Using Artificial Neural Network to predict the financial distress: the case of some Algerian Companies

استخدام الشبكة العصبية الاصطناعية للتنبؤ بالضائقة المالية: حالة بعض الشركات الجزائرية

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Abstract:

The main objective of this study is to use one of the modern financial analysis methods and one of the most important artificial intelligence techniques to predict financial distress, by designing a back-propagation artificial neural network model and applying it on the (10) selected Algerian companies for the period between (2015-2019). To the best of our knowledge, there are very few studies that treated this issue in Algeria. We concluded that the model was able to distinguish the financial situation of the companies under test in accordance with their actual financial situation, as the percentage of its predictive accuracy reached to 100%, knowing that the error rates were almost non-existent.
Keywords: *Financial distress, Forecasting, Artificial intelligence, Artificial neural networks.*
Jel Classification Codes: *C45, C53, C67, G17, G33.*

ملخص:

الهدف الرئيسي من هذه الدراسة هو استخدام أحد أساليب التحليل المالي الحديثة وإحدى أهم تقنيات الذكاء الاصطناعي للتنبؤ بالتعثر المالي، وذلك من خلال تصميم نموذج الشبكات العصبية الاصطناعية ذات الانتشار الخلفي وتطبيقه على الشركات الجزائرية المختارة والبالغ عددها (10) شركات للفترة الممتدة ما بين (2015-2019)، وعلى حد علمنا، هناك عدد قليل جدا من الدراسات التي تناولت هذه المسألة في الجزائر، وتوصلنا الى أن النموذج تمكن من تمييز الحالة المالية للشركات موضع الاختبار وفقا لحالتها المالية الفعلية، حيث بلغت نسبة دقته التنبئية 100%، مع العلم أن معدلات الخطأ كانت شبه معدومة.
الكلمات المفتاحية: التعثر المالي، التنبؤ، الذكاء الاصطناعي، الشبكات العصبية الاصطناعية.
تصنيف JEL : C45، C53، C67، G17، G33.

1. INTRODUCTION:

Financial distress is one of the main financial problems facing companies, it tops the list of the financial risks since it precedes the financial failure situation and legal bankruptcy in terms of time, it also indicates that the company falls within the danger zone that could develop in the absence of searching for ways to address it, knowing that the most important way to deal with financial distress lies in detecting it, diagnosing its causes and identifying the manifestations that prove its penetration into the company financial structure, this helps the company management in maintaining the correct

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pace, and it helps investors to avoid investing in the companies shares that facing financial problems.

Financial distress directly affects the financial position of the company, and it raises doubts about its continuity ability in the future. In light of the great losses that can result from this phenomenon, it was imperative to search for ways and methods to help detect financial distress and predict it before it happens, which contributes to hedging its risks and finding urgent solutions to address it.

The researchers made great efforts to find the most effective method in terms of results accuracy and the least in terms of error rates, these methods and ways differed and gradually developed to the point of reaching modern methods that proven their high ability to predict financial distress.

Financial distress prediction is an effective tool to classify distressed companies from the healthy companies, as the financial analysis provides many techniques that allow anticipating this phenomenon before its occurrence, based on the financial information extracted from the financial statements of the concerned companies, these techniques are confined between modern and traditional techniques, and they vary in terms of ease of use and results accuracy, artificial neural networks are considered among the most important modern financial analysis techniques.

Artificial intelligence techniques have revolutionized in the informatics field, on top of them are artificial neural networks, as they have been relied upon in various fields such as medicine, the world of filmmaking, programming language, robotics, and many other fields, nevertheless, only a few used them to conduct applied studies related to the financial field in general and to predict financial distress in particular, despite the lack of these studies, all of them point to consistent and uniform results that artificial neural networks have the ability to accurately predict financial distress with almost non-existent error rates.

Problem of Study:

The study problem is summarized in the following main question:

- To What extent can the back-propagation network (BPN) model predict financial distress in Algerian companies?

Importance of Study:

The importance of financial distress prediction stems from the advantages that this tool achieves for the company management, which aims to uncover the imbalances that affect on financial soundness, and then take corrective and preventive measures, it also helps the investor to choose the appropriate investment alternative that brings to him the highest degree of profitability and the lowest level of risk, the Loan donors are also concerned with predicting financial distress to distinguish between healthy and distressed companies before making decisions about granting credit or not, while the interest of the auditors in forecasting financial distress is due to the great responsibility that lies on their duty in auditing the financial statements of the company, in order to assess its level of performance, and to detect imbalances and deviations in a pre-emptive manner, consequently, financial distress prediction has become a top priority to achieve the interests of many interested parties.

In addition to this, relying on artificial intelligence networks to predict financial distress is a very recent topic, as this topic remains ambiguous due to the requirements and conditions that must be available in the financial analyst in order to design an effective model that can achieve the desired goal. It should be noted that this study is the first study that focused on the subject of predicting financial distress by relying on neural networks, and by applying on the Algerian companies.

Objective of Study:

The main objective of the paper is the use of Artificial Neural Network to predict the financial distress. This study also aims to help all interested parties in the financial distress prediction results, by building a modern model based on one of the most important artificial intelligence techniques, represented in artificial neural networks, consequently, contributing to proving the accuracy of the financial analysis modern generation techniques results by conducting the applied study, also, in order to learn about neural networks and their design stages, their training methods, and then test their predict ability. We also aim to learn about the back-propagation network (BPN) model ability to predict financial distress in the Algerian business environment and by applying on the companies that belonging to the different activity fields.

2. LITERATURE REVIEW AND THEORETICAL BACKGROUND:

Through the theoretical part, we try to clarify the most basic concepts related to the financial distress as follows:

2.1. Financial Distress:

In Oxford Dictionary, the word ”Distress” means inability, pain, sorrow, lack of financial resources and poverty,[1] and there are several definitions for financial distress including different financial situations, during the last 50 years, numerous investigations has been focused on this topic, which in general can be said to be the situation in which a company is certain of some type of financial difficulty,[2]the term “financial distress” is used in a negative connotation in order to describe the financial situation of a company confronted with a temporary lack of liquidity and with the difficulties that ensue in fulfilling financial obligations on schedule and to the full exten, and it is divided into two forms, the first one is default on a debt payment, and the second one is an attempt to restructure the debt in order to prevent the default situation.[3]

Company is in financial distress if it is not able to meet its obligations or in a situation where the value of its liabilities exceeds the value of its assets, in this sense, so called relative and absolu inability of company are distinguished here,[4]so it can be said that financial distress is a situation where the liabilities exceed assets in a company and it generally happens due to undercapitalisation, not maintaining sufficient cash, resources not being utilised properly, inefficient management in all activities, sales decline and adverse market situation,[5]also it is a condition where a company faces financial difficulties, which is also referred to as "Business" or "Corporate Failure". Financial distress can induce a great impact on any company, stakeholders, and the economy of a country.[6]

Default, literally occurs when a firm fails to fulfil an obligation, especially to pay a loan or appear in a low court, using more corporate terms, default happens when the debtor violates a condition of an agreement with creditor and can be the grounds for legal action.[7]

Finally the financial distress is defined as negative earnings per sharefor listed companies, and the financial distress as occur when a company’s interest cover is less than 0.7 and there is a decline in fixed assets or a decrease in share capital, it has also been difined as when the net worth of a company falls below half of its share capital, also financial distress defined to be that EBITDA are lower than the financial expenses or a decline in its market value for two consecutive years.[8]

2.2. Financial Failure:

The definition of business failure has been adopted by "Dun & Bradstreet" (D&B), a leading supplier of relevant statistics on unsuccessful business, failure includes businesses that ceased operations following assignment or bankruptcy, with loss to creditors, and voluntarily withdraw, leaving unpaid obligation, or were involved in court actions such as receivership, reorganization, or arrangement,[9]then the corporate failure defines as firm was unable to pay back the financial obligations when mature, when a company was face bond default, overdraft on bank or non payment for preference stock dividend, the corporate might consider as financial failure, also it defines as company fail to earn a return on risk capital, hence the company was failed to pay its financial obligation when due.[10]

As a general approach financial failure, which is defined as inability of a company to meet its current obligations as they come due, is a less ambiguous concept than economic failure. The company does not have sufficient liquidity to meet current liabilities, this can occur even when the company has a positive net worth, with the exceeding asset values over liabilities. As it is understood from the definition, besides inability of a company to meet due debts, in other term default, having difficulties in meeting due debts can also be considered as financial failure.[11]

Under an economic aspect, a failure can be defined through the company's financial performance that can be represented by: [12]

- "Insufficient revenues to cover costs and where the average return on investment is below the firm's cost of capital
- "negative equity and/or negative earnings"
- "reductions in dividends, violations of debt covenants"
- "going private for a publicly listed company" which is similar to delisting the companies' shares.

It has been suggested that failures can be predicted either by observing the performance:

Table 1. Set of factors affecting the performance of a business entity

Internal Factor	External Factor
Poor management (Quality Mangement)	Social environment
Dissonance to the environmental developments	Industrial Environment
Insufficient communication	Economic Environment
Unbalanced growth	Natural Environmental
Failure in the main projects	Technological Environment
	Legal and Political Environment

Source: Babela, I., Mohammed, R. (2016). Business Failure Prediction using Sherrod and Kida Models: Evidence from Banks Listed on Iraqi Stock Exchange (2011 -2014). Humanities Journal of University of Zakho, 4(2), pp 37-38.

2.3. Bankruptcy:

Although many people use the term bankruptcy to refer to a company that has failed, a company is not legally bankrupt unless the company has been declared bankrupt by applicable law,[13] where as the bankruptcy is that state of insolvency in which a company or an organization cannot discharge their financial obligation or are unable to meet the payments to their creditors, as the company cannot keep up with their debts, they cannot continue with their activities, the prediction of this stage of the company is important to the various stakeholders of the company such as the investors, the creditors, the regulators and the lenders.[14]

When the company violates the agreement to maintain the stated maximum debt ratio or minimum current ratio, such situations signal the deteriorating performance of the company. Formally a company becomes the default when it fails to pay the principal amount or the interest. In this case after the grace time (normally 30 days), the company is announced as "in default". After the grace period, if the company really fails to pay the full due, it is necessary to restructure or file for bankruptcy. A company is denoted as bankrupt if the liabilities surpass the value of assets according to the going concern concept, but it's difficult to recognize the company as bankrupt until there is a declaration by the court.[15]

2.4. Difference between Financial Distress and bankruptcy:

Financial distress costs as the most important sourc of bankruptcy costs. Study-ing only bankruptcy leads to an important bias because firms usually get into a financial distress cycleand a lack of financial flexibility several years before filing for bankruptcy. Bankruptcy is onlyone of the possible outcomes of financial distress, which is mainly of a legal nature, without anyspecific economic and univocal significance. Accordingly, financial distress more broadly as the non-sporad-ic situation where companies can no longer meet their liabilities when they become due, and either break their commitments with creditors or face them with severe difficulties.[16]

2.5. Artificial neural network:

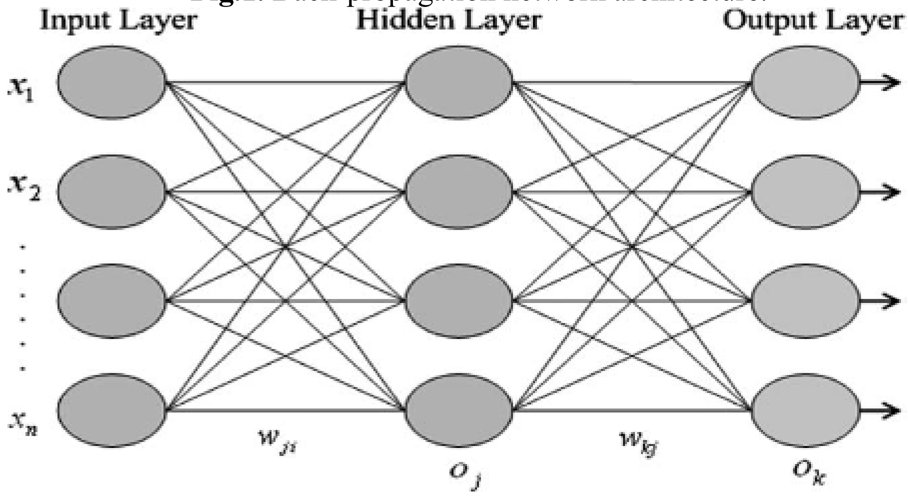
Neural network is a machine that is designed to model the way in which the brain performs a particular task or function of interest; the network is usually implemented by using electronic components or is simulated in software on a digital computer.[17] Recent technological advances, have made ANN models a viable alternative for many decision problems and they have the potential for improving the models of numerous financial activities such as forecasting financial distress in firms,[18] (Sudarsanam, 2016, p 36) and according to "Castillo ": "an expert system is similar to a computer system because they also emulate human experts in an area of specialization".[19]

ANNs are flexible, nonparametric modeling tools. They can perform any complex function mapping with arbitrarily desired accuracy. An ANN is typically composed of several layers of many computing elements called nodes. Each node receives an input signal from other nodes or external inputs and then after processing the signals locally through a transfer function, it outputs a transformed signal to other nodes or final result. ANNs are characterized by the network architecture, that is, the number of layers, the number of nodes in each layer and how the nodes are connected. In a popular form of ANN called the multi-layer perceptron (MLP), all nodes and layers are arranged in a feedforward manner. The first or the lowest layer is called the input layer where external information is received. The last or the highest layer is called the output layer where the network produces the model solution. In between, there are one or more hidden layers which are critical for ANNs to identify the complex patterns in the data. All nodes in adjacent layers are connected by acyclic arcs from a lower layer to a higher layer.[20]

The most popular forms of learning are:[21]

- Supervised learning: Patterns for which both their inputs and outputs are known are presented to the ANN. The task of the supervised learner is to predict the value of the function for any valid input object after having seen a number of training examples. ANN employing supervised learning has been widely utilized for the solution of function approximation and classification problems.
- Unsupervised learning: Patterns are presented to the ANN in the form of feature values. It is distinguished from supervised learning by the fact that there is no a priori output. ANN employing unsupervised learning has been successfully employed for data mining and classification tasks. The self-organizing map (SOM) and adaptive resonance theory (ART) constitutes the most popular exemplar of this class.

Fig.1. Back-propagation network architecture.



Source: Chen, W. S., Du, Y. K. (2009). Using neural networks and data mining techniques for the financial distress prediction mode, Op.cit, p 4076.

Fig.1 shows the l _ m _ n (l denotes input neurons, mdenotes hidden neurons, and "n" denotes output neurons) architecture of a BPN model (Back-propagation network). The input layer can be considered the model stimuli and the output layer the input stimuli outcome. The hidden layer determines the mapping relationships between input and output layers, whereas the relationships between neurons are stored as weights of the connecting links. The input signals are modified by the interconnection weight, known as weight factor "wji", which represents the interconnection of the "ith" node of the first layer to the "jth" node of the second layer. The sum of the modified signals (total activation) is then modified by a sigmoid transfer function (f). Similarly, the output signals of the hidden layer are modified by interconnection weight "wkj" of the "kth" node of the output layer to the "jth" node of the hidden layer. The sum of the modified signals is then modified by sigmoid transfer (f) function and the output is collected at the output layer.

Let $I_p = (I_{p1}, I_{p2}, \ldots, I_{pl})$, p = 1,2, . . . ,N be the "pth" pattern among N input patterns. Where "w_{ji}" and "w_{kj}" are connection weights between the "ith" input neuron to the "jth" hidden neuron, and the "jth" hidden neuron to the "kth" output neuron, respectively.

Output from a neuron in the input layer is:

$$O_{pi} = I_{pi}, \quad i = 1, 2, \ldots, l \qquad (1)$$

Output from a neuron in the hidden layer is:

$$O_{oj} = f\,(NET_{pj}) = f\,\left(\sum_{i-0}^{1} W\text{ji}O\text{pi}\right),\ j = 1, 2, \ldots, m \qquad (2)$$

Output from a neuron in the output layer is:

$$O_{pk} = f\,(NET_{pk}) = f\,\left(\sum_{j-0}^{m} W\text{kj}O\text{pj}\right),\ k = 1, 2, \ldots, m \qquad (3)$$

BPN (Back-propagation network) has been applied to various areas, such as investigating long-term tidal predictions, improving customer satisfaction, predicting flank wear in drills, enhancing job completion time prediction in the semiconductor fabrication factory, and providing the required accuracy for focal ventricular arrhythmias diagnosis.

3. EMPIRICAL EVIDENCE:

We have selected a group of previous studies related to the subject of our study, and through that we try to summarize the most important findings of these studies, then after that we mention the elements that distinguish our study from previous studies:

- Fernández-Gámez, M. Á., et al. (2016). Applying a probabilistic neural network to hotel bankruptcy prediction

Using a probabilistic neural network and a set of financial and non-financial variables, this study aimed to improve the ability of the existing bankruptcy prediction models in the hotel industry, and to construct a hotel bankruptcy prediction model that provides high accuracy, using information sufficiently distant from the bankruptcy situation, and which is able to determine the sensitivity of the explanatory variables. Based on a sample of Spanish hotels that went bankrupt between 2005 and 2012, empirical results indicated that using information nearer to bankruptcy (one and two years prior), the most relevant variable is EBITDA to current liabilities, but using information further from bankruptcy (three years prior), return on assets is the best predictor of bankruptcy, results also confirmd a higher power of NN in the development of models to predict bankruptcy in hotels, it has also been found that using the non-financial variables of the hotel together with the traditional financial variables can help improve the accuracy levels of bankruptcy.[22]

- Gholizadeh, M., et al. (2011). Corporate financial distress prediction using artificial neural networks and Using micro-level financial indicators

The main goal of this research has been to predict corporate financial distress using artificial neural networks and internal factors affecting on company, using financial micro variables. The study population was consisted of (444) companies listed in Tehran Stock Exchange for the years (1386-1384) and the sample includes (144) company. MATLAB software to verify the hypothesis of the study and Neural Network Toolbox and using it in the code, is a neural network design and analysis. The results of this study indicate that the use of micro-economics can play an important role to play in financial distress or further fractures.[23]

- Shahedi, S. H., et al. (2014). Analysis of the Power of Predicting Financial Distress of Companies Listed in Tehran Stock Exchange using Artificial Neural Networks

The present study was designed and conducted to predict bankruptcy of companies listed in Tehran Stock Exchange using Artificial Neural Networks. The study sample consisted of 167 firms (47 bankrupts and 120 non-bankrupts) and a 6-years period for the years 2006 to 2011 was considered. Thus the observation rises to 6 *167 (year-companies). In the present study, practical, descriptive correlation and expost facto methods were used in terms of objective, implementation and data status, respectively. According to the obtained results, the neural network in the all years had the most accuracy in prediction of companies' financial distress. The neural network classified all companies with financial distress in an appropriate group based on data related to one year before bankruptcy. Investigations indicated that estimates based on data related to one year before bankruptcy had the most accurate value of prediction. In general, the neural network approach has been successful with greater accuracy and lower error value in bankruptcy prediction. The obtained results indicate the superiority of Artificial Neural Network in bankruptcy prediction.[24]

- Parkash, R., Nabi, A. A. (2020). Use of Artificial Neural Network (ANN) in Predicting Financial Distress: A Case of Emerging Economy

The objective of the study is to use Artificial Neural Network (ANN) algorithm to identify the important factors those can accurately predict financial distress (FD) of non-manufacturing firms of Pakistan using a panel data of (271) companies from 2013 to 2016. The results of the study based on Artificial Neural Network established that firm-specific variables (profitability, liquidity and leverage) are very important variable in predicting financial distress. Further the results concluded that sustainable growth rate, going concern (TATA and FCF), earning manipulation and size of the firm play moderately important role in financial distress prediction. On the other hand, macroeconomic indicators (GDP growth and Inflation) contribute least in forecasting financial distress of a firm.[25]

- Paule-Vianez, J., et al. (2020). Prediction of financial distress in the Spanish banking system An application using artificial neural networks

Using artificial neural networks, specifically the Multilayer Perceptron network with a hidden layer, been reached to prediction model that is capable of predicting short-term financial distress with an overall accuracy of more than 97% using training, testing and reserve sub-samples, therefore, this research contributes to financial distress literature by providing the first neural network model applied in Spain to predict financial distress. It should also be pointed out that this study is one of the few that has been carried out with a reserve sub-sample, thus increasing its capacity to generalize and eliminate the problem of over-adjustment, which is so common in this type of model. Furthermore, the only error observed was a type 2 (false positive) error, indicating that in the sample used, there were no cases atsoever in which an entity in financial distress in a period of 12 months was not correctly predicted. The reliability of the results was achieved with ROC curves, showing major differences between entities suffering and not suffering from financial stress. The network specifically obtained showing a differentiation capacity of 99.7%, all of which was based on the accounting and macroeconomic data recorded in the 12 months prior to the event. Moreover, to demonstrate the robustness and adequacy of artificial neural networks compared to other methods, multivariate discriminant analysis has been applied to the data. The results obtained show that artificial neural networks are a highly suitable method for studying financial distress in Spanish credit institutions and for predicting all cases in which an entity has short-term financial problems.[26]

Our study is distinguished from previous studies in terms of the time difference and the application place, as the study was conducted on companies that belong to the Algerian work environment for the period between (2015-2019), and our study deliberately selected companies that do not belong to the same field of activity in order to generalize interest on All types of companies. In addition to this, the study sample was divided into the training sample and the test sample on the basis of the difference in the study period and not on the basis of the difference in the number of companies, as the training sample included data for the (10) companies for the period extending between (2015-2018), and the test period included data for the same companies but only for the year (2019). This study also focused on designing and testing a Back-propagation artificial neural network model.

4. APPLICATION FARMEWORK:

We are trying, through conducting the applied study, to transfer theoretical concepts to the field, with the aim of reaching new results that will generalize the benefit to all interested parties:

4.1. Sample of Study Description:

In this study, we have relied on a dataset of mixed companies, or in another concept are belonging to different economic sector, among these companies (4) are listed on the Algerian stock market. It should be noted that the financial statements of these companies are publicly published and available to the public. Whereas, the remaining (6) companies, their data were obtained by resorting to a competent official Algerian authority (Direction des Grands Entreprises DGE) after undertaking not to mention the names of these companies in order to preserve their confidentiality and privacy

The study period extends between (2015-2019), where the final sample consists of (10) Algerian economic companies, the financial data of the (10) companies are divided into a training data set and a test data set for the purposes of assessing the level of efficiency of the BPN model, and the following table shows the study sample companies activity field:

Table 2. The study sample companies activity field

Company Name	Field of activity
Saidal	Pharmaceutical industry
Aurassi	Hotel services
Biopharm	Pharmaceutical industry
Rouiba	Beverage production
Company A	Services
Company B	Services
Company C	Services
Company D	Industrial services
Company E	Services
Company F	Services

Source: Prepared by researchers depending on the companies identification card

4.2. Description of the companies actual financial situation:

The following table shows the actual financial situation of the companies under study and application, where the description of the financial situation differed between distress and the absence of distress, this allows the BPN model to be trained to understand and determine the distress situation or not distress, based on the financial ratios that was previously selected with high accuracy, thus, this model can predict the actual situation of the company with the least possible degree of error, what we will be sure about after testing the predictive ability of the model on the test sample.

It should also be noted that the state of distress or non-distress was assessed according to the self evaluation based on the indications of the financial indicators, according to the following table:

Table 3. Description of the actual financial situation of the companies under study

	2015	2016	2017	2018	2019
Saidal	Distress	Distress	Distress	Distress	Distress
Aurassi	Distress	Distress	Distress	Distress	Distress
Biopharm	No-Distress	No-Distress	No-Distress	No-Distress	No-Distress
Rouiba	Distress	Distress	Distress	Distress	Distress
Company A	Distress	Distress	Distress	Distress	Distress
Company B	No-Distress	No-Distress	Distress	No-Distress	No-Distress
Company C	Distress	Distress	Distress	Distress	Distress
Company D	Distress	No-Distress	No-Distress	No-Distress	No-Distress
Company E	Distress	Distress	Distress	Distress	Distress
Company F	Distress	Distress	Distress	Distress	Distress

Source: Prepared by researchers depending on companies financial statements

4.3. Modeling

Existing literatures build the prediction model mostly using the variables from the aspects of the capital, assets, management, earnings, liquidity, Sensibility, But in this study we relied on financial indicators that have proven their great ability to predict financial distress, according to previous studies, as shown in the following table:

Table 4. Finanacial variables

Categories	Code	Financial variables
Profitability Ratios	X_1	Profit before interest and taxes / Total assets
	X_2	Profit before taxes / Total assets
	X_3	Profit before interest and taxes / Total tangible assets
	X_4	Profit before taxes / Current liabilities
	X_5	Net Profit after interest and taxes / Total assets
Liquidity Ratios	X_6	Monetary assets / Total assets
	X_7	Current assets / Current liabilities
	X_8	Net Working capital / Total tangible assets
Leverage Ratios	X_9	Property rights / Total liabilities
	X_{10}	Borrowed money / Total assets
Acivity Ratios	X_{11}	Net sales / Total assets
	X_{12}	Net sales / Total tangible assets

Source: Prepared by researchers depending on Previous studies

4.4. Experimentation

Our applied study starts from the neural network model training phase, which in turn is divided into several sub-stages, the first of which is the model design that fits with the financial aspect, and has the ability to predict financial distress and the ability to classify companies with their actual state.

4.4.1. First phase: design of the Back-propagation artificial neural network model:

The first phase includes identifying the basic elements in a neural network model building, knowing that these variables have been determined according to scientific foundations that allow achieving homogeneity that leads to building an effective neural network model and has the full ability to predict financial distress with the least degree of error, the best variants were selected after several attempts and adjustments in order to reach the best results, whereas, the lowest requirement error rate was estimated by 1e-09.

Table.5 summarizes the most important steps we took to design the BPN model as follow:

Table 5. Design phase variants

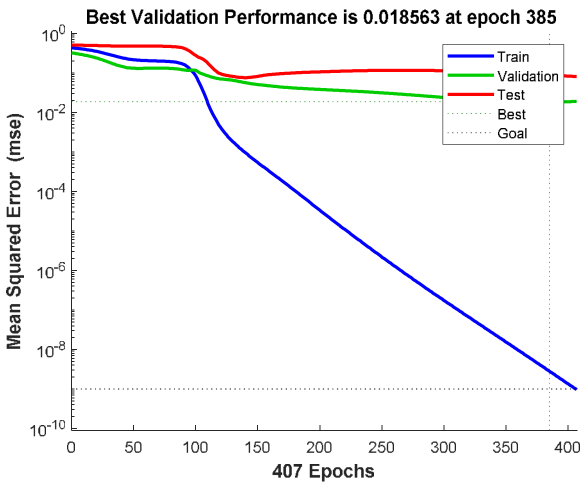
Elements of the design stage	Description
The number of input neurons	12 neurons
The numberof Hidden layer neurons	8 neurons
The number of output neurons	1 neuron
The number of output layer neurons	1 neuron
Learning rate	0.01
Push rate	0.7
Lowest permissible value of error	0.000000001
Min - gradient	0.000000001
Training function	Gradient descent with momentum & adaptive
Training method	Feed-Forword Back-propagation
Transfer function	LOGSIG
Adaption learning function	LearnGDM
Performance function	Mean square error

Source: : Prepared by researchers after trying and experimenting

4.4.2. Second phase: training phase of the Back-propagation artificial neural network model:

After designing the model and identifying the most important parameters that allow us to accurately predict financial distress, the financial information represented in the financial ratios of the (10) companies for the period between (2015-2018) have been included in the model inputs, and we excluded the financial ratios for the year (2019) since these financial ratios relate to the test sample. Fig.2 shows the steps that BPN model went through during the training phase:

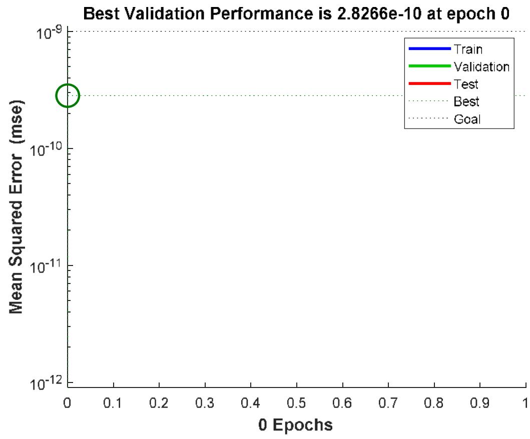
Fig.2. Initial steps for the training phase



Source: : Prepared by researchers using MATLAB

The above figure shows the initial phases that the model training process went through in predicting financial distress and translating the indications of various financial indicators into the actual financial situation that the company is going through. We note that the best (MSE) was reached after 407 training courses, and this is a very low rate compared to the MSE which was stipulated and specified at the design phase of the model estimated by 1e-09, so, we note that the model still needs to undergo many training courses that allow developing the learning ability of the neural network, which is shown by the following figure:

Fig.3. The final steps of the training phase



Source: Prepared by researchers using MATLAB

After making several additional training attempts, the best results were reached that help to achieve an accurate prediction of financial distress in the test sample, whereas, we note that the (MSE) rate was 2.8266e-10 and exceeded the rate stipulated at the beginning of the model design phase estimated at 1e-09, this indicates that the training phase was completed with great success, and we can rely on the designed neural network to test the test sample.

4.4.3. Third phase: training phase results of the Back-propagation artificial neural network model:

We are evaluating the training results of the BPA model, where we have included the inputs for the training sample and its number (10) companies for the period extending between 2015-2018 by relying on measures of prediction accuracy. We used two types of these measures, the first being the mean square error, while the second type is the mean absolute error.

Table.6 below shows the results of the model prediction accuracy test:

Table 6. Prediction accuracy measures of the training phase outputs

measures of prediction accuracy	Distress Y(0)	No Distress Y(1)
MSE	0.0000000005	0.0000000013
MAE	0.000011506	0.000019

Source: Prepared by researchers using training sample outputs

We notice from the above table that the error rates are very small and almost non-existent, whether for classification of distressed companies or non- distressed, this indicates that the designed model is usable and has the ability to predict financial distress, this is confirmed by the training results, which indicate 100% complete accuracy, as the following table shows:

Table 7. Results of the taxonomic ability of the training phase outputs

	2015		2016		2017		2018	
	Y(0)	Y(1)	Y(0)	Y(1)	Y(0)	Y(1)	Y(0)	Y(1)
Distress Y(0)	8	0	7	0	8	0	7	0
No Distress Y(1)	0	2	0	3	0	2	0	3
Total	8	2	7	3	8	2	7	3
percentage	100%	100%	100%	100%	100%	100%	100%	100%

Source: Prepared by researchers using training sample outputs

We note that the model after undergoing several training courses as shown in Fig.2 and Fig.3, was able to train on the correct classification of the actual financial situation of the companies.

4.4.4. Fourth phase: Test phase results of the Back-propagation artificial neural network model:

The testing phase mainly depends on testing new financial data that the model has not previously been trained on, and since the training sample that included the data for the extended period between (2015-2018), 2019 data were harnessed and relied upon to test the predictive ability of the designed model.

The following table shows the actual situation of the test sample companies in the year (2019) compared with the predicted outputs depending on the BPN model:

Table 8. Results of the testing phase outputs

Company	Company actual situation	Y	Y Output	Distress or no Distress pecent
Saidal	Distress	0	0.0000007466	100%
Aurassi	Distress	0	0.0000001292	100%
Biopharm	No-Distress	1	1	100%
Rouiba	Distress	0	0.0000008106	100%
Company A	Distress	0	0.0000017578	100%
Company B	No-Distress	1	0.99998	100%
Company C	Distress	0	0.000017497	100%
Company D	No-Distress	1	1	100%
Company E	Distress	0	0.0000012097	100%
Company F	Distress	0	0.0000032345	100%

Source: Prepared by researchers using testing sample outputs

The above table indicates that the model has the full ability to classify the actual financial condition of the companies, as the prediction accuracy percentage reached to 100% with the least degree of error.

After inserting the main variables (financial ratios) of the test sample for the test period extending between (2015-2019) in the inputs of the BPN model, we assessed the financial prediction accuracy using (MSE) & (MAE).

Table.9 shows the results of evaluating the BPN model accuracy for the test sample:

Table 9. Prediction accuracy measures of the testing phase outputs

measures of prediction accuracy	Distress Y(0)	No Distress Y(1)
MSE	0.000000000046055	0.0000000001333
MAE	0.0000036264	0.0000066667

Source: Prepared by researchers using testing sample outputs

We note that the error rates obtained after application on the test sample were much smaller than the error rates obtained after application on the training sample, and this indicates that the model was able to arrive at the correct and very effective method that allows us to accurately diagnose the financial position of the companies in light of the error rates close to zero. It can be said that these results were not expected, given that the most of the prediction models reach good results at the training stage, but the quality of the results decreases and error rates are multiplied directly when testing the model on a sample that it has not previously dealt with, this is confirmed by the statistics of the following table:

Table 10. Results of the taxonomic ability of the testing phase outputs

	2019	
	Distress Y(0)	**No Distress Y(1)**
Distress Y(0)	7	0
No Distress Y(1)	0	3
Total	7	3
percentage	100%	100%

Source: Prepared by researchers using testing sample outputs

Table.10 shows that the model was able to classify companies by 100% in all cases, and this confirms that the model is usable in the financial aspect and that results can be relied on with a complete percentage to predict financial distress.

5. CONCLUSION:

Finally, after broaching to the financial distress concept and all the concepts related to it in the theoretical part, without ever condoning the simplification of the artificial neural networks content, and in particular we mention here the Back-propagation networks, then we tried to translate these intellectual concepts and apply them in the field on institutions that active in The Algerian work environment, and it can be said that the research has reached many results that will provide an addition to the Algerian academic field, and also help the concerned institutions to uncover their financial imbalances and determine their financial position based on artificial intelligence techniques, among these **results** are the following:

- The BPN model achieved almost non-existent error rates, either for its results in the training phase or in the testing phase;
- The error rates in the test phase were lower than the error rates in the training phase, and this indicates that the model was able to use the conditions on which it was trained to serve the basic goal of forecasting in the best possible way, and it proved its successful in predicting financial distress;
- The outputs of the BPN model correspond to the actual situation of the companies with a percentage of 100%, whether for the training phase or the testing phase;
- It can be said that the applied model was compatible with companies data that belong to the Algerian business environment;
- Despite the different of the companies activity field, the neural network model overlooked that and did not prevent achieving the best results.

Depending on the results of the study, we reached a set of **recommendations**, the most important of which are:

- The necessity to rely on neural network models in financial and economic issues;
  Quoting from previous studies, it can be said that the statistical financial distress prediction models fail to reach a prediction accuracy of 100%, and on the contrary, the neural networks model was able to achieve this ratio, and therefore financial analysts must choose the neural network models in the first place when choosing between available alternatives;
- Taking into account the small details when designing the neural networks model and determining the basic elements according to scientific foundations that guarantee the homogeneity and compatibility of these elements with each other and contribute to achieving the

desired purpose of the prediction, because the difference in the purpose of forecasting leads to the necessity of modifying these elements to ensure the creation of interaction between them;

- The financial managers of Algerian companies must rely on artificial neural networks to predict financial imbalances that affect on the company interests and its path in the near future and may worsen until the activity of the company stops, or what is known as "bankruptcy";
- The necessity of urging economic institutions to modernize their financial management by taking into account the valuable recommendations made by researchers, and giving this topic its importance and dealing seriously with its developments, which will develop the institutional sector in the future ;
- Relying in building models for the financial distress prediction on the largest possible number of financial ratios, would give more accurate and comprehensive results ;
- It is imperative to change the ways of thinking of financial decision-makers in business enterprises, by dispensing with traditional methods of facing risks and replacing them with modern methods that have proven their success in various academic and applied international studies.

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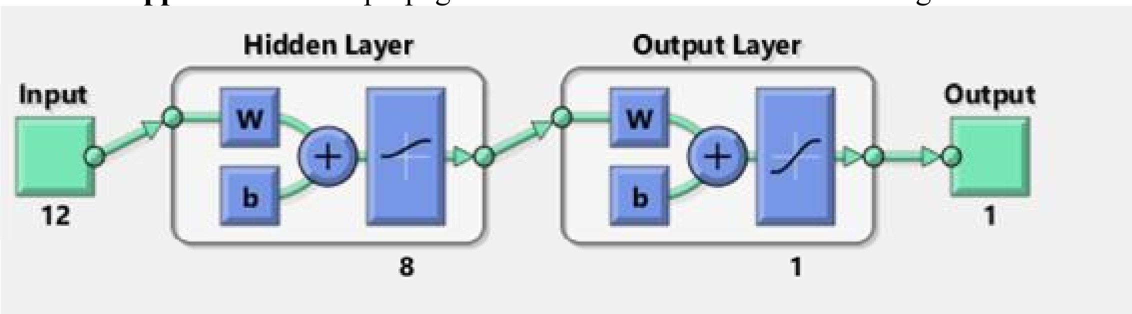
7. Appendices:

The appendices related to the study are divided into the following:

Appendix 1. Back-propagation network architecture of the designed model



Source: Prepared by researchers using Matlab

Appendix 2. Training sample outputs

	2015		2016		2017		2018	
	Y	Y Output	Y	Y Output	Y	Y Output	Y	Y Output
Saidal	0	0.0000028018	0	0.000001747	0	0.0000010582	0	0.000001383
Aurassi	0	0.000025663	0	0.000001191	0	0.0000070278	0	0.000002126
Biopharm	1	1	1	1	1	1	1	1
Rouiba	0	0.0000031311	0	0.0000013882	0	0.00000044	0	0.0000009180
Co. A	0	0.0000008782	0	0.00000322	0	0.0000029075	0	0.000001533
Co. B	1	0.99992	1	1	0	0.0000412069	1	1
Co. C	0	0.000010564	0	0.0000020884	0	0.00004495	0	0.000002948
Co.D	0	0.00008054	1	0.99994	1	0.99995	1	1
Co. E	0	0.000025327	0	0.000066137	0	0.0000008827	0	0.000001306
Co. F	0	0.0000070296	0	0.0000028644	0	0.000001671	0	0.0000002647

Source: Prepared by researchers using training sample outputs.

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