Predicted		
Sample	Observed	0	1	Percent Correct
Training	0	52	2	96.3%
	1	4	17	81.0%
	Overall Percent	74.7%	25.3%	92.0%
Testing	0	14	0	100.0%
	1	2	4	66.7%
	Overall Percent	80.0%	20.0%	90.0%
Holdout	0	11	0	100.0%
	1	2	2	50.0%
	Overall Percent	86.7%	13.3%	86.7%

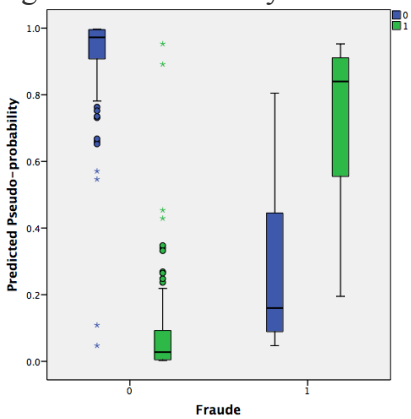
The ROC curve, presented in Figure 1, gives a visual display of the sensitivity and specificity for all possible cutoffs in a single plot. The chart displays two curves, one for the category 0 and one for the category 1. This chart is based on the combined training and testing samples. The area under the curve is a numerical summary of the ROC curve, and the values in the table represent, for each category, the probability that the predicted pseudo-probability of being in that category is higher for a randomly chosen case in that category than for a randomly chosen case not in that category. For example, for a randomly selected Fraud cases and randomly selected non- Fraud cases, there is a 0.948 probability that the model-predicted pseudo-probability of default will be higher for the Fraud cases than for the non-Fraud cases. While the area under the curve is a useful one-statistic summary of the accuracy of the network, we need to be able to choose a specific criterion by which Fraud cases are classified. The predicted-by-observed chart provides a visual start on this process.

Figure 1. ROC curve



For categorical dependent variables, the predicted-by-observed chart, present in Figure 2, displays clustered boxplots of predicted pseudo-probabilities for the combined training and testing samples. The x axis corresponds to the observed response categories, and the legend corresponds to predicted categories. The left most boxplot shows, for cases that have observed category 0, the predicted pseudo-probability of category 0. The portion of the boxplot above the 0.5 mark on the y axis represents correct predictions shown in Table 6. The portion below the 0.5 mark represents incorrect predictions. We saw from Table 6 that the network is very good at predicting cases with the 0 category using the 0.5 cutoff, so only a portion of the lower whisker and some outlying cases are misclassified. The next boxplot to the right shows, for cases that have observed category 0, the predicted pseudo-probability of category 1. Since there are only two categories in the target variable, the first two boxplots are symmetrical about the horizontal line at 0.5. The third boxplot shows, for cases that have observed category 1, the predicted pseudo-probability of category 0.

Figure 2. Predicted-by-Observed Chart



The importance of an independent variable is a measure of how much the network's model-predicted value changes for different values of the independent variable. Normalized importance is simply the importance values divided by the largest importance values and expressed as percentages. From Table 6, we can conclude that the noninterest income to earning assets (NONIIY_1), the core capital (leverage) ratio (RBC1AAJ_1), the net operating income to assets (NOIJY_1), the return on assets (ROA_1), the retained earnings to average equity (ROEEINJR_1), the assets per employee (ASTEMPM_1) and the

cash dividends to net income (IDDIVNIR_1) are the most important variables that detect Financial Statements Fraud of Tunisian Banks.

Table 6. Independent Variable Importance

	Importance	Normalized Importance
LAGS(ASTEMPM,1)	.068	56.4%
LAGS(EEFFR,1)	.051	42.5%
LAGS(IDDIVNIR,1)	.067	55.7%
LAGS(IDLNCORR,1)	.040	33.2%
LAGS(INATRESSR,1)	.026	21.3%
LAGS(INLSDEPR,1)	.060	49.6%
LAGS(INTEXPY,1)	.056	46.7%
LAGS(INTINCY,1)	.057	47.1%
LAGS(NIMY,1)	.024	20.2%
LAGS(NOIJY,1)	.091	75.9%
LAGS(NONIIY,1)	.120	100.0%
LAGS(NONIXY,1)	.037	30.7%
LAGS(ROA,1)	.077	63.9%
LAGS(ROE,1)	.014	11.9%
LAGS(ROEEINJR,1)	.073	60.5%
LAGS(EQV,1)	.009	7.8%
LAGS(ROLLPS5TA,1)	.033	27.6%
LAGS(RBC1AAJ,1)	.098	81.5%

Consequently, in order to detect and predict and detect Financial Statements Fraud of Tunisian Banks, we should have a close monitoring of the variables mentioned above.

CONCLUSION

This paper presents a model for prediction and detection of fraud for Tunisian banks. The methodology is to take a battery of financial ratios used by the Federal Deposit Insurance Corporation (FDIC) as indicators of the financial situation of a U.S. bank and tries to test their predictive power before the occurrence of fraud. The results were obtained by performing a Multilayer Perceptron Network to predict that a given bank is fraudulent. The model results show that performance ratios, namely, the noninterest income to earning assets (NONIIY_1), the net operating income to assets (NOIJY_1), the return on assets (ROA_1), the retained earnings to average equity (ROEEINJR_1), the assets per employee (ASTEMPM_1) and the cash dividends to net income (IDDIVNIR_1) are the most important variables that detect Financial Statements Fraud of Tunisian Banks. In addition, the core capital (leverage) ratio (RBC1AAJ_1) is also an indicator of financial statements fraud for Tunisian banks.

Incorporating into the model a panel data can enhance this work. In fact, including multi-year ratios variables into the model is a better representation of the real world fraud cases. Many studies showed that the fraud is not committed in one period but a multi-period process. In addition, comparing the results of a Logistic Regression or a Discriminant Analysis, will make us more confident that the data do not contain relationships that cannot be captured by MLP model; thus, we can use them to further explore the nature of the relationship between the dependent and independent variables.

REFERENCES

[1] Association of Certified Fraud Examiners (ACFE). Report to the nations on occupational fraud and abuse, 2014.

[2] Boumediene, S. L. Detection and Prediction of fraud in the financial statements of Tunisian banks. *Accounting & Taxation*, 2014, 6(2), 1-10.

[3] Carcello J. V., Palmrose Z. V. Author litigation and modified reporting on bankrupt clients. *Journal of Accounting Research*, 1994, 32(Supplement), 1–30.

[4] Carter, R., Stover R. Management ownership and firm value compensation policy: evidence from converting savings and loan associations. *Financial Management*, 1991, (Winter), 80–90.

[5] Committee of Sponsoring Organizations of the Treadway Commission (COSO). *Fraudulent Financial Reporting: 1998-2007, An Analysis of U.S. Public Companies*, 2010.

[6] Dechow, P. M., Sloan, R. G., Sweeney, A. P. Causes and Consequences of Earnings Manipulation: An Analysis of Firms Subject to Enforcement Actions by the SEC. *Contemporary Accounting Research*, 1996, 13(1), 1-36.

[7] Garner, B. (ed.). *Black's Law Dictionary*. 8th Ed., s.v. "fraud", 2004.

[8] Griffin, R. W., & Lopez, Y. P. "Bad behavior" in organizations: A review and typology for future research. *Journal of Management*, 2005, 31(6), 988-1005.

[9] IFAC, 2009. *The Auditor's Responsibilities Relating to Fraud in Audit of Financial Statements*. Retrieved July 25, 2013 from http://www.ifac.org/sites/default/files/downloads/a012-2010-iaasb-handbook-isa-240.pdf

[10] Kreutzfeldt, R. W., Wallace, W. A. Error Characteristics in Audit Populations: Their Profile and Relationship to Environmental Factors. *Auditing: A Journal of Practice & Theory*, 1986, 6 (1), 20-43.

[11] Kreutzfeldt, R. W., Wallace, W. A. Control Risk Assessments: Do They Relate to Errors? *Auditing: A Journal of Practice & Theory*, 1990, 9(Supplement), 1-26.

[12] Latham C., Jacobs F. Monitoring and incentives factors influencing misleading disclosures. *Journal of Managerial Issues*, 2000, 12(2), 169–187.

[13] Lys, T., Watts, R. Law suits against auditors. *Journal of Accounting Research*, 1994, 32(Supplement), 65-93.

[14] Maletta, M. J., Wright, A. Audit Evidential Planning: An Examination of Industry Error Characteristics. *Auditing: A Journal of Practice and Theory*, 1996, 15(Spring), 71-86.

[15] McAteer, M. J. Financial Ratios as Predictors of Financial Fraud in community Banks: The Analytic Model of Management Fraud. Retrieved July 10, 2013 from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1430984.

[16] Palmrose, Z. An analysis of auditor litigation and audit service quality. *The Accounting Review*, 1988, LXIII(1), 55-73.

[17] Ramage, J. G., Krieger, A. M., Spero, L. L. An Empirical Study of Error Characteristics in Audit Populations. *Journal of Accounting Research*, 1979, 17(Supplement), 72-107.

[18] Ravisankar, P., Ravi, V., Rao, G. R., Bose, I. Detection of Financial Statement Fraud and Feature Selection Using Data Mining Techniques. *Decision Support Systems*, 2011, 50(2), 491-500.

[19] St. Pierre, K., Anderson, J. A. An analysis of the factors associated with lawsuits against public accountants. *Accounting Review*, 1984, LIX(2), ,242-263.