

The contribution of the application of artificial intelligence approaches to predicting the failure of borrowing enterprises

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Abstract:

This study aims to develop a model that assists commercial banks in predicting the default of small and medium-sized enterprises (SMEs), with the goal of facilitating lending decisions. To achieve this, we constructed a database obtained from the National Center for Commercial Registration (CRNC) for a sample of 60 SMEs, evenly divided between healthy and distressed firms. The study data underwent various statistical tests using the SPSS software to determine descriptive characteristics of the sample and assess the suitability of this data for the credit risk measurement model employed in this study. The study's findings revealed that the application of an artificial neural network model achieved accurate classification rates of up to 100% for the total classified institutions. This suggests that the proposed model could serve as an effective tool for commercial banks to optimize loan risk management and make sound credit decisions.

Keywords: Financial institutions, financial distress, artificial neural networks.

Jel Classification Codes : C17 ; G47.

Résumé:

Cette étude vise à développer un modèle qui aide les banques commerciales à prédire le défaut de paiement des petites et moyennes entreprises (PME), dans le but de faciliter les décisions de prêt. Pour y parvenir, nous avons construit une base de données obtenue auprès du Centre national d'enregistrement commercial (CRNC) pour un échantillon de 60 PME, réparties de manière égale entre entreprises saines et entreprises en difficulté. Les données de l'étude ont subi divers tests statistiques à l'aide du logiciel SPSS pour déterminer les caractéristiques descriptives de l'échantillon et évaluer l'adéquation de ces données au modèle de mesure du risque de crédit utilisé dans cette étude. Les résultats de l'étude ont révélé que l'application d'un modèle de réseau neuronal artificiel a permis d'obtenir des taux de classification précis allant jusqu'à 100 % pour l'ensemble des institutions classées. Cela suggère que le modèle proposé pourrait servir d'outil efficace aux banques commerciales pour optimiser la gestion du risque de prêt et prendre des décisions de crédit judicieuses.

Mots clés : Institutions financières, détresse financière, réseaux de neurones artificiels.

Jel Classification Codes : C17 ; G47.

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I. Introduction

Financial institutions' primary goal is to turn a profit, but they also have a significant impact on social and economic advancement. They give their clients credit facilities so they can use their funds to various uses. They must, however, have strategies, rules, and procedures to regulate the process of giving these money because they bear risk in providing these services.

In addition to the technical revolution brought about by globalization, banks have entered new markets and taken on new roles, which has resulted in drastic changes to the banking industry. Changes in economic activity, including privatization, the initiation of economic reform initiatives, and the liberalization of international trade, have resulted from this. Changes in the financial activities of banks have also resulted from it, including an increase in monetary and financial transactions on international capital markets, the replacement of new transactions, an expansion of banks' role in financing international trade, and the introduction of new financial and banking innovations.

A number of bank crises have had a detrimental impact on national economies. The majority of these crises are linked to issues with banking, particularly with credit concerns. In order to lower these risks, commercial banks must implement control mechanisms including precise customer identification and sufficient guarantee provision. Through the use of credit control instruments and performance monitoring of banks, the central bank assumes a vital role in managing banking risks.

It is noteworthy that one of the most significant statistical techniques for assessing credit risks will be covered in our study: artificial neural networks. This technique primarily draws on artificial intelligence techniques, which are renowned for their high learning capacities and capacity to handle logical and mathematical puzzles that prove challenging for conventional statistical techniques.

From this standpoint, we will try to answer the following problem:

- How can the application of artificial intelligence approaches contribute to improving the performance of financial institutions in Algeria?

II. Generalities about artificial intelligence

II.1 Artificial Intelligence

The US Navy's 1938 analog computer and Konrad Zuse's 1939 digital computer were crucial to the development of artificial intelligence, which began to emerge in the middle of the 20th century. The phrase "artificial intelligence" was first used in 1956, at Dartmouth College, in the title of a research session, by

John McCarthy and Marvin Menke. (Arvind & Heinz, 2021)

II.1.1 Definition of artificial intelligence

Artificial intelligence can be defined as a combination of different technologies, such as cognitive automation, machine learning, reasoning, hypothesis generation and analysis, and natural language processing. Together, these technologies result in systems capable of generating insights and analysis at or above the level of humans. (Alice & Nawaz, 2021)

AI uses advanced analysis and logical techniques to interpret events, support decisions, and automate actions. Most of the developments in AI have occurred in the field of machine learning, which allows for the processing of vast amounts of data and forms of learning based on repeated exposure to experimental conditions, combined with complex learning algorithms. Machine learning can be used to train programs to perform various tasks, such as recognizing images, translating languages, identifying hazards, and finding patterns and trends. In its current form, machine learning relies on the availability of large amounts of information, both structured and unstructured. (Yun, Paul, & Seth, 2021)

There are many ways to apply AI, such as machine learning (neural networks are the most commonly used), random forest, classification and regression. AI techniques have a significant impact on companies developing forecasting methods. Increases in data volume do not necessarily lead to improved forecasting. More important is preprocessing the data, improving computational algorithms and reducing errors. (Larry, 2018)

Machine learning can use three methods—supervised learning, unsupervised learning, and reinforcement learning—to learn from data. Supervised learning involves classifying data so that the computer can learn to predict the outcome using the inputs. The machine can learn without supervision when the incoming data is not classified. Clustering is the most often used technique for this kind of AI to identify patterns in the data. Every time an algorithm is used in reinforcement learning, it makes a decision. (hicham & hanane, 2022)

II.1.2 Artificial Intelligence Features

- Artificial intelligence uses real-time data from various sources to perform complex and rapid analysis, helping to make better decisions;
- AI relies on machine learning and big data analytics techniques, which allow it to collect data and discover patterns;
- These patterns can be used to define rules and apply them to specific cases. AI can also learn from experience, making it adaptable;
- AI is adaptive, as it can learn from data and make decisions based on that data.

II.2 Uses of Artificial Intelligence in the Financial Industry

Research on intelligent decision support systems for banking began more than 40 years ago, with the first dedicated personal selling system designed in 1984. In the 1990s, intelligent decision models were used to mine data, improving core banking operations. However, these developments have been slow even in developed markets. In recent years, research has focused on decision-making tasks, such as increasing sales and digital marketing. Artificial intelligence has improved the efficiency of banking operations. (Arjun, Abhisek, & Suprabha, 2021)

II.2.1 Uses of Artificial Intelligence in the Financial Industry

AI is a rapidly evolving and complex field, and its use may increase risks for existing organizations or introduce new risks. The financial services industry is also highly regulated and includes a wide range of business models and products, requiring companies to apply an appropriate level of caution in managing their business. (Tom, et al., 2021)

Bank risks can be divided into the following:

A. Operational risks

One area of operational risk where AI can have a significant impact is in helping financial institutions combat fraud, particularly money laundering and terrorist financing. AI can analyze data more quickly and accurately than humans, helping to detect suspicious patterns and behavior. The use of AI has already led to a significant reduction in the volume of suspicious transactions. (Jenny & Natalia, 2021)

B. Liquidity risk

Liquidity risk is treated separately from other risks and takes two forms: asset liquidity risk and funding liquidity risk. Financial institutions are exposed to asset liquidity risk when they are unable to trade assets in the market quickly enough over a period of time without affecting the market price. Funding liquidity risk usually refers to their inability to meet cash flow obligations and is also called cash flow risk. (Martin, Suneel, & Koilakuntla, 2019)

Cash flow forecasting is included in this function. Machine learning can be used to address liquidity risks, such as cash flow forecasting, estimating liquidity risks and their likelihood. Machine learning can also distinguish the most important liquidity risk factors and activate automatic response protocols to help solve the problem.

II.2.2 Evaluation of the customer's creditworthiness

It is a set of models that support the financial decision-making process related to granting credit to a group of individuals by lenders. In the fifties of the last century, the concepts and techniques of credit assessment developed rapidly, supported by the development of expertise and technology, in order to keep pace with the increasing customer demand, especially after the emergence of the credit card (Minh-Duc, Linh, & Trang, 2020). The lender who identifies customers who

pay higher than normal credit risk premiums can obtain a profitable share in the market by granting loans to these customers at low prices. In addition, he can reduce losses by charging them more or rejecting their loan application. (D. Wall, 2018)

Credit scoring can hurt a bank's relationship with its customer, but increasing competition from fintech companies and the success of AI use in other areas have prompted banks to explore it.

Traditional credit assessment relies on historical data, but it may be insufficient. Therefore, banks and fintech companies are turning to artificial intelligence to improve decision accuracy. Artificial intelligence has proven effective in improving credit decisions, identifying threats, and addressing financing gaps in emerging markets. Many data mining techniques have also been successfully used in credit assessment, such as decision tree, discriminant analysis, dynamic programming, Bayesian methods, and Markov chain. (Sang & Hung, 2020)

Non-alternative data is data collected for official reporting purposes. It is reliable and understandable, but may be outdated or inaccurate. Alternative data is data collected for other purposes. It is reliable, current, and rare, and can provide new information about economic structure. Examples of alternative data include geographic location, credit card transactions, and website visits. Non-alternative data is data collected for official reporting purposes. It is reliable and understandable, but may be outdated or inaccurate. Alternative data is data collected for other purposes. It is reliable, current, and rare, and can provide new information about economic structure. Examples of alternative data include geographic location, credit card transactions, and website visits. (Tuan, Tan, & Son, 2021)

II.2.3 Evaluation of the customer's creditworthiness

Chatbots are a new alternative to human customer service representatives in the retail sector. They are expected to become extremely popular in the coming years, supporting 95% of online customer interactions by 2025. Intelligent chatbots can answer most customer questions, and they are always available. They can also provide additional assistance, such as helping you select products or pay. (Terrence, Ting, Debbie, & Ko, 2021)

The market for automated advice bots has been growing rapidly, generating revenues of over \$250 million in 2017. These bots are trained and tested on a variety of banking data, and feature intelligent analysis and emotional intelligence. They are also user-centric, with key characteristics of automated advice users identified for the first time. (hicham & hanane, 2022)

III. Constructing an Artificial Neural Network Model, an Applied Study:

III.1 Description of the characteristics of the study variables:

III.1.1 Study community and sample:

The study community is made up of small and medium-sized enterprises that were registered in the National Center for Commercial Registers (C R N C)

database between 2017 and 2023 and were active in a variety of economic sectors, including trade, services, industry, public works, and agriculture. The study sample was chosen based on how similar the asset sizes were throughout the participating institutions and how long the study was conducted, rather than using the random sample approach.

III.1.2 Study variables:

In our study, we relied on a qualitative dependent variable and 15 independent quantitative variables that can be defined as follows:

First: The dependent variable

The dependent variable expresses the state of the economic institution, where it takes the value 0 in the case of a troubled institution and the value 1 in the opposite case.

Second: Independent variables

This study relied on 15 financial ratios most commonly used in the forecasting process, which we extracted from the financial statements of the small and medium enterprises in the study sample. The following table shows how to calculate them:

Table No. (01): Financial factors in measuring credit risk.	
variable	Mathematical formula
R1	Current ratio = Current assets / Current liabilities.
R2	Quick ratio = Liquid assets / Current liabilities.
R3	Cash ratio = Cash + Cash equivalents / Current liabilities.
R4	Return on Equity = Net Income / Shareholders' Equity.
R5	Return on Assets = Net Income / Average Total Assets.
R6	Return on Sales = Net Income / Total Sales.
R7	Accounts Payable Turnover Ratio = Supplier Purchases / Average Fixed Assets.
R8	Inventory turnover ratio = Cost of goods sold / Average inventory.
R9	Accounts Receivable Turnover Ratio = Net Credit Sales / Average Accounts Receivable.
R10	Fixed Asset Turnover Ratio = Net Sales / Average Fixed Assets.
R11	Current assets financing ratio = Working capital / Total current assets.
R12	Debt ratio = Total debt / Total assets.
R13	Permanent Funding Ratio = Permanent Funds / Fixed Values.
R14	Financial independence ratio = equity / permanent funds.
R15	Interest Coverage Ratio = Net Profit (Before Interest and Tax) / Debt Service.

Source: Prepared by the researchers based on study data.

In order to verify that the study is objective, some statistical tests were used on the independent variables, where we calculated the arithmetic means and standard deviations using SPSS version 24.

Table No. (02): Arithmetic means and standard deviations of financial variables.

Ratios	Healthy institutions		Distressed institutions		Total	
	Arithmetic mean	standard deviation	Arithmetic mean	standard deviation	Arithmetic mean	standard deviation
R1	1,1890	0,2720	0,7610	0,2545	0,9750	0,2632
R2	1,0822	0,4465	0,5448	0,4337	0,8135	0,4401
R3	1,8165	0,4135	0,2352	0,3614	1.0258	0,3874
R4	1.2326	0,0801	0,0140	0,1475	0.6236	0,1138
R5	1.2983	0,1758	0,0147	0,2417	0,6565	0,2087
R6	0.3934	0,1641	0,1271	0,2189	0,2602	0,1915
R7	5,5192	2,8481	0,4524	2,0567	2.9858	2.4524
R8	7.5772	4,5336	3,7436	3,8743	5.6604	4.2039
R9	4.0199	2,1553	0.8218	1,8343	3.0876	1.9948
R10	9.4757	4,6489	2,8036	2,8272	6.1396	3.7380
R11	1,6487	0,3672	0,7132	0,2485	1.1809	0,3078
R12	1.6827	0,3612	0,8165	0,2256	0,2496	0.2934
R13	0.4513	0,5228	0,2868	0,4372	0,3690	0,4800
R14	2.0236	0,0183	1.0625	0,1851	0,5430	0.1017
R15	0.7255	0,1585	0,3885	0,1217	0,5570	0.1401

Source: It was prepared by the researchers based on the outputs of SPSS V24.

Table No. (02) shows the outputs of the arithmetic mean and standard deviation for all independent variables, which include all SMEs (healthy and distressed). The highest value of the arithmetic mean for healthy SMEs was R10= 9.4757 (Fixed-assets-turnover-rate), and this ratio is of good significance as it measures the efficiency of using fixed assets in the company's operational processes, which is important for understanding how the company benefits from its fixed-assets. While the highest value of the arithmetic mean for distressed SMEs was R=83.7436 (Inventory-turnover-rate), which helps in understanding how the company manages its inventory and the efficiency of its use.

On the other hand, the weakest mean value for distressed firms was (return-on-sales-rate) R6 =0.3934, while the weakest mean value for healthy SMEs was (return-on-equity-rate) R4 =0.0140.

Table No. (03): Results of F and t values for financial variables.

Ratios	F value	T value	Significance level	Degrees of freedom
R1	0,1730	1.4952	0.000	58
R2	0,2435	2.8288	0.019	58
R3	0,1165	0.8571	0.010	58
R4	0,0891	2.395	0.03	58
R5	0,1708	2.132	0.041	58

R6	0,1641	1.7621	0.000	58
R7	2,9461	3.6813	0.000	58
R8	4,7556	5.9425	0.059	58
R9	2,3644	2.9545	0.073	58
R10	4,5978	5.7453	0.000	58
R11	0,3902	0.3763	0.068	58
R12	0,3012	0.2905	0.000	58
R13	0,5348	0.5158	0.533	58
R14	0,0203	0.0195	0.000	58
R15	0,1645	0.1586	0.000	58

Source: It was prepared by the researchers based on the outputs of SPSS V24.

Table No. (03) shows, by examining the F values, the existence of statistically significant differences with regard to the financial variables represented by (accounts payable turnover rate, inventory turnover rate, accounts receivable turnover rate, fixed assets turnover rate), because the significance values exceeded 0.05. As for the financial variables of both healthy and distressed institutions that remain, it can be assumed that their standard deviations are equal.

Regarding examining the results of the t-value, it appears to us from the same table that most of the calculated t-values specific to the financial study variables exceeded the tabular t-value at (58-0.05) estimated at 2.01. Accordingly, it can be concluded that there are statistically significant differences between the arithmetic means of the financial study variables for both healthy and distressed institutions.

III.2 Steps to build an artificial neural network model:

Through this stage, we seek to build an artificial neural network model to predict the financial distress of the study sample, one year before the distress occurs. The MATLAB 2012 program will be used. To achieve this, the following steps must be taken:

III.2.1 Selecting model variables:

The first steps in building an artificial neural network model, which consists of the dependent variable and the independent variables, are:

- The dependent variable is a categorical variable that takes either the value 0 if the institution is in distress or the value 1 if the institution is healthy.
- The independent variables are 15 financial ratios derived from the financial statements of 60 small and medium enterprises in the study sample.

III.2.2 Processing the proposed model data:

The data used to build the artificial neural network model will be processed by modifying the values of the calculated financial ratios and replacing them with the values of the modified financial ratios as follows:

$$Xi = (Xcal - X)/\sigma$$

Xi : Adjusted ratio values;

$Xcal$: Calculated ratio values;

$\bar{X}$: Arithmetic mean ; σ : Standard deviation.

III.2.3 Data partitioning:

The data division stage is essential in building the artificial neural network model, as it is done randomly through the MATLAB program, which distributes it into three basic groups according to the following:

- Training group: includes 70% of the total sample, equivalent to 42 institutions out of the total number of institutions in the study sample.
- Validation group: includes 15% of the total sample, equivalent to 9 institutions out of the total number of institutions in the study sample.
- Test group: includes 15% of the total sample, equivalent to 9 institutions out of the total number of institutions in the study sample.

III.3 Determine the architecture and engineering of the neural network model:

III.3.1 Determine the structure of the proposed neural network model:

At this stage, the type of network, inputs, outputs, number of layers, and number of existing nodes are determined. The network used in the proposed model is the backpropagation network with a supervisor (teacher); it learns on the inputs and outputs of the problem and there is a correction of the outputs after we compare them with the required outputs, after we correct the weights according to the following rule:

$$\Delta W(i, j) = n\delta(j)X(i) - W(i, j)$$

$\Delta W(i, j)$: Adjusted weight value or new weight;

n : Learning ratio value in the base;

$\delta(j)$: The error rate between the

obtained value and the actual value;

$X(i)$: Inputs;

$W(i, j)$: Current weight value of input.

Furthermore, the network structure used depends on:

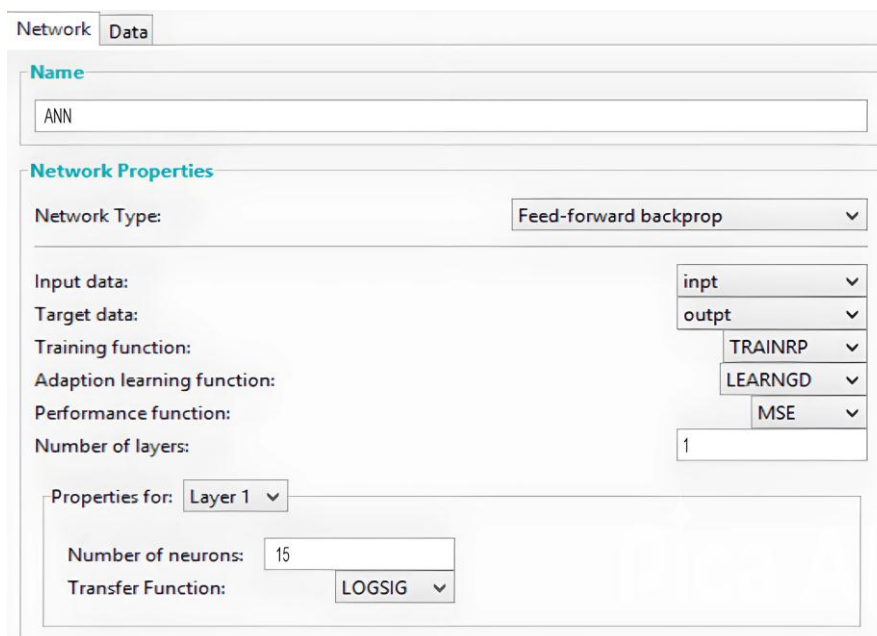
- **Input layer:** It includes 15 elements known as input neurons, which are represented by the financial ratios shown in Table (1).
- **Hidden Layer:** The number of hidden layers and their neurons was determined automatically after several attempts. We started training with one hidden layer and ten neurons, but this attempt did not achieve the desired goal. After that, the features were modified repeatedly with an increase in the number of neurons, and each time we calculated the correlation coefficient R and the mean square error ratio, which should be weak. After that, we relied on two hidden layers and made adjustments to some of the features, but the results we obtained using one hidden layer achieved a weak error ratio compared to the results obtained previously.
- **Output layer:** It consists of one node, so it takes the value 1 in the case of a healthy organization and the value 0 in the case of a troubled organization.

III.3.2 Create a network in MATLAB:

After entering the MATLAB program and suggesting a name for the neural network for the proposed model ANN, the properties of this network are set according to:

- Select the type of network, which is a multi-layer back-propagation network with feedback;
- Specify input values;
- Determine output values;
- Selecting the training function of type Rprop;
- Select the general delta learning rule, with (teacher);
- Selection of performance function mse sum of squares error;
- Identify a single hidden layer consisting of 15 neurons according to the logistic transfer function LOGSIG.

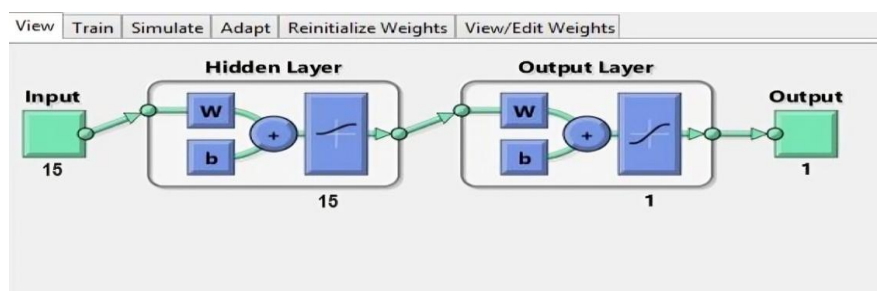
Fig. (01): Create an artificial neural network



Source: Prepared by the researcher based on MATLAB 2012.

After we have installed all the above-mentioned features, we see the architecture of the new neural network as follows:

Fig. (02): Artificial neural network architecture

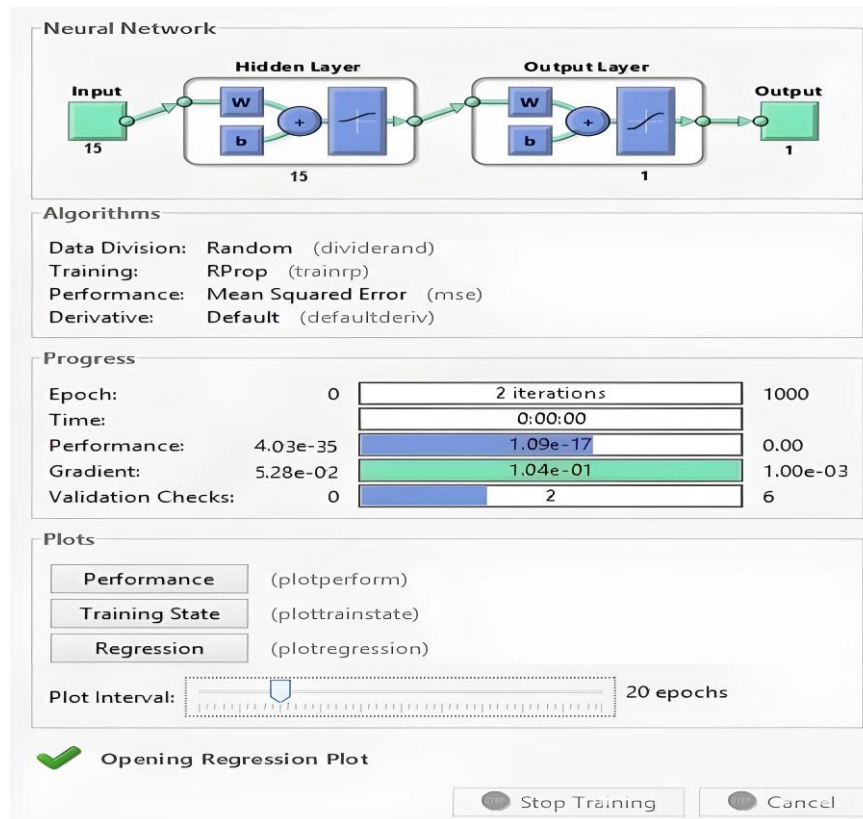


Source: Prepared by the researcher based on MATLAB 2012.

III.3.3 Artificial neural network training:

During the training process of the model to predict financial distress, we compare the values of (desired outputs with actual values), calculate the mean squared error to measure the difference between these values, and measure the correlation coefficient between the inputs and outputs on different samples, such as the training sample, validation sample, and test sample. If the training results are not satisfactory, it may be necessary to retrain with modifications to the weights and procedures used. After several attempts, improved results can be obtained that contribute to improving the model's ability to predict financial distress.

Fig. (03): Artificial neural network training results



Source: Prepared by the researcher based on MATLAB 2012.

Figure (03) shows that the network can perform (1000 training attempts) at most, but it stopped during (attempt 2) at (second 0), as it did not reach the maximum number of possible cases of validation failure, which is estimated at (6 cases).

III.4 Analysis and discussion of results:

III.4.1 Artificial Neural Network Model Performance:

The most important characteristics of the proposed model can be explained through the following table:

Table No. (04): Properties adopted in artificial neural network engineering.

Type of network used	Multilayer back propagation
Learning Algorithm	Feedback (Rprop)
Number of Neurons in Input Layer	15
Number of Hidden Layers	1
Number of Neurons in Hidden Layer	15
Number of Neurons in Output Layer	2
Learning Rate	0.01
Maximum Training Trials	0100
Initial Weight Change	0.08
Increase Weight Change	1.3
Decrease Weight Change	0.5
Maximum Weight Change	50
Performance Function	Mse Sum of Squares Error

Source: Prepared by the researcher based on MATLAB 2012.

The most important characteristics of the network were determined through several attempts, where the maximum limit for training attempts was (1000 attempts), in addition to taking the maximum limit for validation failures at (6 cases), and the initial weight change was estimated at (0.08) and then the weight was reduced by (0.5), and the following data shows us the most important results obtained according to the MATLAB program:

Table No. (05): Best performance for validating artificial neural network.

Try order	Attempt 02
Mean squared error value MSE	4.0144e⁻¹⁰

Source: Prepared by the researcher based on MATLAB 2012.

During the second experiment, the best performance was recorded to verify the validity of the proposed model, as the value of the sum of squared errors (MSE) reached about **4.0144e⁻¹⁰**, which is considered a very small value that highlights the ability and quality of the network to predict the financial distress of the small and medium enterprises under study.

Table No. (06): Best performance for validating artificial neural network.

Stage type	Correlation coefficient value
Training Phase	1
Verification Phase	1
Testing Phase	1

Source: Prepared by the researcher based on MATLAB 2012.

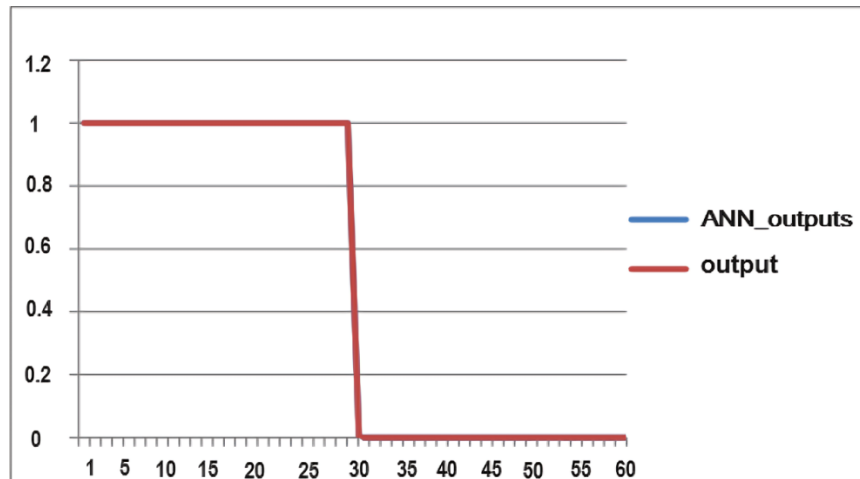
From the results recorded in the table above, it becomes clear to us that the value of the correlation coefficients (equals 1), and it pertains to each of: the training sample, the validation sample, and the test sample, which explains that the relationship between the required outputs and the actual outputs is a strong relationship.

Therefore, it can be said that:

- The proposed model was able to classify the training sample, test sample and validation sample with 100% accuracy.

This expresses the effectiveness of the proposed model and its accuracy in predicting the status of the small and medium enterprises in the study sample, whether they are healthy or struggling. The following figure shows the close convergence between the actual and required output values.

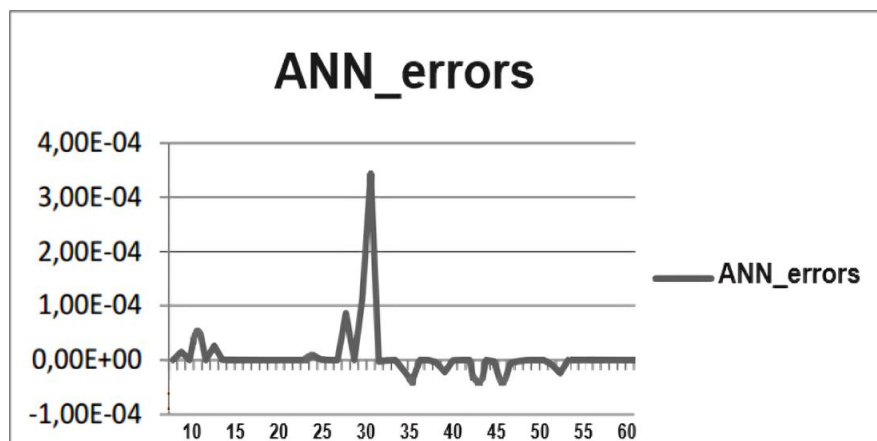
Fig. (04): Comparison between desired output values and actual output values.



Source: Excel outputs prepared by researchers.

The figure above shows the similarity of the original state of all the institutions under study with the state of the predicted institutions, and this is confirmed by the similarity between the two curves shown in the figure above. On the other hand, this is evident from the value of the errors recorded between them, which were shown in the following figure:

Fig. (05): Errors recorded between desired output values and actual output values.



Source: Excel outputs prepared by researchers.

The figure above shows the accuracy of the proposed model, through the weak errors between the actual and required values, which supports the accuracy

and quality of the proposed model for predicting the financial distress of the economic institutions under study.

III.4.2 Classification quality of artificial neural network model:

In order to examine the quality of the classification, we entered the data of the institutions under study into the proposed model and obtained the following results:

Table No. (07): Evaluation of artificial neural network model.

Sample	Valid observations %	False observations %	Total %
Training sample	100%	0%	100%
Validation sample	100%	0%	100%
Test sample	100%	0%	100%

Source: Prepared by researchers based on the results of the proposed ANN.

The table above shows the quality of the proposed model's classification of the status of all the economic institutions under study, whether they were healthy and distressed, during the three stages: training, verification and testing. The classification rate for each of the previous stages achieved 100%.

IV. Conclusion

Artificial intelligence is a promising technology that has the potential to revolutionize the financial industry. By using AI methods such as artificial neural networks, financial institutions can improve their performance in many areas, including:

- Credit risk assessment: Artificial neural networks can help financial institutions assess credit risk more accurately, reducing the risk of losses;
- Liquidity management: Artificial neural networks can help financial institutions manage liquidity more effectively, reducing financial risk;
- Anti-money laundering: Artificial neural networks can help financial institutions combat money laundering more effectively, reducing legal risk.

There are some challenges that need to be overcome before AI technologies become common in the financial industry. For example, financial institutions need to develop the technical capabilities necessary to implement these technologies, and they also need to collect the data needed to train AI models.

Based on the above, the following recommendations can be made to financial institutions in Algeria:

- Develop the technical capabilities needed to apply AI technologies;

- Collect the data needed to train AI models;
- Start applying AI technologies in areas where you have a competitive advantage, such as credit risk assessment.

By following these recommendations, financial institutions in Algeria can leverage the potential of AI to improve their performance and enhance their competitiveness.

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