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Predicting of Financial Distress of Companies Using the Artificial Neural Networks: A Case Study of Listed Industrial Companies on Amman Stock Exchange

التنبؤ بالتعثر المالي للشركات باستخدام نموذج الشبكات العصبية الاصطناعية: دراسة حالة الشركات الصناعية المدرجة في بورصة عمان

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Abstract:

This study aims to determine the effectiveness, of artificial neural networks, in predicting the financial distress of industrial companies, listed on the Amman Stock Exchange, in Jordan during the period 2013-2018, using the multi-layers networks model. To achieve this goal, a sample of 54 companies was selected, of which 26 were sound and 28 were faltering, using 21 financial ratios and SPSS.

This study found the most important findings: the model classified the companies, at an accurate and correct rate achieving 100%, ratings ratios for all the companies, and considering both the return on total assets, dividends distributed to the market value, the earnings per share, market value to return and the net earnings to revenues are the strongest financial ratios, that have the ability to distinguish between the safety or faltering of industrial companies.

Keywords: prediction, financial distress, financial ratios, artificial neural network, industrial companies, Amman Stock Exchange.

JEL Classification Codes: C150, C38, C45, G33.

ملخص:

تهدف هذه الدراسة إلى التعرف على مدى فعالية الشبكات العصبية الاصطناعية، في التنبؤ بالتعثر المالي للشركات الصناعية، المدرجة في بورصة عَمّانْ الأردن خلال الفترة 2013- 2018، وذلك

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باستخدام نموذج الشبكات متعددة الطبقات، ولتحقيق هذه غاية، تم اختيار عينة تحوي 54 شركة منها 26 سليمة و 28 متعثرة، وذلك باستخدام 21 نسبة مالية، وبالاستعانة ببرنامج SPSS.

توصلت هذه الدراسة إلى أهم النتائج: أن النموذج قام بتصنيف الشركات بمعدل تصنيف دقيق وصحيح، حيث حقق نسبة تصنيف بلغت 100% لجميع الشركات، كما أعتبر كل من: العائد على مجموع الموجودات، الأرباح الموزعة إلى القيمة السوقية، عائد السهم الواحد، القيمة السوقية للعائد وصافي الربح إلى الإيرادات، هي أقوى النسب المالية التي لها القدرة على التمييز بين سلامة أو تعثر الشركات الصناعية.

كلمات مفتاحية: تنبؤ، تعثر مالي، نسب مالية، شبكة عصبية اصطناعية، شركات صناعية، بورصة عمان.

تصنيفاتJEL : C150, C38, C45, G33

1. INTRODUCTION

The term financial distress has considerable attention from researchers and companies; they used many mathematical models, to reach accurate results within a short time. Given the seriousness of corporate financial distress, to which companies are exposed and economic conditions and conditions change over time, it forced the updating of prediction models continuously. Therefore, technology has facilitated the work of many companies, in predicting their financial position and the speed, of decision-making before they are in financial distress. The best of these models is neural networks, which has proven its worth and its efficiency in various economic fields, through, its ability to predict companies, that are exposed to financial distress risks, using analysis of financial ratios, you can deal with a large number of data as inputs, so the current study relied on a modern model in the financial field, namely Artificial Neural Networks, which is one of the most important models of Artificial Intelligence, in order to test the situation of Jordanian industrial companies, with financial distress resulting, from failure to fulfil their obligations, when they are due, it is also a tool to help capitalists, to cope with the problem of distress before the financial crisis worsens and reach more accurate and faster results.

1.1 Problematic: based on the foregoing the main question is:

How effective are Artificial Neural Networks in predicting, the financial distress of Amman listed industrial companies from 2013-2018?

The preceding question may be divided into the following set of sub-questions:

- Can financial ratios help Jordanian industrial companies, predict financial distress?
- Does the Artificial Neural Networks model have high precision, in predicting financial distress for Jordanian companies?

1.2 Objectives of the study: this study aimed to reveal:

- The ability of financial ratios to help Jordanian industrial companies, predict financial distress;

- The ability of the artificial neural networks model, to predict highly accurately financial distress for Jordanian companies.

1.3 The importance of the study: many Jordanian industrial companies have problems, with their financing structures (see table 1), some of Jordan's ailing industrial companies have been capitalized at JD 426 million, its losses up to 31/12/2018 amounted to 294 million JD, this distress affected its financial structures and losses, on the level of its efficiency in the financial market, this has led to a deterioration and imbalances in, its financial and operational performance, the latter is what exposes them to financial stumbling, through a lack of financial resources, and a lack of investment opportunities, this does not help stakeholders in achieving their goals, to mitigate these risks, they must search and explore mechanisms, to help them anticipate the risks of financial distress, to avoid them and expedite the provision, of appropriate solutions to improve their financial situation, before the problems worsen. So the importance of this study is to help shareholders and corporate owners, predict the risk of financial distress, in companies listed on the Amman stock exchange, using a sophisticated high-accuracy, high-speed model, in order, to be cautious before they fall, into a state of real hardship for the company, which in turn leads to failure, this is according to the Artificial Neural Networks model.

Table 1. The financial structure of some industries, public joint stock companies in Jordan is ranked downward-by the size of their losses in 2018.

Types of Industry	Affiliates	Capital	Losses
Extractive and mining industries	10	124 596 810	-115 605 535
Engineering and construction industries	4	81 019 460	-69 387 426
Medicine and the medical industry	3	40 182 083	-46 390 043
Electrical industries	3	65 272 250	-30 935 416
Tobacco and cigarettes	1	15 083 657	-10 100 312
Chemical industries	3	43 625 000	-8 388 497
Food and beverages	2	35 174 217	-7 416 801
Garment, leather and textile industries	2	21 218 309	-6 094 227
Total	28	426 171 786	-294 318 257

Source: prepared by researchers, on the basis of financial reports, of industrial companies, listed on the Amman stock exchange, 2018.

1.4 Hypotheses: this study tests the following hypotheses:

- Financial ratios are capable of helping Jordanian industrial companies, forecast financial distress;
- Artificial Neural Networks can predict, the financial distress of Jordanian industrial companies with high accuracy.

1.5 Previous Studies:

- Study (Mehdi, 2014): this study tackled a modern method and model that, protects against financial distress in the future, using ANNs models and genetic algorithms, in predicting financial distress cases in Saudi joint stock companies comparing them with traditional, statistical prediction models, its sample relied on 47 joint stock, companies listed in the Saudi financial market, for the period (2008-2012), using 25 financial ratios and reached the most important results: the preference of ANNs, over conventional models in predicting financial distress, to a large degree and its accuracy is 100%, reaching the accuracy of financial distress prediction, for the discriminatory analysis model 63.4%, and the accuracy of predicting financial distress, for the logistic regression model 90.6%, the designed and trained network model, with genetic algorithms also, had a predictive accuracy of 100%. (Mehdi, 2014, pp. c-d)

- The differences between this and our study are the sample size selected, the period, the number of ratios used for forecasting, similarities were in the use of one of the same models “Artificial Neural Networks”;

- Study (Mokhatab Rafiei et al, 2011): this study examined three models: ANNs models, multiple discriminate analysis and general logarithms, to distinguish between troubled and non-troubled companies, and aimed to design a forecasting model, for financially non troubled companies, it used 17 ratios and financial indicators, for 180 industrial companies, out of the 461 companies listed on the Tehran stock exchange, for a period of one year in 2008. The study reached the following results: the accuracy of forecasting the financial distress, of companies using models of ANNs with a rate of 98.6%, compared to the discriminatory analysis model, which was 80.6%, the general logarithm model was 92.5%. (Mokhatab Rafiei, Manzari, & Bostanian, 2011, p. 10210).

- This study differed from our sample the number of indicators used to forecast and the duration of the study, which was limited to one year only, however, it shared one of the models used in this study is the ANNs;

- Study (Weller, 2010): this study discussed the issue of bankruptcy of a large number of companies in the USA, there was a need to improve a model for forecasting bankruptcy, and aimed to compare the predictive power of the ANNs model, with the Altman models of (1968, 1983) and Zmi Jewski model (1984), the financial statements were selected from 151 companies, operating in the textile sector in the USA, of which 47 were bankrupt, 104 non-bankrupt companies during 1998-2004, the results of the study found that, Altman's model had a bankruptcy forecasting capability, for a year before the bankruptcy. The ANNs model has a more productive capacity, for two years before the bankruptcy, as for, non-bankrupt firms over time, there was a preference for the ANNs model in bankruptcy prediction, indebtedness ratios also had a greater and a more pronounced, impact on the bankruptcy of textile companies. (Weller, 2010, p. I).

- This study addressed bankruptcy, as opposed to our study that addressed stumbling; the number of firms selected, which is larger than our sample study, as was the period. But we agree on the point of using the same tool ANNs;

- Study (Park, 2008): this study discussed the preference of ANNs, in predicting corporate bankruptcy, for the sample study over conventional statistical methods. In addition, to knowing the best financial ratio used to distinguish, between firms that are bankrupt and those that are not, this study selected a sample of 128 companies, using 18 ratios and a financial index, its main findings are: the advantage of ANNs models, over statistical models in predicting financial distress by 93%. (Park, 2008, pp. -)

- This study addressed bankruptcy, which we considered the last stage of financial distress; the latter is the subject of our study. We also disagreed in the number of sample studies, with financial indicators. However, we have Shared the same study tool ANNs;

  - Study (Saudi, 2007): this study discussed a mechanism, to help anticipate the risks of financial distress, in businesses in the Egyptian market. To achieve their objective, they attempted to provide accounting, input to predict the financial distress of these enterprises; it's composed of 160 troubled and sound enterprises, from 1995 to 2005. A neural network model was built, on financial ratios and indicators derived from financial statements, in addition, to the use of genetic algorithms, to determine the most important ratios and financial indicators, that affect the prediction of financial distress, this study concluded that: the model of ANNs with back propagation with all variables, the predictive accuracy reached 97.73%, designed and trained in algorithms for all study variables, the predictive accuracy is 99.43%. The accuracy of the most important variables was 97.16%; it also found that ANNs model is better than conventional models, the discriminatory analysis with predictive accuracy of 88.5%, logistic regression with predictive accuracy of 87.5%. (Saudi, 2007, pp. 1-5).

- We differed with this study, in the number of samples represented, its time period, except we agreed to use the same tool as ANNs;

  - Study (Suarez, 2004): this study discussed bankruptcy rates, in the construction industry in USA, to achieve their goal, they sought to propose a model for predicting financial failure, using neural network model, this study used data from 67 bankrupt and non-bankrupt companies in USA, construction and construction market, and 26 financial ratios and indices were used to forecast bankruptcy, the study concluded, that the ANNs model has a better predictor of company failure, than other models, I've concluded that there are three financial ratios, have a direct and greater impact of changes in corporate financial position: indebtedness/equity ratio, indebtedness/asset ratio and gross profit margin ratio. (Suarez, 2004, pp. xvi-xvii).

- This study used the same tool used in our study is an ANNs model; they differ in their treatment of bankruptcy, which is the last stage of financial distress and in their sample and financial indicators to forecast bankruptcy.

2) **Financial Distress:** according to our review of some subjects, we have noted that there is confusion, between the term financial failure and financial distress, but the latter is really, the step or phase that precedes

financial failure.

2.1 Definition: of course, the term ‘financial distress’ is ambiguous. Approximately speaking, what is meant here are sites, where financial institutions, fail or nearly fail and/or markets seize up, leading to broader systemic disruptions, with potential material costs for the real economy (Borio, 2007, p. 9), generally, speaking it refers to the inability to pay obligations (e.g. debt) when due. Operational definitions of financial distress have focused, on two main events -bond default and bankruptcy. (Beaver & Correia, 2010, p. 3)

2.2 Signs of Financial Distress (Kenton, 2019): there are multiple warning signs, to indicate a company is experiencing financial distress. Poor profits may indicate a company is financially unhealthy. Struggling to break even indicates a business cannot sustain itself from internal funds and needs, to raise capital externally. This raises the company’s business risk and lowers, its creditworthiness with lenders, suppliers, investors and banks. Limiting access to funds typically results in a company (or individual) failing.

2.3 Predict financial distress: at an intuitive level it may appear axiomatic, that it would be important to be capable, to predict the probability of financial distress. However, predicting the probability of distress can be viewed, as the first step taken before assessing the loss, distribution conditional upon financial distress. Moreover, in many cases, data on investor losses under financial distress is much more difficult, if not impossible to obtain (Beaver & Correia, 2010, p. 5). The main reasons behind financial distress can be attributed, to inappropriate asset mix corporate governance or financial structure. (Kihooto, Omagwa, Wachira, & Ronald, 2016, p. 87)

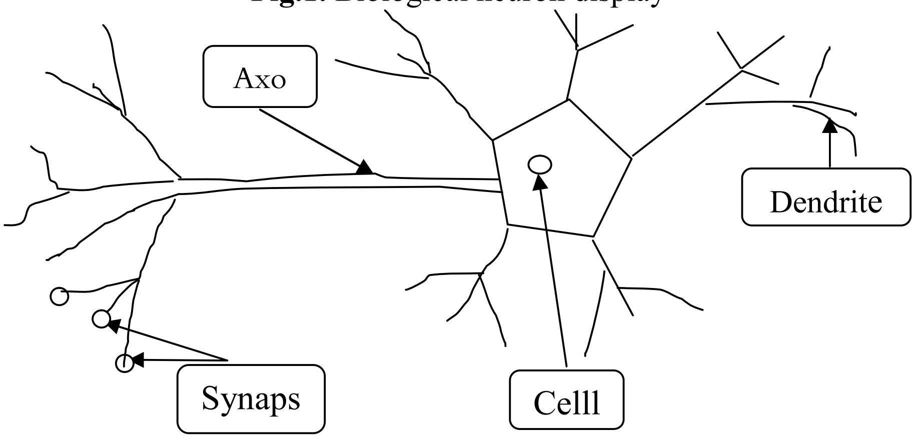
The most important reason for financial distress can be shown as: (Arkan, 2015, pp. 236-238)

- **External Factors:** the environmental factors that can lead businesses, to distress are described below: a social, industrial, economic, natural, technological, legal and political environment;
- **Internal Factors:** which are under the control of the business affecting business performance can be listed, in general, terms under the following headings: poor management, dissonance to environmental development, insufficient communication, unbalanced growth, failure in the main projects.

3. Neural Network Model: are one of the most important and most widely used models of artificial intelligence, which in turn resembles the architecture/engineering of the human brain, but the latter is more complex, than we expect and to learn, about their concept more will understand the following terms:

3.1 The biological model: (Jain, Mao, & Mohiuddin, 1996, p. 35) is a special biological cell, with information processing ability. A schematic drawing of a neuron is shown in Fig.1. Is composed of soma or a cell body and two types of out-reaching tree-like branches: axon and dendrites.

Fig.1. Biological neuron display



Source: (Berrais, 1999, p. 54)

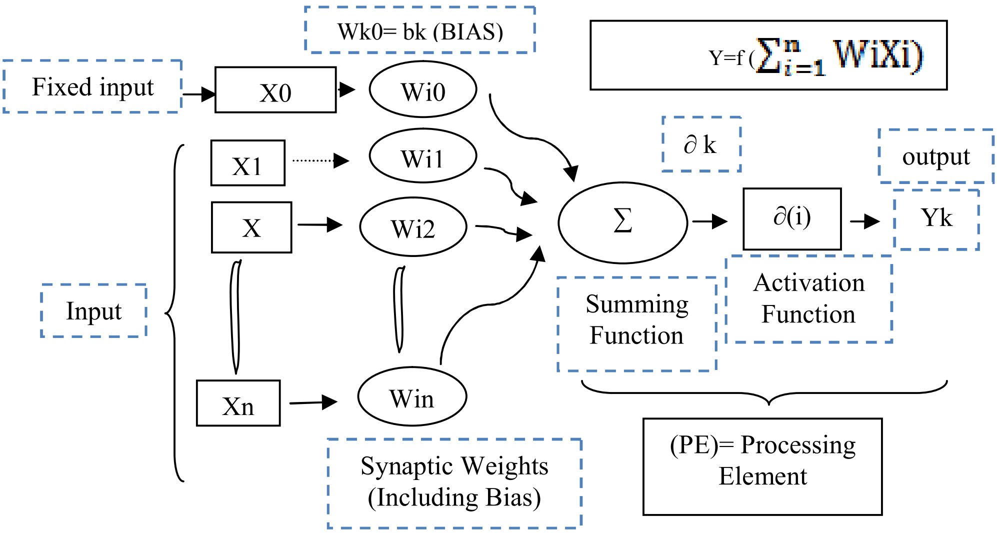
3.2 The Artificial Neural Networks (ANNs): are systems encouraged by the distributed, massively parallel computation, in the brain that enables it to be so successful at complex control, and recognition classification tasks. The biological neural network that accomplishes, this can be mathematically modelled, caricatured by a weighted, directed graph of highly, interconnected nodes (neurons). (Fine, 1996, p. 1322). Basically the mimic is a simulation of the biological neural network, which is there and the artificial neuron is called perceptron. So, in many books you can see it is call termed as perceptron. So, neuron or ANN is basically is the basic units which can solve many problems (Debases, -, pp. 8-9). For to build the model is must, to divide collected data into three parts: training, validation and testing data (Larasati, DeYong, & Slevitch, 2012, p. 97), ANNs include: there are 3 principal layers: Input Layer, Hidden Layer, Output layer. (Staub, Karaman, Kaya, Karapinar, & Guven, 2015, p. 1479)

3.3 Back propagation algorithm Neural Networks: (Kukreja, Bharath, Siddesh, & Kuldeep, 2016, pp. 29-30) are one of the most commonly used network. Here the difference in targeted output, and the output obtained is propagated back to, the layers and the weights adjusted. A back propagation neural network uses a supervised learning method, feed forward architecture. A neural network uses for techniques for classification and prediction.

3.4 Multilayer preceptor (MLP): (Al Shamisi, Assi, & Hejase, 2011, p. 220) are the most common type of feed-forward networks. Fig.2 shows an MLP, which has three types of layers: an input layer, an output layer and a hidden layer. Neurons in input layer, only act as buffers for distributing the input signals, xi (i=1, 2 …n) to neurons in the hidden layer. Each neuron (j) in the hidden layer sums, up its input signals, xi after weighting them, with the strengths of the respective connections Wji, from the input layer and computes its output yj, as a function f of the sum; f can be a simple threshold function or a sigmoid, hyperbolic tangent or radial basis function.

The sum is the weighted sum of the inputs, multiplied by the weights, between one layer and the next. The activation function used is a sigmoid function, which is a continuous and differentiable approximation of a step function. An interconnection of such individual neurons, forms the neural network. (Kukreja, Bharath, Siddesh, & Kuldeep, 2016, p. 29)

Fig. 2. Artificial Neural Networks



Source: (Nouman, 2015, p. 2)

2. Method and Materials:

2.1 Study Approach: to reach the aim of this study, a descriptive analytical approach was used in the theoretical and practical frameworks therein; the data necessary for the study were also compiled from two origins: primary sources are annual financial reports of listed industrial companies from 2013 to 2018; secondary sources are books, thesis, letters, articles...etc.

2.2 Study sample and society: community consists of industrial companies, listed on the Amman stock exchange, where we looked at all varieties of industrial companies: (The extractive and mining industry, medicine and the medical industry, chemical industries, food and beverages, engineering and construction industries, the electrical industries, tobacco and cigarettes, garment, leather and textile industries). It is considered an important sector of the state. We randomly selected companies, the sample search included 54 companies, listed on the Amman Jordanian stock exchange, and 21 financial ratios were used for 5 years, by applying a multilayer perceptron network model, we identified the state of companies' from distress or safety through two criteria:

- Standard1: the companies achieve losses for 3 consecutive years and thus, we consider them it stumble (because the distress is in the short term);
- Standard2: as for companies achieving profits for 3 consecutive years, they consider sound companies.

2.3 The study's variables and how to measure them: based on previous studies and researchers' diligence, the main variables in the study were listed, as follows depending on the stock exchange website (exchange, 2020):

❖ Independent variables: they are financial ratios and are input synapses for the ANNs;

Table 2. Financial ratios used

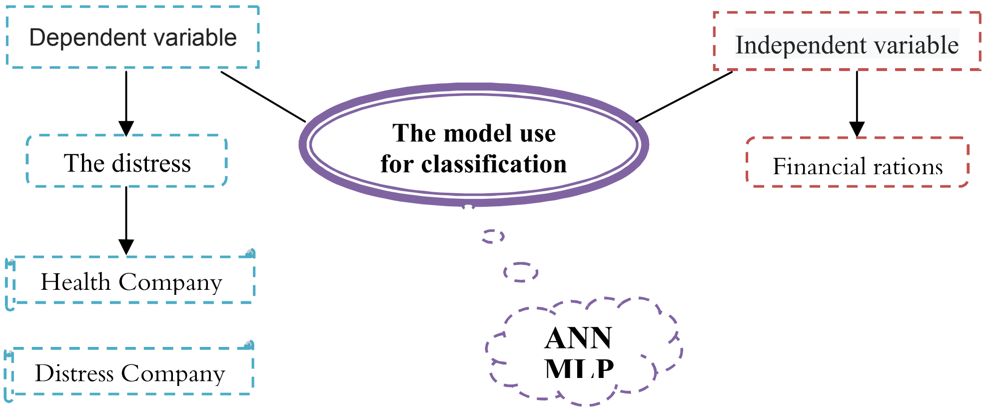
variable	method of calculate	variable	method of calculate
X1	Share turnover	X12	Return on total assets
X2	Earnings per share = net profit after tax / number of shares subscribed	X13	Return on equity
X3	Dividends per share = dividends paid / number of ordinary shares	X14	Debt rate = total liabilities / total assets
X4	Book value per share = shareholders equity / number of shares subscribed	X15	Ownership ratio = total capital / total assets
X5	Market value to return	X16	Interest coverage rate = (net profit before tax + interest) / interest
X6	Dividends distributed to market value	X17	Asset turnover = net sales / average assets
X7	Dividends per share to earnings per share	X18	Fixed assets turnover = net sales / average fixed assets
8X	Market value to the book value	X19	Working capital turnover = Net sales / current assets
X9	Total profit from operations to revenue	X20	Trading ratio = current assets / current liabilities
X10	Net profit before interest and tax to revenue	X21	Working capital = total current assets - sum of current liabilities
X11	Net earnings to revenue		

Source: prepared by researchers based on financial reports of industrial companies listed on the Amman stock exchange, 2018.

- ❖ Dependent variable: it is the financial distress and it represents the outputs of the ANNs, where we distinction is made between two cases of industrial company: 1= intact, 0= faltering.

2.4 Study model: the multilayer perceptron model of ANNs was used in this study, based on the SPSS program. The suggested model for the study can be illustrated by the following figure:

Fig 3. Posed model for the study



Source: prepared by researchers

3. results and discussion:

The goal of this study was to check whether ANNs (MLP), can help Jordanian industrial companies predict financial distress correctly or not, by analysing the data obtained through different financial ratios, this is what the program output shows in table 3 (See appendices):

Number of neurons per layer for autonomous variables 21, or what's known for neural network by input defined as X1 through X21, the method for re-measuring common variables was Standardized;

Selection of neural network architecture was automatic, by choosing one hidden layer with 3 nodes, the activation function was used is the hyperbolic tangent;

While it contains the output layer on two nodes to encode the corporate classification of the dependent variable, using the Softmax function, Cross entropy was used as an error function due to the utilization of the softmax function;

As for the architecture of the neural network through the program: the network diagram that SPSS used to predict financial distress, where it gave (0 = a faltered company, 1 = a sound company) from 21 financial ratios, as shown in Fig.4. (See appendices). Related to network architecture, it also shows 21 entry nodes (input nodes), 3 nodes in the hidden layer, the output has two nodes, which represents the right and faltered companies, the connections in blue are weights below 0, the gray connections are weights greater than 0, broad connections mean the strength of the link, vice versa, for thin links that express weak link through this architecture, we note that the strongest connections are shown in the following ratios: X12 that represents the return on total assets, X6 dividends distributed to the market value, X2 earnings per share, X5 market value to return and X11 net earnings to revenue, in the classification of companies in terms of safety (i.e. the strength of the company's integrity correlated with the profitability of its shares), the weakest link is expressed by the ratio of X3 which represents the dividend per share, X17 assets turnover ratio, X7 dividend per share to earnings per share, that is linking the strength of the company's, default depends on the companies 'non-distribution, of earnings and on the basis of them these companies faltered. This is explained in table 4 (see appendices), where the model summary provides, that the information is related to the results of training and testing and a hold sample, a cross entropy error was given for both the training and test sample, since the error function the network decreases, during the training phase is a small value and equals 1.052, from this error it indicates the strength of the model, for predicting classification results, according to the table, the percentage of incorrect predictions, based on the training and the test sample, respectively is 0% and 5.9%, where the learning procedure was implemented until 10 consecutive steps were obtained, with no decrease in the error function of the test sample.

Table (5) (see appendices), which is considered one of the most important outputs of the neural network is presented. It is a classification table for predicting the financial distress of the companies under study, according to each sample (training or test), in general, the predicting is determined to be sound, if the predicted probability is greater than 0.5 as is evident, the multilayer ANNs correctly ranked 37 out of 37 companies in the training sample, 16 out of 17 in the test sample as 100%, of the training cases were correctly classified. The MLP model mistook only one company, it expected that it would stumble, that it was in fact through its financial statements sound the error rate is considered to be very small, given that the possibility of predicting its distress was correct should be minimal. The error rate is considered to be very small, given that the possibility of predicting its distress was correct, should be at a minimum i.e. 80%.

Table 6 (see appendices) shows the effect of each independent variable in the ANNs model, in terms of relative and normal importance, this is supported by Figure 5 (see appendices). Also stressing the importance of variables, i.e. How sensitive the model is to change each input variable, it is clear from them that the independent variables related to the following financial ratios: X12, X6, X2, 5X, X11, respectively: (Return on total assets, profits distributed to market value, earnings per share, market value of return, net earnings to revenue), have the greatest impact on how companies are ranked, in terms of safety and default, the X4, X19 and X10 are the following, respectively: (Book value per share, working capital turnover, net interest before interest and tax to revenue), it is also a major determinant of typical predictive power, it is much more important than the 13 remaining financial ratios to classify companies, as shown in Figure 5 (see appendices).

4. CONCLUSION

The aim of this study is to determine the effectiveness of ANNs, in predicting the financial distress of Jordanian industrial companies, based on the financial ratios of the economic companies, in the industrial sector collected and calculated, although, future work will need to validate these results in larger and more diverse samples, however, there is strong evidence that the proposed model can be used effectively, to forecast the financial distress of economic companies in various sectors, accordingly, we reached the following results:

Relying on the analysis of financial ratios and indicators to predict financial stumbles, which is instrumental in alerting corporate operators and stakeholders to the risk of stumbles, which in turn leads to bankruptcy, and also has the potential to help Jordanian industrial companies predict their financial stumbles, this is proven by the validity of the first hypothesis;

The results showed that the strongest financial ratios, that have a great ability to distinguish, between the safety and distress of companies are: return on total assets, profits distributed to market value, earnings per share, return market value, net earnings to revenue;

The accuracy of the prediction of a multilayer neural network, that trained by the propagation reverse propagation algorithm, with the ability of industrial companies to distress financially successfully, therefore, the classification accuracy rate was very high in the classification of companies to sound and faltering, this is proven by the validity of the second hypothesis;

The superiority of ANNs in the 100% classification of the companies under study.

Based on the above we suggest the following recommendations:

The need to use sophisticated statistical predictive programs that help stakeholders and companies, from knowing the risk of stumbling before falling, into the most dangerous stage of it, which in turn leads to bankruptcy;

Establishing a department for corporate risk management and control, which in turn creates awareness among its workers, the necessity to rely on predictive models with a high ability to classify, forecast and to catch up before a real financial crisis;

Taking care of the subject of stumbling and not confusing it with failure, because not every faltered company is necessarily a failure.

As we know, every study has inadequacies, therefore, through this study we propose:

Mixing the qualitative and quantitative variables using the ANNs model in the same studied sector;

Using all economic sectors and not limiting them, to one sector until we see the ability of ANNs, to predict stumbling in other sectors and their accuracy in classification.

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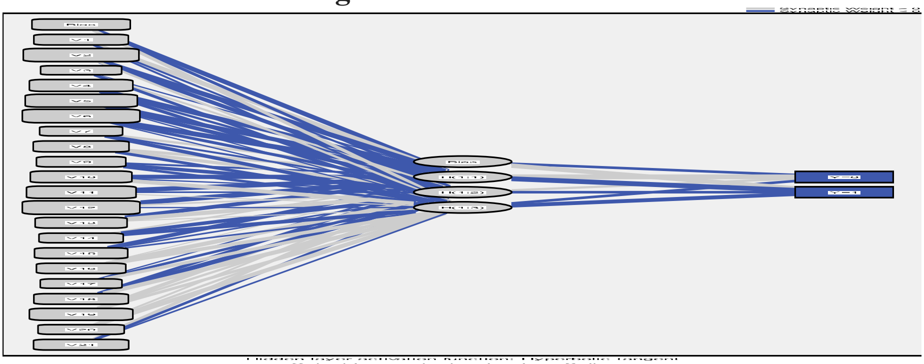
27. Appendices:

Table 3. Network Information

Input Layer	Covariates	1	X1
		2	X2
		3	X3
		4	X4
		5	X5
		6	X6
		7	X7
		8	X8
		9	X9
		10	X10
		11	X11
		12	X12
		13	X13
		14	X14
		15	X15
		16	X16
		17	X17
		18	X18
		19	X19
		20	X20
		21	X21
	Number of Unitsa		21
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1a		3
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Dependent
	Number of Units		2
	Activation Function		Softmax
	Error Function		Cross-entropy

a. Excluding the bias unit - **Source:** SPSS output

Fig.4. Neural network architecture



Source: SPSS output

Table 4. Model Summary

Training	Cross Entropy Error	1,052
	Percent Incorrect Predictions	,0%
	Stopping Rule Used	Training error ratio criterion (,001) achieved
	Training Time	00:00:00,004
Testing	Cross Entropy Error	3,403
	Percent Incorrect Predictions	5,9%

Dependent Variable: Dependent

Source: SPSS output

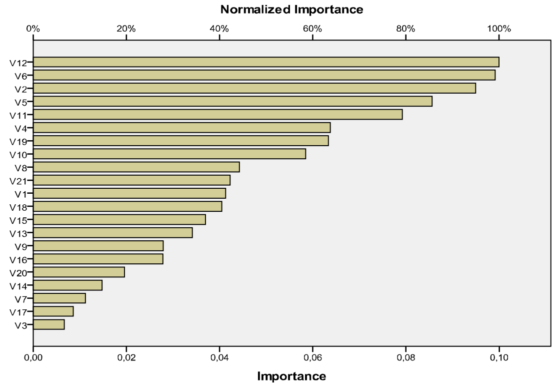
Table 5. Classification

Sample	Observed	Predicted		
		Motathera	**salima**	**Percent Correct**
Training	Motathera	16	0	100,0%
	Salima	0	21	100,0%
	Overall Percent	43,2%	56,8%	100,0%
Testing	Motathera	12	0	100,0%
	Salima	1	4	80,0%
	Overall Percent	76,5%	23,5%	94,1%

Dependent Variable: Dependent

Source: SPSS output

Fig.5. The importance of normalization



Source: SPSS output

Table 6. Independent Variable Importance

	Importance	Normalized Importance
X1	,041	41,3%
X2	,095	94,9%
X3	,007	6,6%
X4	,064	63,8%
X5	,086	85,6%
X6	,099	99,1%
X7	,011	11,2%
X8	,044	44,2%
X9	,028	27,9%
X10	,058	58,5%
X11	,079	79,2%
X12	,100	100,0%
X13	,034	34,1%
X14	,015	14,8%
X15	,037	37,0%
X16	,028	27,8%
X17	,009	8,6%
X18	,040	40,5%
X19	,063	63,3%
X20	,020	19,6%
X21	,042	42,2%

Source: SPSS output