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Crunching Numbers, Making Decisions: Artificial Intelligence and Statistics for Financial Distress Forecasting in Algeria and Saudi Arabia

Analisando números, tomando decisões: inteligência artificial e estatísticas para previsão de dificuldades financeiras na Argélia e na Arábia Saudita

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ABSTRACT
Predicting financial distress has been a significant concern for both researchers and practitioners for long period. This topic has garnered substantial interest due to the potential benefits of using predictive models to anticipate financial troubles and help companies steer clear of financial risks that could lead to bankruptcy and liquidation. The primary aim of this research is to forecast financial distress, comparing the effectiveness of Artificial Neural Network (ANN) with Logistic Regression (LR). This evaluation is based on data from 12 Algerian companies and 12 Saudi companies during the period from 2015 to 2019. The study's findings indicate that the LR model outperformed the Wide Neural Network (WNN) model in accurately predicting financial distress, achieving optimal classification accuracy for both Algerian and Saudi companies. Consequently, the LR model emerges as the preferred choice for forecasting financial distress in both countries.
Key words: financial distress, forecasting, artificial neural network, logistic regression

RESUMO
A previsão de dificuldades financeiras tem sido uma preocupação significativa tanto para pesquisadores quanto para profissionais há muito tempo. Este tema tem despertado um interesse substancial devido aos benefícios potenciais do uso de modelos preditivos para antecipar problemas financeiros e ajudar as empresas a evitar riscos financeiros que poderiam levar à falência e à liquidação. O objetivo principal desta pesquisa é prever dificuldades financeiras, comparando a eficácia da Rede Neural Artificial (RNA) com a Regressão Logística (RL). Esta avaliação baseia-se em dados de 12 empresas argelinas e 12 empresas sauditas durante o período de 2015 a 2019. As conclusões do estudo indicam que o modelo RL superou o modelo de Rede Neural Ampla (RNA) na previsão com precisão de dificuldades financeiras, alcançando uma precisão de classificação ideal para empresas argelinas e sauditas. Consequentemente, o modelo RL surge como a escolha preferida para prever dificuldades financeiras em ambos os países.
Palavras chaves: *dificuldades financeiras, previsão, rede neural artificial, regressão logística*

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1. INTRODUCTION

The importance of financial distress prediction cannot be overstated, particularly in today's interconnected global economy. Companies across diverse sectors now recognize its crucial role in mitigating potential financial risks that could otherwise spell the demise of their operations. This heightened interest in financial distress prediction is particularly evident in large businesses, where they have witnessed tangible benefits from leveraging advanced forecasting models. By doing so, these enterprises have managed substantial additional expenses and losses that could have thrown their financial equilibrium into disarray. It's important to note that the repercussions of such financial imbalances extend beyond the distressed companies themselves. Given the interdependence of businesses within a state's economy, the contagion effect rapidly spreads, affecting other enterprises with shared interests. Inevitably, this can ultimately led to the state economy damage. This phenomenon shows no signs of abating and continues to permeate financial systems, potentially leading to bankruptcies and a mounting burden on state treasuries as they strive to support distressed or bankrupt companies.

The field of predicting financial distress is marked by a dynamic evolution of techniques over time. Initially, the focus was primarily on traditional financial analysis methods when interest in this topic first emerged. However, the present era witnesses a significant shift towards modern methodologies that harness the synergy of statistical techniques and artificial intelligence methods. Numerous prior studies have consistently validated the remarkable classification and prediction capabilities offered by these contemporary approaches. This recognition has spurred financial researchers to harness the power of these techniques, which have proven their mettle across various scientific domains, and tailor them for application in the financial sector. This strategic move has undoubtedly been well-founded, given the impressive and tangible results achieved through the integration of these advanced techniques into financial analysis and prediction processes.

The increasing prominence of forecasting financial distress underscores its paramount significance within the realms of finance and accounting. This burgeoning importance catapults it to the forefront of the most critical subjects in these domains.

Consequently, the focus of this study is to underline the urgency and importance of embracing proactive measures for predicting financial distress. It serves as a clarion call to all companies that might still be hesitant or complacent in their approach, relying on chance rather than data driven strategies when managing their financial affairs.

In another context, this study aims to build new models with different combinations based on a set of financial ratios that include a significant number of independent variables (Financial Ratios) that affect on the dependent variable (Financial Distress Prediction), carefully chosen in order to achieve the desired objective of this study, which is to search for the optimal models that led to accurately predicting financial distress in both Algerian and Saudi companies.

2. LITERATURE REVIEW

Since the 1930s, researchers have conducted trials evaluating a variety of reasonable approaches in response to the need for forecasts, and the results of those tests have greatly improved our understanding of forecasting (Osho & Idowu, 2018). The company's various stakeholders, including investors, creditors, regulators, and lenders, are interested about the financial distress prediction. Certain stakeholders who own shares of the company in their derivatives portfolio would need the information promptly in order to determine the probability of financial distress (Kapil & Agarwal, 2019).

A Financial Distress Prediction Model's main goal is to predict whether a company will experience financial distress in the future. Bankruptcy, insolvency, and other formal signs of financial distress in a company. The initial and traditional statistical models used in the field of distress prediction are discriminant analysis and the logit model. These traditional linear techniques are simple but unrealistic, and thus cannot be used to create a robust model for making real-time predictions (El-Bannany, Sreedharan, & Ahmed, 2020).

There are two types of corporate failure prediction models: statistical-based models and algorithm-driven models that use Machine Learning (ML) techniques. Statistical methods were used by the pioneers of bankruptcy prediction to distinguish between distressed and non-distressed companies. Nonetheless, and while statistical methods are still used, some authors adopted Machine Learning techniques such as neural networks for predicting company failures in the 1990s.

Machine Learning (ML) is defined as "the science of making computers act without being programmed." This process attempts to detect meaningful patterns between the inputs and build an autonomous model capable of describing these patterns without the need for human intervention (Bonello, Bredart, & Vella, 2018).

The results showed that as the data is used two years in advance, statistical models' ability to predict bankruptcy decreases, with
accuracies of 72.0 percent Altman and 95.5 percent Ohlson. When predictions are made three years in advance, the accuracy rate drops to 86.2 percent (Angel, Gámez, José, & Ruiz, 2016).

The second period starts in the late 1980s, when many authors began conducting research to determine whether non-parametric methods could successfully predict the risk of bankruptcy or financial failure in order to get around the limitations of previous studies. This period witnessed the emergence of non-linear techniques like Artificial Neural Networks, Support Vector Machines, k-Nearest Neighbor, and Nave Bayesian Classifier that frequently outperformed the majority of then-current techniques (Mousavi, Amini, & Raftar, 2012).

On the other hand, machine learning techniques such as logistic regression were used Extreme Learning Machines for prediction, which rely on a single layer Artificial Neural Network evolved with knowledge of financial ratios to discover the most optimal neural network structure. (Sabek & saihi, 2021) used back-propagation Neural Network to predict financial distress, and concluded that this network has a high ability to classify correctly. (Sabek A. , 2023) compared two types of Artificial Neural Networks (ANNs) with Logistic Regression (LR), and concluded that some types of ANNs are better than LR in classification and others are not. (Sabek & Horak, 2023) used Gaussian Process Regression (GPR) to predict financial distress, compared its results with deep learning models, including LR, and concluded that GPR is better than LR and all other models, except for Support Vector Machine, which achieved the same classification accuracy.

2.1. Artificial neural networks

A neural network is a system that is designed to replicate how the brain performs a specific activity or function of interest; the network is often constructed with electronic components or is simulated in software on a digital computer (Hardinata & Warsito, 2018).

Artificial neural networks (ANNs) are simplified models of brain cell interactions. it characterised as "extremely simplified models of the human nervous system, displaying capacities such as learning, generalisation, and abstraction." However, recent technical improvements have made ANN models a viable alternative for many decision problems, and they have the potential to improve the models of many financial activities, such as forecasting financial distress in corporations (Sudarsanam, 2016).

Although the efficiency, robustness, and adaptability of ANN ensembles make them a valuable tool for classification, decision support, financial analysis, and credit scoring, some researchers have shown that ensembles of multiple neural network classifiers are not always superior to a single best neural network classifier (Tang, Ji, Zhu, Gao, Tang, & Todo, 2019).

Numerous works on classification difficulties have effectively employed NN approaches. Aside from bankruptcy, the NN technique has been used to address other concerns such as inefficient management, capital structure, bad economic effects, and volatility (Callejón, Casado, Fernández, & Peláez, 2013).

Neural Networks are particularly well-suited to anticipating the bankruptcy, making them a strategic choice. Similarly, their qualities make them frequently utilised in financial applications because to their superior performance in dealing with non-linear data and self-learning capabilities. In a survey of the topic of bankruptcy prediction is provided, with an emphasis on NN models. More recently, a wide range of other intelligent techniques such as fuzzy set theory, decision trees, rough sets, case-based reasoning, and support vector machines have received extensive treatment (Ribeiro, Silva, Vieira, & Gaspar-Cunha, 2010).

2.2. Logistic regression

Logistic Regression is a member of the generalised linear models family, GLMs offer a consistent framework for modelling response from any exponential family distribution, such as Gaussian, Binomial, or Poisson. In GLM framework, the model is quantified from a binary target variable, Y which represents the status of a loan over the outcome window where bad (defaulted) loan is labelled as 0 and good loan is labelled as 1 and related to the linear combination of predictor $\beta 1 * X1 + \ldots + \beta m * Xm$ (Bayraci & Susuz, 2019).

Ohlson published a study in 1980 that used "Logit" or Multiple Logistic Regressions to build a bankruptcy prediction model. Ohlson believed that his study had a significant benefit in that it allowed one to determine whether the company filed for bankruptcy before or after the financials were released. According to Ohlson, earlier studies did not specifically address the timing issue (Ohlson, 1980). Although these intelligence techniques have been widely used in recent decades, pioneer statistical techniques such as univariate and multivariate discriminant analysis are still worth mentioning in the modelling of corporate bankruptcy prediction. Linear classification algorithms such as linear discriminant analysis and logistic regression are very popular. All of these methods try to discover the best linear combination of explanatory input variables (Ribeiro, Silva, Vieira, & Gaspar-Cunha, 2010).

3. METHODS

With the aim of comparing Artificial Intelligence with Statistics, we aspire to create a LR model and an ANN model in order to predict financial distress in both Algerian and Saudi companies, comparing the classification accuracy of the two methods to identify the optimal model. We chose the Wide Neural Network (WNN) in particular because, to the best of our knowledge, this network is not commonly used. Through this, we aspire to answer the following question: Are all types of ANN better than LR, even the uncommon networks?

Both Algerian and Saudi firms were selected as the focal point of this study because the application of Artificial Intelligence methods to forecast financial distress is a relatively novel concept in these countries. To the best of our knowledge, this subject has received only limited attention in both Algeria and Saudi Arabia, and the available research has been somewhat superficial. While we could have opted for a more extensive dataset from the Kaggle database related to another countries, we deliberately chose to emphasize the Algerian and Saudi contexts, even though our sample size is relatively small.

We relied on several metrics to measure error, Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE). For the LR model, we evaluated it statistically using certain metrics provided by Spss, -2 Log Liklihood, Cox & Snell R Square, Nagelkerke R Square.

3.1. Sample

The scope of our analysis could potentially encompass a broader selection of companies hailing from various countries. Nonetheless, we chose to work with a limited sample due to the challenges involved in acquiring financial statements from Algerian companies. To mitigate this limitation, we used data from 12 Saudi companies listed on the Saudi Stock Exchange in addition to the data from 12 Algerian companies and extended the study duration to encompass five years from 2015 to 2019, thereby aiming to augment the quantity of financial cases under examination. Therefore, we used a data of (4) companies listed on the Algerian Stock Exchange. (7) companies, their data were obtained by resorting to a competent official Algerian authority after undertaking not to mention the names of these companies. Finally, Sycma's data was obtained after submitting an official request to its financial department.

The study period extends from 2015 to 2019, where the final sample consists of 12 Algerian companies and 12 Saudi companies. The financial data of the 24 companies is divided into a training sample which concerns data from 2015 to2017. The test sample that concerns data from 2018 2019 to evaluat the efficiency of WNN. As for the LR, and according to Spss, it does not require the training process. Therefore, we will test it directly.

3.2. Data

Table 1 displays the real financial status of the companies analyzed during the period from 2015 to 2019. In this table, the financial status is categorized as "0" for distress and "1" for non-distress. This categorization enables both the WNN model and LR model to grasp and assess the distress status based on the previously selected financial ratios with high accuracy. Consequently, these models can predict the actual financial status with minimal error, a claim that we will validate through the testing of both models on the test sample. It is important to note that the assessment of distress, labeled as "0," or non-distress, labeled as "1," was determined through a self-evaluation process utilizing the cues provided by the financial indicators, as detailed in Table 1.

Table 1 - Description of the actual financial status

Company	2015	2016	2017	2018	2019
			Algerian Companies		
Company A	1	1	1	1	1
Company B	1	1	1	1	1
Company C	1	1	1	1	1
Company D	1	1	1	1	1
Company E	1	1	1	1	1
Company F	1	1	1	1	1
Company G	0	0	0	0	0
Aurassi	1	1	1	0	0
Biopharm	1	1	1	1	1
Ruiba	1	1	0	0	0
Sycma	0	1	0	0	0
Saidal	1	1	1	1	1
			Saudi Companies		
Sabic	1	1	1	1	1
Spimaco	1	1	1	1	0
Budget	1	1	1	1	1
Saudi Ceramics	1	1	0	0	1
Saudi Airlines Catering	1	1	1	1	1
Aldress	1	0	0	0	0
Mesk	1	0	0	1	1
Batic	1	1	1	1	1
Jazadco	1	1	1	0	0
Halawani	1	1	1	1	1
Sadr	1	1	1	1	0
Chemanol	0	0	0	1	0

Source: prepared by the authors.

3.3. Variables

Many prior research endeavors, which predominantly utilized financial ratios to construct prediction models based on variables related to capital, assets, management, earnings, liquidity, and sensitivity. We chose to employ financial indicators that have already demonstrated their strong predictive capacity for financial distress, as evidenced by earlier research, as indicated in Table 2.

Table 2 - Finanacial variables

Current Assets/Current Liabilities	Net income/Fixed assets
Profits before taxes/Current liabilities	Net income/Sales
Current Liabilities/Assets	Current Liabilities/Current Assets
Net income/Assets	Net working capital/Assets
Sales/Assets	Debts/Assets
Fixed assets/Assets	Sales/Net working capital
Current Assets/Assets	Net income/Net working capital
Equity/Assets	Sales/Invested Capital
Non-current liabilities/Current assets	Net working capital/Sales
Net income/Equity	Cash/Assets
Sales/Equity	/

Source: prepared by the authors.

This group of financial ratios was chosen according to the formulas of traditional statistical models, including, but not limited to, (Beaver, 1966), (Altman, 1968), (Ohlson, 1980), ... etc. We gathered an extensive array of ratios and subsequently curated a selection of the most commonly employed ones. These chosen ratios were incorporated into our analysis without conducting additional statistical assessments to validate their predictive capability for financial distress. This omission was justified by the fact that these ratios had previously undergone rigorous statistical testing as part of the development of conventional models. Their inclusion in those models was a result of achieving the necessary statistical significance.

4. RESULTS

To train the LR model, we used Spss V.23 Software, and the financial informations of the study sample from 2018 to 2019 were included, as the data from 2015 to 2017 were excluded because according to Spss, the LR model does not require a training process before testing, in contrast to the WNN model.

To train the WNN model, we used Matlab Software, and the financial data from 2015 to 2017 were allocated to training the ANN model, while the data from 2018 to 2019 were allocated to test the ability of the two models to predict financial distress for one year and two years before the financial distress occurrence. Based on the Stepwise Conditional Method, LR model was created, and the following results were reached, as shown in Table 3.

Table 3 - Testing results of the Logistic Regression

	Algerian Companies				**Saudi Companies**			
	2018		**2019**		**2018**		**2019**	
	Actual	**Predicted**	**Actual**	**Predicted**	**Actual**	**Predicted**	**Actual**	**Predicted**
Company A	1	1	1	1	1	1	1	1
Company B	1	1	1	1	1	1	0	0
Company C	1	1	1	1	1	1	1	1
Company D	1	1	1	1	0	0	1	0,99971
Company E	1	1	1	1	1	1	1	0,99412
Company F	1	1	1	1	0	0	0	0
Company G	0	0	0	0	1	0,9065	1	0,52412
Aurassi	0	0	0	0	1	0,99999	1	0,99996
Biopharm	1	1	1	1	0	0	0	0
Ruiba	0	0	0	0	1	0,8935	1	0,99919
Sycma	0	0	0	0	1	0,99996	0	0,68293
Saidal	1	1	1	1	1	1	0	0

Source: prepared by the authors.

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We note from Table 3 that the LR model was able to achieve very appropriate results without a classification error regarding the Algerian companies, as for Saudi companies, it was less accurate.

In order to further clarify the results shown in the Table 3, we will rely on Table 4 to evaluate the LR model classification accuracy, as we have previously indicated that the process of creating this model was done by using Stepwise Conditional Method, which leads to improve the model classification ability by several steps. At the end of the last step, the model reaches the optimal results with the highest classification accuracy, which can be clarified in the Table 4.

Table 4 - Classification accuracy of the Logistic Regression

Observed		Algerian Companies		
		Predicted Y		Percentage Correct
		0	1	
Step 1 / Actual Y	0	5	3	62.50
	1	1	15	93.80
Accuracy				**83.30**
Step 2 / Actual Y	0	8	0	100
	1	0	16	100
Accuracy				**100**
Observed		**Saudi Companies**		
		Predicted Y		**Percentage Correct**
		0	1	
Step 1 / Actual Y	0	5	3	62.50
	1	1	15	93.80
Accuracy				
Step 2 / Actual Y	0	7	1	87.50
	1	0	16	100
Accuracy				**95.84**

Source: prepared by the authors.

Through Table 4, the vision becomes clearer, where we can note that the model went through two phases in order to reach the appropriate combination of weights that lead to achieve the required objective with a very high classification accuracy. In the first step regarding Algerian companies, LR was able to achieve a full classification accuracy of 83.30% by correctly categorizing (5) cases of financial distress, but it erred in categorizing (3) cases of distress. On the other hand, it was able to categorize (15) cases of non-distress and unable to classify one case of non-distress. Almost the same thing applies to his performance for the Saudi sample. Almost the same applies to its performance towards

Saudi companies.

Predominately, the model results are considered very acceptable in the first step, but the use of Stepwise Conditional Method contributed to improving the classification quality continuously until reaching the optimal possible results.

While achieving full classification accuracy with the LR model is undoubtedly a noteworthy accomplishment, it is imperative to consider various related factors. It is possible that this high percentage was attained due to the relatively limited number of financial cases under examination. If the number of cases were to increase, it is probably that classification accuracy would decrease while error rates would rise. The model's classification accuracy for the Saudi sample confirms that full classification accuracy is not a common case, and this accuracy was achieved for the Algerian sample only. Furthermore, as this study also involves testing the WNN model, the classification accuracy it achieves will impact the significance of the LR model's results. If the WNN model achieves lower classification accuracy, it would reinforce the significance of the LR results, despite the small number of financial cases. However, if this is not the case, it raises the question of why the WNN also did not achieve full classification accuracy, or why the LR did not achieve full classification accuracy for the Saudi sample.

Statistically, the significance of the LR model can be evaluated by relying on the statistical measures shown in Table 5.

Table 5 - Significance evaluation of the Logistic Regression

Step	-2 Log Liklihood	Cox & Snell R Square	Nagelkerke R Square
		Algerian Companies	
1	19.211	0.377	0.523
2	0.000	0.720	1.000
		Saudi Companies	
1	18.447	0.396	0.550
2	4.025	0.669	0.929

Source: prepared by the authors.

We note from Table 5 that the -2 Log Liklihood scale was indicating a high value in the first step for the Algerian companies, but its value decreased to zero immediately after moving to the second step. Noting that the lower value of this scale is, the better for the model, and since the value in the second step reached zero, this is considered a very positive and indicates the variance of the model and the development of its performance. The significant decrease in the -2 Log Liklihood value from the step 1 to the step 2 indicates the effectiveness of the Stepwise Conditional method used in creating LR. It should be noted that Spss provides several other methods for creating LR, and after experimenting and retrying, we obtained the best results using this method.

In contrast to the other two scales, Cox & Snell R Square and Nagelkerke R Squar, the closer the value of these scales is to the correct one, the more this proves the strength of the model and its statistical significance. As we note from the above table that the values of these scales were average in the first step, but they rose very appropriately in the second step, which proves that the model can correctly translate the effect of financial ratios on the dependent variable. Almost the same applies to statistical tests for Saudi companies, but with less significance.

Predominately, the results of testing the model statistically indicate the strength of the model, its high significance, and its ability to distinguish between both distressed and non-distressed companies. The same applies to the accuracy of its classification results as shown in Table 4.

By utilizing Matlab, the Wide Neural Network model was constructed by establishing the fundamental structure of the model in alignment with the study's objective, ultimately yielding precise results when compared to the actual financial status.

After completing the design phase of the WNN model, the financial data for the period from 2015 to 2017 was included in order to train the model to understand the study objective, which is to predict financial distress one year and two years before it occurs. In the following, the results achieved after training the model can be clarified, as shown in Table 6.

Table 6 - Training results of the Wide Neural Network

Accuracy	Prediction Speed	Training Time
	Algerian Companies	
91.7	120 obs/sec	67.40 sec
	Saudi Companies	
86.1	94 obs/sec	26.85 sec

Source: prepared by the authors.

We note from the Table 6 that the WNN model's training process achieved a suitable accuracy for both Algerian and Saudi companies, but with less accuracy for Saudi Arabia. Therefore, the model successfully completed the training phase and become able to create the appropriate weights that correspond to the required study objective. Thus, the ability of this model to distinguish the financial distress cases can now be tested.

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As a final phase, WNN model can be tested based on the financial data for the period from 2018 to 2019. It should be noted that these data was completely excluded from the training phase, which ensures the testing results credibility. In the following, the results obtained in the testing phase can be clarified, as shown in Table 7.

Table 7 - Testing results of the Wide Neural Network

	Algerian Companies				**Saudi Companies**			
	2018		**2019**		**2018**	**2019**	**2018**	**2019**
	Actual	**Predicted**	**Actual**	**Predicted**	**Actual**	**Predicted**	**Actual**	**Predicted**
Company A	1	1	1	1	1	1	1	1
Company B	1	1	1	1	1	1	0	0
Company C	1	1	1	1	1	1	1	1
Company D	1	1	1	1	0	0	1	1
Company E	1	1	1	1	1	1	1	1
Company F	1	1	1	1	0	1	0	0
Company G	0	0	0	0	1	0	1	1
Aurassi	0	0	0	0	1	1	1	1
Biopharm	1	1	1	1	0	1	0	1
Ruiba	0	0	0	1	1	0	1	1
Sycma	0	0	0	0	1	1	0	1
Saidal	1	1	1	1	1	1	0	0

Source: prepared by the authors.

It can be observed from Table 7 that the WNN model was able to achieve generally acceptable results for the Algerian companies, but some of these results do not significantly correspond to the actual financial status. The results were worse for Saudi companies. In order to evaluate the WNN model's classification accuracy more clearly, we will rely on Table 8.

Table 8 - Classification accuracy of Wide Neural Network

Observed		**Algerian Companies**		
		Predicted Y		**Percentage Correct**
		0	1	
Actual Y	0	7	1	87.50
	1	0	16	100
Accuracy				**95.84**
Observed		**Saudi Companies**		
		Predicted Y		**Percentage Correct**
		0	1	
Actual Y	0	4	4	50
	1	2	14	87.50
Accuracy				**75**

Source: prepared by the authors.

Considering we conclude from Table 8 that the WNN model was unable to achieve better classification accuracy, as its accuracy in predicting financial distress was 95.84% for Algerian companies. It was able to correctly identify (7) cases of financial distress, but, it erred in classifying (1) case. On the other hand, it was able to accurately classify (16) cases of non-distress. The results were worse for Saudi companies, moderate classification accuracy, and many errors. In order to identify the optimal model in terms of classification accuracy in predicting financial distress among the previous two models, we will rely mainly on the comparison between the overall classification accuracy. In addition, we will also rely on the comparison between the prediction accuracy measures, as shown in the Table 9.

Table 9 - Classification accuracy comparison

	Accuracy	**Error I**	**Error II**	**Error III**
		Algerian Companies		
LR	100	0	0	0
WNN	95.84	0.0417	0.2041	0.0417
		Saudi Companies		
LR	95.84	0.0569	0.1724	0.0297
WNN	75	0.2500	0.5000	0.2500

Source: prepared by the authors.

It appears from Table 9, which aims to compare the classification accuracy of the two models by comparing the overall classification accuracy and the prediction accuracy measures (Mse, Rmse, Mape) that the LR model has a high classification ability for both Algerian and Saudi companies. However, prediction accuracy measures confirm the same conclusion that indicates the strength of the LR model in predicting financial distress. Figure 1 further demonstrates the disparity between results of WNN and LR's results.

In order to make the comparison between the two models more accurate, although the final result has been decided in the results of Table 9, we decided to compare the accuracy of the two models in predicting financial distress a year and two years before the distress occurrence, which can be clarified in Table 10.

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Figure 1 – Parallel Coords Plot

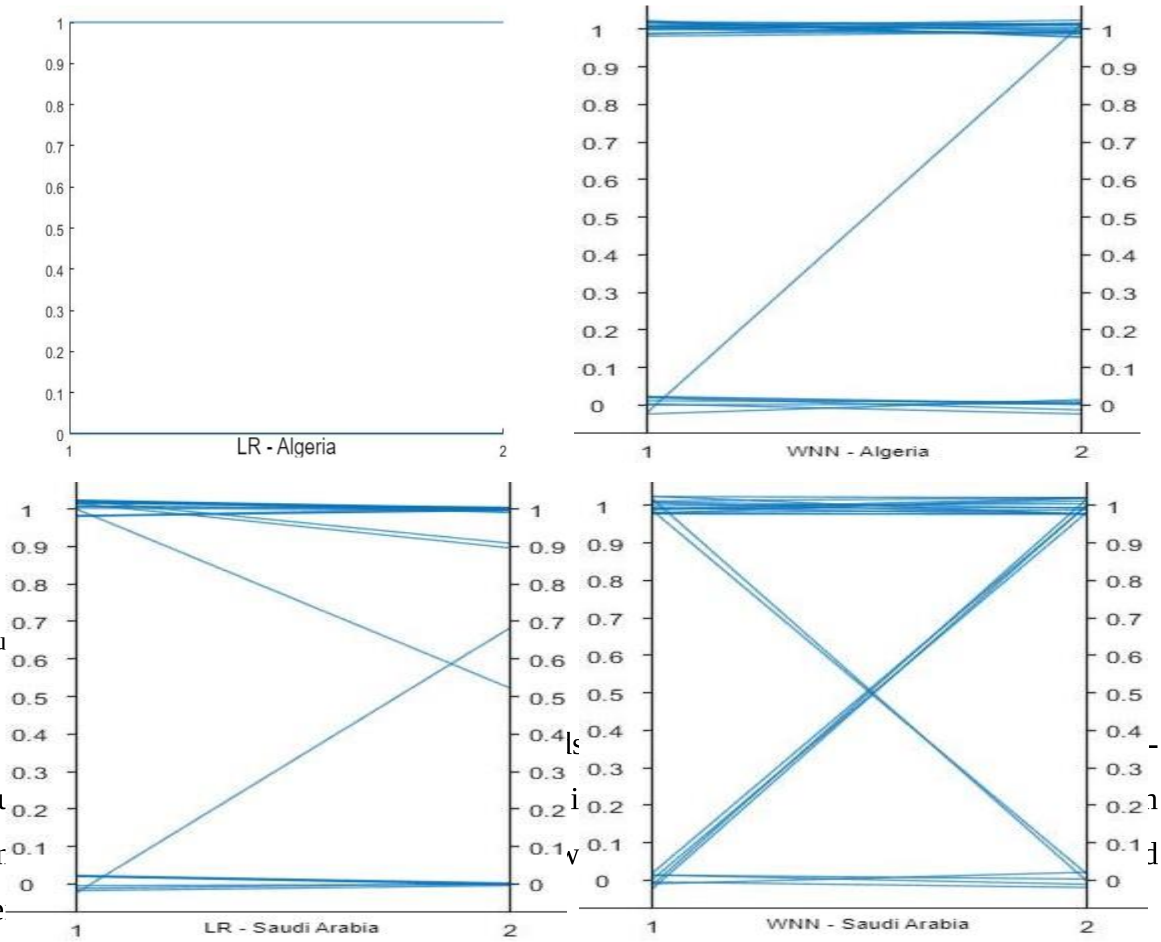

Table 10 - Classification accuracy of N-1 & N-2

	Accuracy	Error I	Error II	Error III
Algerian Companies				
N-1				
	Accuracy	**Error I**	**Error II**	**Error III**
LR	100	0	0	0
WNN	100	0	0	0
N-2				
	Accuracy	**Error I**	**Error II**	**Error III**
LR	100	0	0	0
WNN	91.67	0.0833	0.2887	0.0833
Saudi Companies				
N-1				
	Accuracy	**Error I**	**Error II**	**Error III**
LR	100	0.0167	0.0409	0.0017
WNN	66.67	0.3333	0.5774	0.3333
N-2				
	Accuracy	**Error I**	**Error II**	**Error III**
LR	91.67	0.0972	0.2403	0.0577
WNN	83.34	0.1667	0.4082	0.1667

Source: prepared by the authors.

We note from Table 10 that the LR model was able to outperform the WNN model in predicting financial distress a year before its occurrence, and the same for predicting financial distress two years before its occurrence for both Algerian and Saudi companies.

Achieving 100% a year before and two years before financial distress occurrence for LR is expected because of achieving an overall classification accuracy of 100%. As we note, this matter is limited to LR's results for the Algerian companies only, as for its results regarding Saudi companies are completely different and less accurate.

Furthermore, WNN was unable to achieve full classification accuracy. Therefore, the results of LR are logical, and adopting the Stepwise Conditional method led to achieving this, and the few number of financial cases is not limited to LR only, but also to WNN. If LR can achieve full classification accuracy, why could not ANN? Thus, the strength of LR in predicting financial distress can be confirmed. Its classification accuracy will certainly decrease if the number of cases increases, but it will achieve better results than the WNN in all cases.

5. CONCLUSION

After addressing the various theoretical aspects surrounding the topic of predicting financial distress, the ability of the LR model to accurately predict financial distress in both Algerian and companies was tested compared to the WNN model, whereby many valuable results were reached. The study results proved that the LR model is the optimal model for predicting financial distress in both countries.

However, the WNN model achieved suitable results in predicting financial distress one year before its occurrence for the Algerian companies, but it failed in predicting distress two years before its occurrence. The opposite was correct for Saudi companies.

For the Algerian companies, LR model achieved very appropriate results that serve the required objective in a very significantly, as it achieved results that are completely devoid of error rates and are fully consistent with the companies actual financial status, whether it was

when predicting the financial distress, a year before its occurrence or two years before. Its results were less accurate for Saudi companies.

Contrary to what was expected, the LR model overwhelmingly outperformed WNN model in terms of classification accuracy. Although the LR model is a statistical model, this did not prevent it from achieving impressive results compared to the contemporary Artificial Intelligence model.

We previously mentioned that the small sample will certainly affect the reliability of the results, especially since the LR achieved a full classification accuracy for the Algerian companies, thus increasing the degree of uncertainty. In addition to the fact that this model is uncommonly used with regard to the few number of cases. It should be noted that the researchers' objective was to achieve maximum classification accuracy, whether for LR or WNN, and it was possible to avoid achieving full classification accuracy and choose another method than the Stepwise Conditional method to create the LR model.

On the other hand, its inability to achieve full classification accuracy for the Saudi companies led to making the LR results for the Algerian companies seem more logical. The WNN's less accurate results are further evidence.

We conclude that the reputation of the Artificial Neural Network in terms of its accurate classification ability did not help it to outperform the statistical model. However, this particular type of Neural Network is probably not compatible with the predicting financial distress requirements, and there are certainly more suitable types.

Besides these valuable results, the study presents few limitations. For example, other types of Artificial Neural Networks should be used to compare with Logistic regression model. On the other hand, it was possible to try other methods for creating LR and compare them with the Stepwise Conditional method. The analysis could be extended to a larger sample of companies from more countries. Therefore, future studies in this field could consider alternative methods and firms from more countries.

REFERENCES

Altman, E. (1968). Financial ratios, discriminant analysis, and the prediction of corporate bankruptcy . *Journal of Finance, 23*(4), 589-609.

Angel, M., Gámez, G. G., José, A., & Ruiz, C. (2016). Applying a probabilistic neural network to hotel bankruptcy prediction. *Tourism & Management Studies, 12*(1), 40-52.

Bayraci, S., & Susuz, O. (2019). A Deep Neural Network (DNN) based classification model in application to loan default prediction. *Theoretical and Applied Economics, XXVI*(4 (621)), 75-84.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research, 4*, 71-111.

Bonello, J., Bredart, X., & Vella, V. (2018). Machine Learning Models For Predicting Financial Distress. *Journal of Research in Economics*(2), 174-185.

Callejón, A., Casado, A., Fernández, M., & Peláez, J. (2013). A System of Insolvency Prediction for industrial companies using a financial alternative model with neural networks. *Int. J. Comput. Intell. Syst, 6*(1), 29-37.

El-Bannany, M., Sreedharan, M., & Ahmed, M. (2020). A Robust Deep Learning Model for Financial Distress Prediction. *International Journal of Advanced Computer Science and Applications, 11*(2), 170-175.

Hardinata, L., & Warsito, B. S. (2018). Bankruptcy prediction based on financial ratios using Jordan Recurrent Neural Networks: a case study in Polish companies. *Journal of Physics, 1025*(1), 1-6.

Kapil, S., & Agarwal, S. (2019). Assessing Bankruptcy of Indian Listed Firms Using Bankruptcy Models. Decision Tree and Neural Network . *International journal of business and economics, 4*(1), 112-136.

Mousavi, S., Amini, M., & Raftar, M. (2012). Data mining techniques and predicting corporate financial distress. *Interdisciplinary Journal of Contemporary Research in Business*, *3*(12), 61-68.

Ohlson, A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, *18*(1), 109–131.

Osho, A., & Idowu, A. (2018). Relevance of Accounting Theory in Forecasting Techniques and Default Prediction in an Organization in Nigeria. *European Journal of Business and Management, 10*(29), 116-129.

Ribeiro, B., Silva, C., Vieira, A., & Gaspar-Cunha, A. :. (2010). Financial distress model prediction using SVM+. *The 2010 International Joint Conference on Neural Networks (IJCNN)*, (pp. 1-7).
Sabek, A. (2023). Unveiling the diverse efficacy of artificial neural networks and logistic regression: A comparative analysis in predicting financial distress. *Croatian Review of Economic, Business and Social Statistics (CREBSS), 9*(1), 16-32.

Sabek, A., & Horak, J. (2023). Gaussian Process Regression´s Hyperparameters Optimization to Predict Financial Distress. *Retos, Revista de Ciencias Administrativas y EconA3micas*, *13*(26), 273-289.

Sabek, A., & saihi, Y. (2021). Using Artificial Neural Network To Predict The Financial Distress: The Case Of Some Algerian Companies. *Journal of North African Economics,* *17*(3), 475-492.

Sudarsanam, S. (2016). A Fuzzy Neural Network Model for Bankruptcy Prediction. *Journal of Engineering Computers & Applied Sciences, 5*(6), 33-40.

Tang, Y., Ji, J., Zhu, Y., Gao, S., Tang, Z., & Todo, Y. (2019). A Differential Evolution-Oriented Pruning Neural Network Model for Bankruptcy Prediction. *Complexity, 2019*, 1-21.

Xie, C., Luo, C., & Yu, X. (2011). Financial distress prediction based on SVM and MDA methods: the case of Chinese listed companies. *Quality and Quantity: International Journal of Methodology*, *45*(3), 671-686.